Bouncing between Models and Data: Stability, Passivity, and Optimality in Hybrid Dynamics

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Abstract

Bouncing a ball with a racket is a simple task that poses **all the challenges of coordinative behavior**. Here we review our work over 15 years on this task exploring the principles of control via a sequence of **experimental and modeling studies**. The emphasis of our experimental work has been on **falsifying models** (Popper, 1959). We overview this research strategy by showing three models and their experimental falsification that have revealed control mechanisms of the central nervous system.

Popper, *The logic of scientific discovery*, Basic Books, 1959

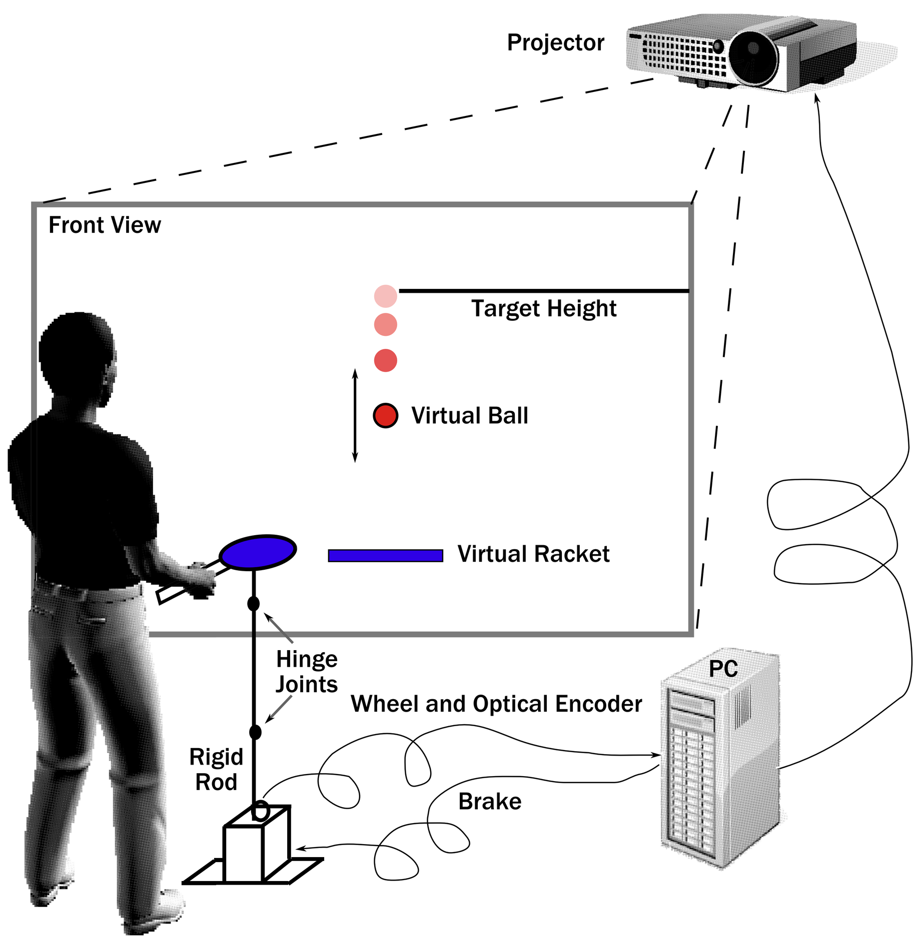
Setup and task

Task: steady-state bouncing to a fixed target height.

