Transfer and Evaluation of Decentralized Reactive Swing-Leg Controls for Powered Robotic Legs

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1 Introduction

Animals and legged robots balance dynamically by placing their feet into proper ground targets [1], which can be identified with simple locomotion models [2][3]. Commonly, fully robotic systems realize identified foot placements using inverse dynamics and kinematics [4], which requires a high-fidelity system model and accurate estimate of a robot's full state, whereas human-in-the-loop applications rely on extensive motion libraries extracted from healthy human gait [5]. Both approaches may fail in highly dynamic situations, such as trips when encountering unexpected obstacles.

Heuristic controllers based on simple locomotion models represent alternative control approaches for legged robotic systems. We recently proposed a swing-leg controller based on double pendulum dynamics [6], which allows an ideal frictionless pendulum simulation to place its feet into ground targets, formulated as a desired landing angle, for a wide range of initial conditions and in the presence of significant locomotion disturbances. While the controller's performance in simulation makes it an attractive candidate to control legged robots, it is unclear if the approach can be used on real-world systems. We here present work to transfer and evaluate this swing-leg controller on robotic hardware.

2 Approach & Results

The approach proposed in [6] is implemented on our hardware platform Robotic Neuromuscular Leg 2 (RNL2), a dynamically scaled, antagonistically actuated robotic leg with joint compliance. The robot's size, weight, and actuation requirements are based on dynamically scaled segment masses, lengths, and capabilities of virtual muscles in a planar, muscle-reflex based walking model [7][8]. A high-fidelity simulation that models the robot at the individual component level is used to transfer the swing-leg controller to hardware. It serves as a tool to evaluate if the controller can be applied to robotic systems and how specific control components need to be implemented to account for hardware constraints.

The controller's ability to regulate foot placements on robotic hardware is evaluated with two sets of experiments. Undisturbed motion experiments (Fig. 1) test the controller's ability to place feet into desired ground targets for unimpeded swing. Disturbed motion experiments simulate tripping and test the controller's ability to place feet into desired ground targets when the robot encounters an unexpected obstacle, which applies an impulse to the ankle, in early, mid, or late swing (Fig. 2).

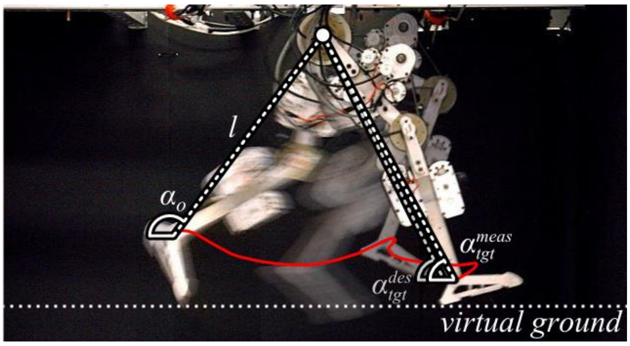

Fig. 1. Swing-leg control experiment. The controller issues joint torque commands to regulate the length *l* of a single segment virtual leg between the robot's hip and ankle, moving it from an initial position α_0 to a target position α_{tgt} when making contact with a virtual ground (dotted). Solid: Trajectory traced out by the ankle point during experiment.

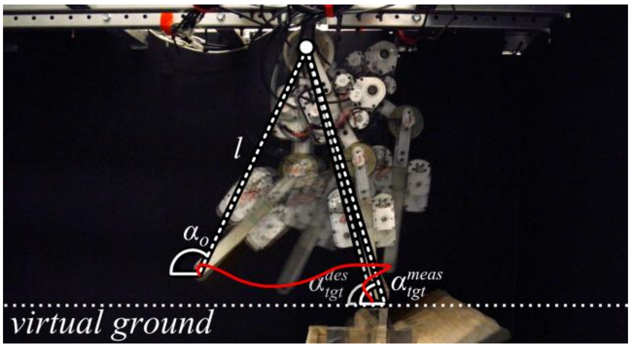

Fig. 2. Example disturbed swing-leg control experiment. Shown: α_{tgt} = 70deg, late disturbance.