Two general assumptions:
- ball trajectory is ballistic;
- instantaneous impacts

Energy loss captured by coefficient of restitution α:

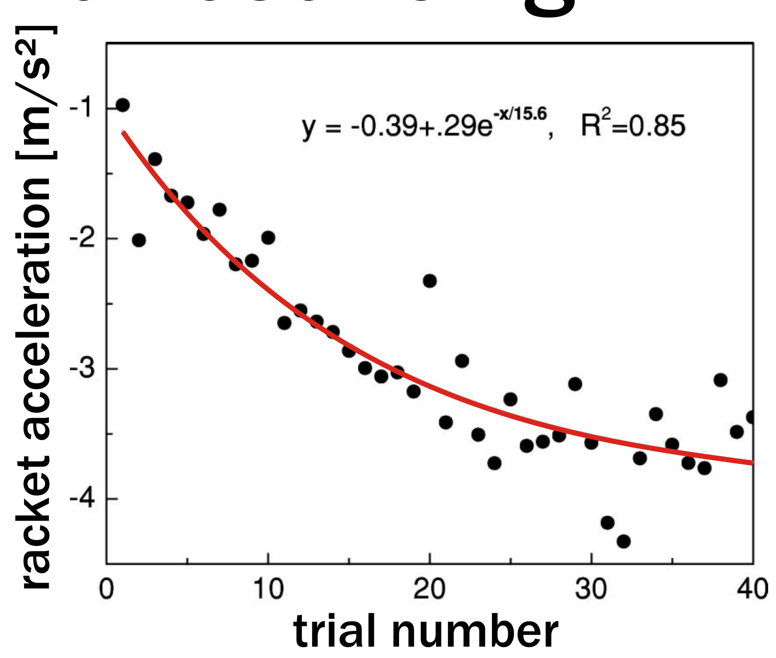
Δ velocity after impact $= -\alpha\ \Delta$ velocity before impact

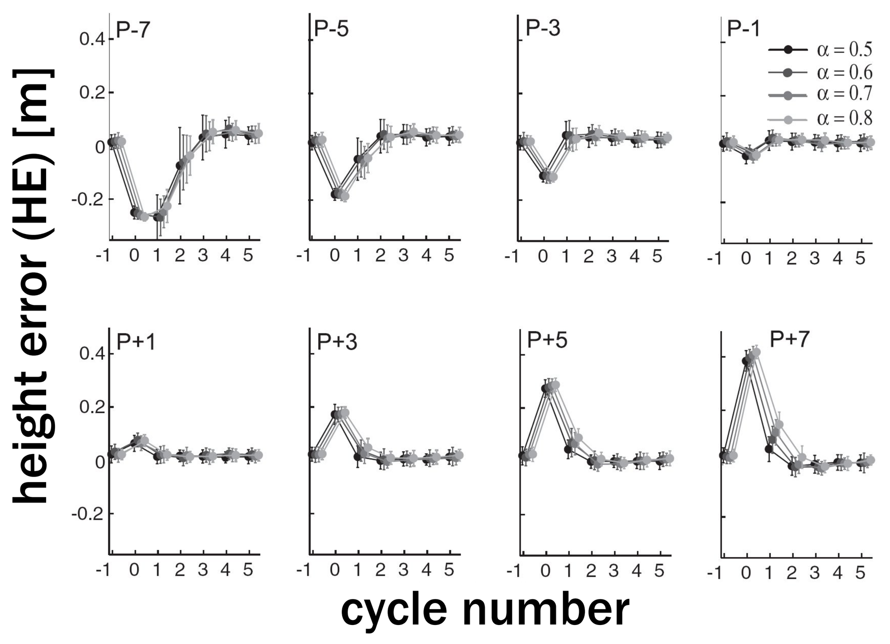


1. Passive model: "blind" bouncing

The movement is passively stable if the racket follows a (quasi-)sinusoidal trajectory and impacts the ball with **negative acceleration**. Humans rely on this passive stability.

Sternad et al., *Physical Review E*, 2001



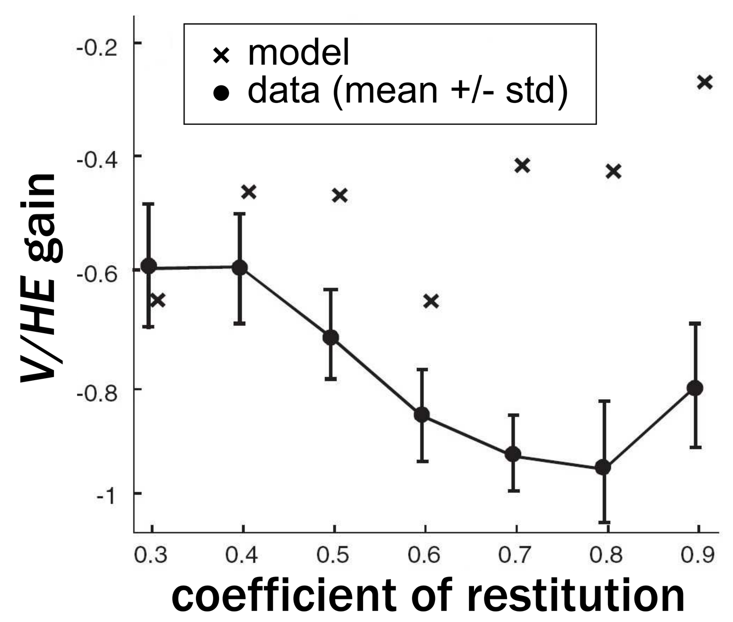


However, later studies found evidences of **active control**:
(1) experimentally applied perturbations were rapidly compensated with non-sinusoidal racket movements;

Wei et al., *J Neurophysiol*, 2007

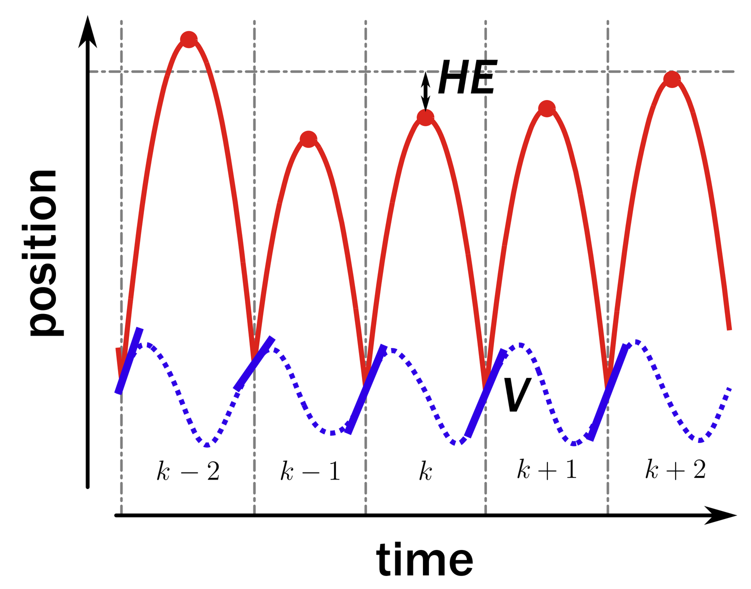
(2) during steady state, the correction between the height error and subsequent racket velocity at impact (*V/HE* gain) was larger than predicted by the model.