TABLE I
MEAN PLACEMENT ERROR FOR α_{TGT} RANGE: 65DEG TO 85DEG

Disturbance	None	Early	Mid	Late
Ideal Sim.	-1.47±0.61	-3.79±0.30	-4.27±0.55	-5.90±0.85
RNL2 Sim.	1.17±0.68	1.24±1.61	1.40±1.39	1.26±1.08
RNL2 Hrdw.	1.17±3.69	-2.70±4.33	-1.49±3.73	-3.51±3.37

In both simulation and hardware, RNL2 places feet with comparable accuracy to the ideal double pendulum for all tested conditions (Tab. I), suggesting that the controller can accurately regulate foot placement of robotic legs. Hardware mean placement error either improves or is within the standard deviation of the ideal double pendulum simulation for all tested conditions. Furthermore, foot point trajectories traced out by the controller during experiments (Fig. 3) suggest that the controller makes the

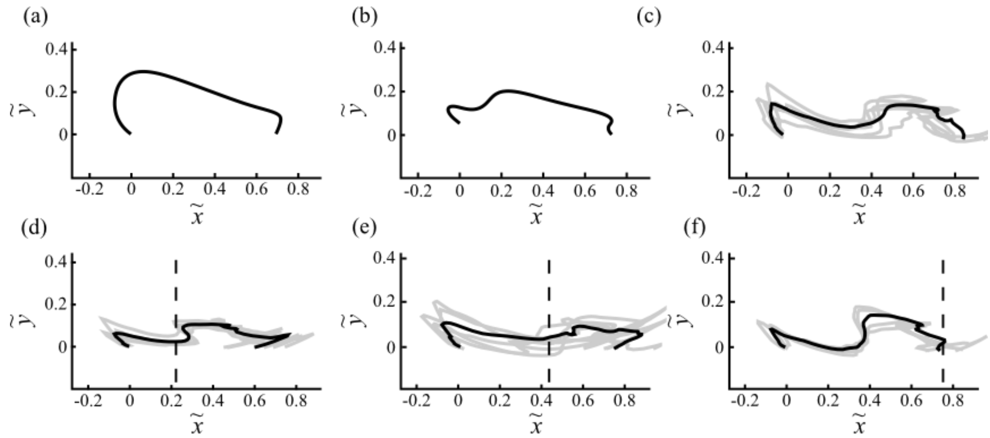

Fig. 3. Foot point trajectories of α_{tgt} = 70deg experiments normalized by respective total leg length (x,y). Disturbance type noted in parentheses. Black: Mean trajectories. Gray: Individual trials. Dashed: Obstacle location. (a) Ideal double pendulum (none) (b) RNL2 sim. (none) (c) RNL2 hrdw. (none) (d) RNL2 hrdw. (early) (e) RNL2 hrdw. (mid) (f) RNL2 hrdw. (late)

TABLE II
MEAN SWING TIME IN MS FOR α_{TGT} RANGE: 65DEG TO 85DEG

Disturbance	None	Early	Mid	Late
Ideal Sim.	394±5	529±3	593±6	516±86
RNL2 Sim.	328±9	366±14	356±25	334±13
RNL2 Hrdw.	481±102	640±103	583±129	546±70

robot execute a human-like foot elevation strategy when encountering obstacles in early swing, indicated by the retraction of the foot point after obstacle collision [9].

While the foot placement accuracy in both the RNL2 simulation and hardware experiments is comparable to the accuracy of the ideal double pendulum simulation, the foot point height is less pronounced in both sets of RNL2 experiments (Fig. 3), and the hardware swing duration exceeds dynamically scaled goals (Tab. 2). This behavior is likely the result of the cost function used to tune the RNL2 simulation and hardware. Whereas ideal double pendulum controller gains were hand-tuned, the cost function used to tune the RNL2 gains did not include explicit terms to consider overall motion cosmesis or swing time.

Having validated that the swing-leg controller can be used to accurately regulate the foot placement of robotic legs, our immediate goal is to transfer the swing-leg controller's neuromuscular interpretation [10] to RNL2 to investigate benefits of multi-articulation for legged robotic systems. To capture the mechanical characteristics of muscle, we have developed a synthesis method for compact nonlinear springs with user defined torque-deflection profiles [11], which we are working on integrating into our robot's actuators.

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