Wei et al., *J Neurophysiol*, 2008



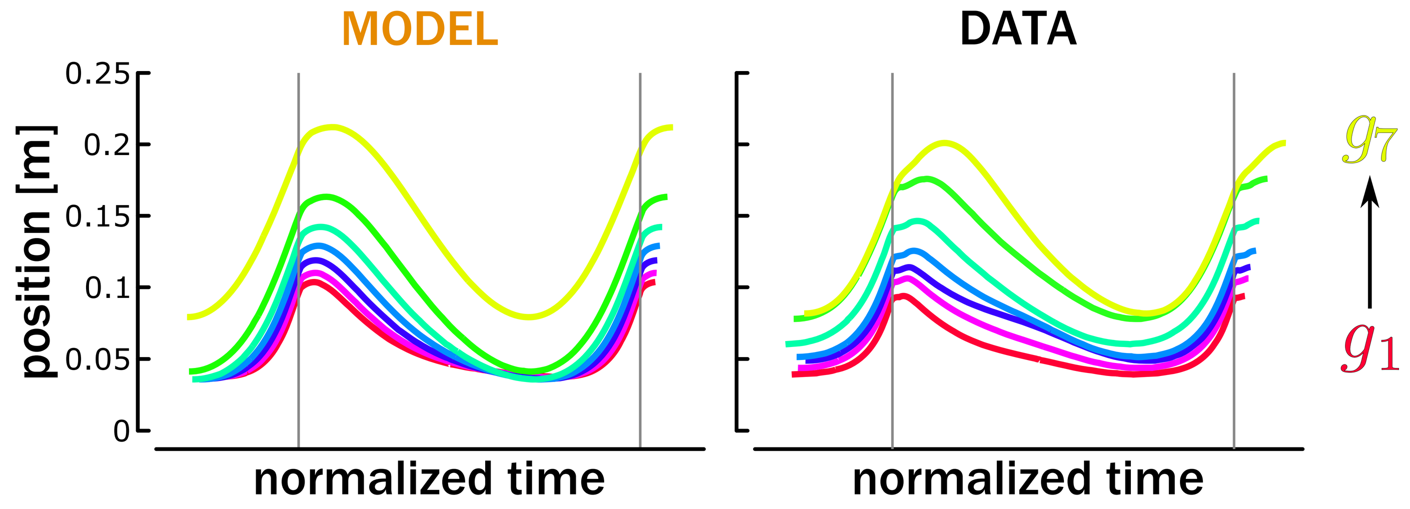
Conclusion 1: Humans tune into passive stability during steady state performance, but they do **NOT** rely on passive stability alone after perturbations.

2. Active model: bounce like you reach

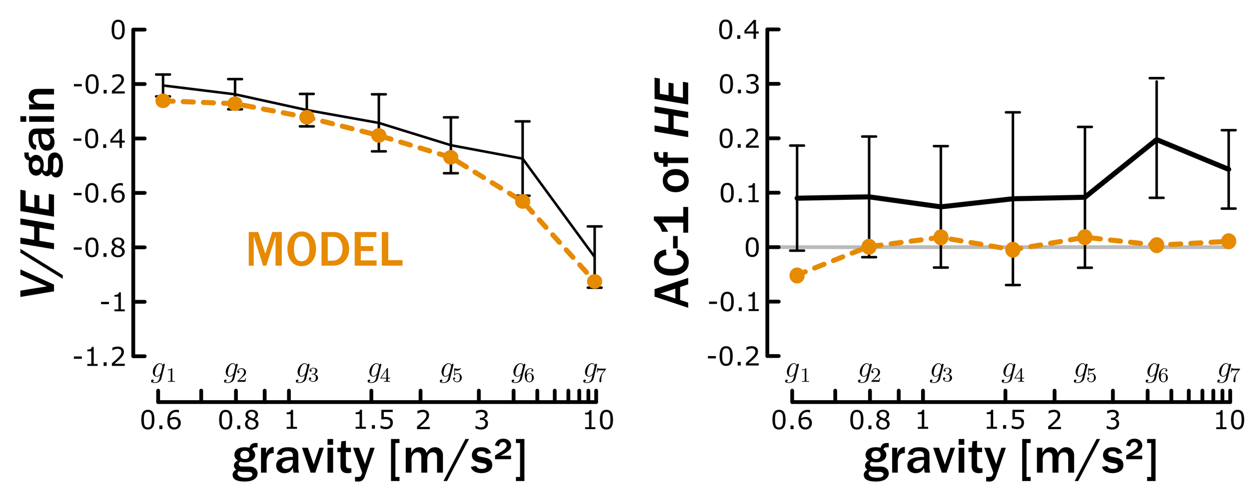


Ronsse et al., *J Neurophysiol*, 2010

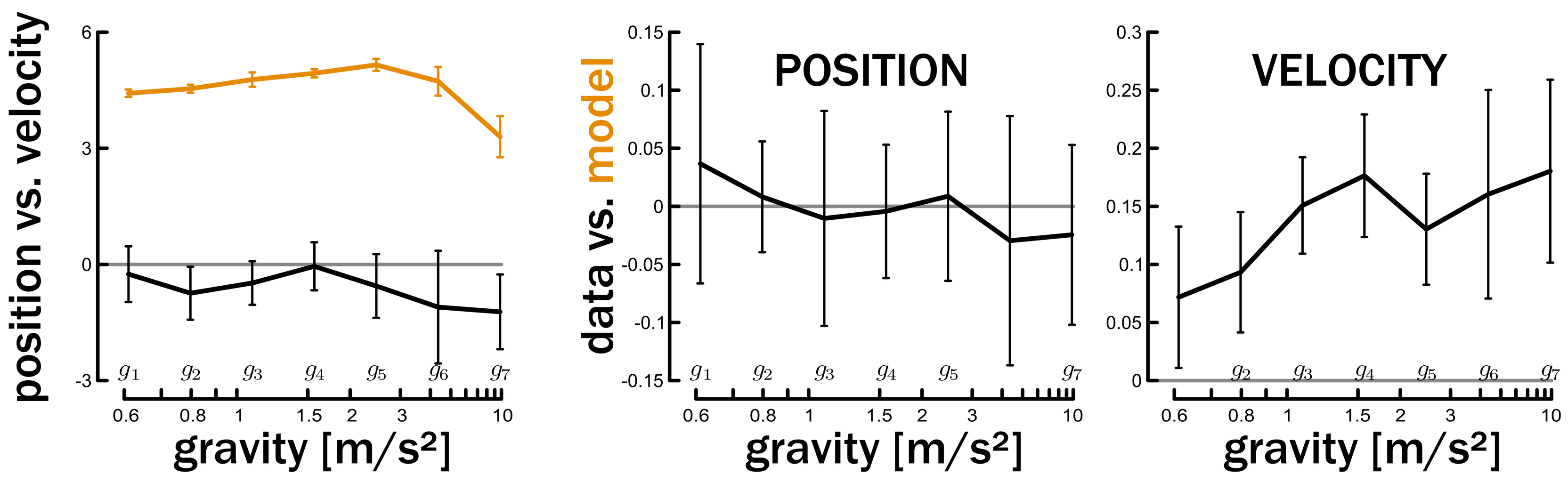
Test of a model for an active controller based on **stochastic optimal control** (applied to reaching tasks). Hybrid control:
- the model finds optimal racket position and velocity at impact (discrete layer);
- optimal control policy to reach this state (continuous layer);
- cost function that maximizes task reward, minimizes racket deviation from rest position, and control effort.



Predictions:
(1) **Intervals of near-zero velocity** (dwell times) for longer bouncing periods (smaller gravity acting on the ball).
(2) Autocorrelations of height error is **close to zero**, with **higher V/HE gains than in passive model**.
The data were consistent with these predictions.



Regression slope of the racket state (position/velocity) reached at each impact (data and active model):



To control the energy delivered to the ball, the active model relies on **position/velocity redundancy**: higher impact is equivalent to faster velocity at impact; BUT participants controlled only the racket velocity.

Conclusion 2: Humans perform racket trajectories with dwell times for longer periods. They do **NOT** reach the racket state predicted by the active model.

3. Model with different time scales

To deal with these findings, we propose a new hybrid (passive/active) model with **different time scales**:
(1) **Slow**: derivation of the "steady state" optimal gains - passive;
(2) **Middle**: calculation of the state to reach at impact - active;
(3) **Fast**: calculation of the racket control input - active.

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