Coordinating Muscles and Limbs for Postural Control in the Cat

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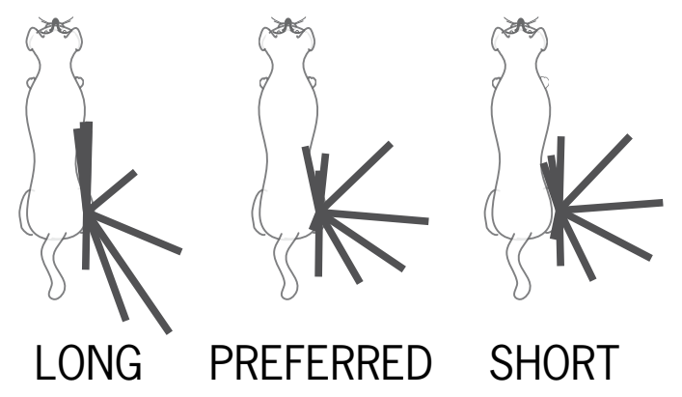
Introduction

A recent study from our laboratory demonstrated that muscle activity and force produced during the automatic postural response in cats can be decomposed into a small set of five underlying "functional muscle synergies" (Torres-Oviedo et al. 2006). Each functional muscle synergy specifies both a pattern of hindlimb muscle activation and a correlated "synergy force vector" at the ground. In particular, synergies from the control condition were sufficient to reproduce responses from other biomechanical configurations (anterior-posterior "stance distances").

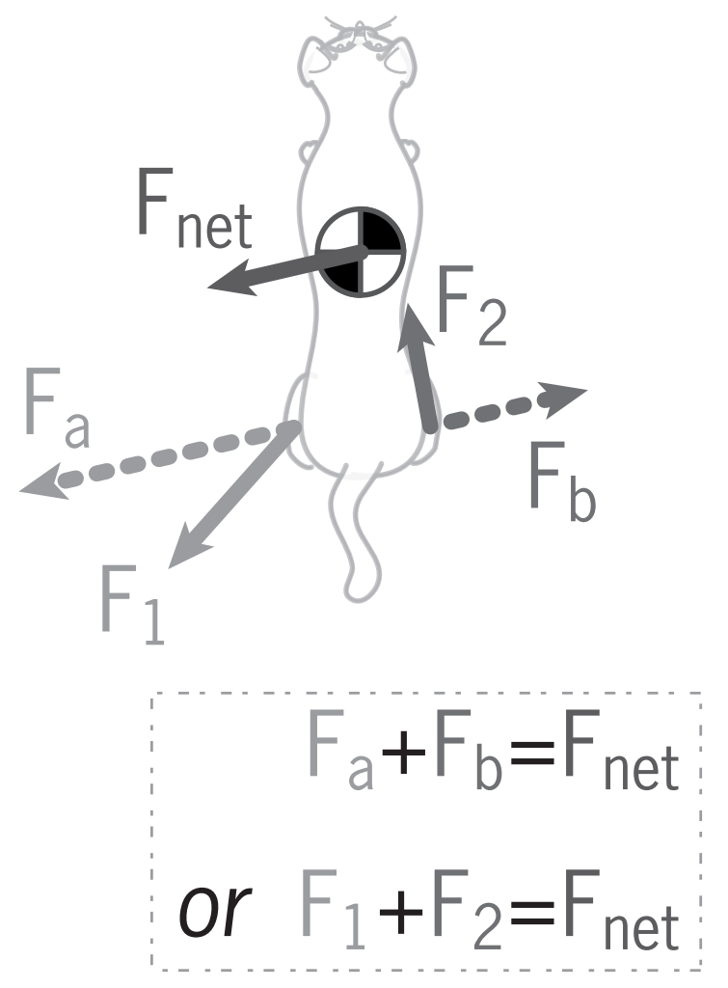


Forces produced at these different biomechanical configurations change systematically. At the self-selected "preferred" stance distance, forces are directed diagonally towards and away from the center of mass. At shorter stance distances, a wider range of force directions are observed. Here, we demonstrate that forces produced during the postural response cannot be predicted from biomechanical or energetic considerations alone. ***We hypothesized that the forces produced during postural response arise due to interlimb coordination of functional muscle synergies across the hindlimbs.*** Our results suggest neural mechanisms that coordinate redundant muscles and limbs determine postural forces.

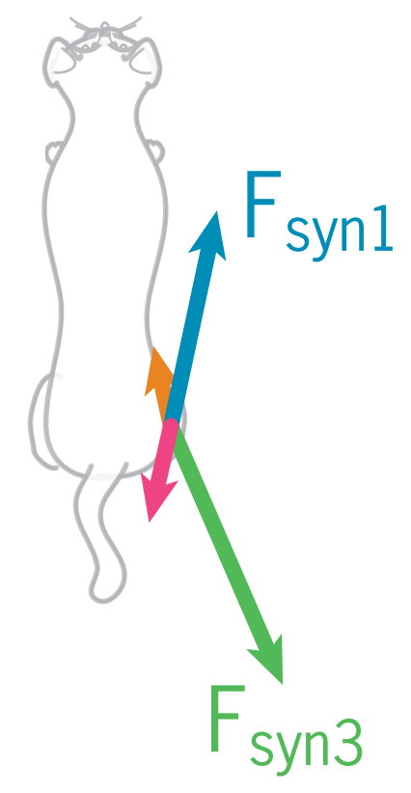
Methods

1. Propose two neural controllers to perform an idealized postural task

- Biomechanically redundant "task": generate a 1N net force with the hindlimbs.
  - Interlimb redundancy and muscular redundancy
  - Multiple possible coordination strategies
  - 12 horizontal plane directions
  - Several stance distances



- *A priori* information: "internal model" of the force produced by each synergy or muscle
  - One leg shown
  - Shadmehr and Mussa-Ivaldi 1994; Kawato 1999



- Hypothesized neural controllers: positive least-squares combination of 1) muscle synergy activation vs. 2) individuated muscle activation.
  - e.g., minimize "signal-dependent noise;" Harris and Wolpert 1998

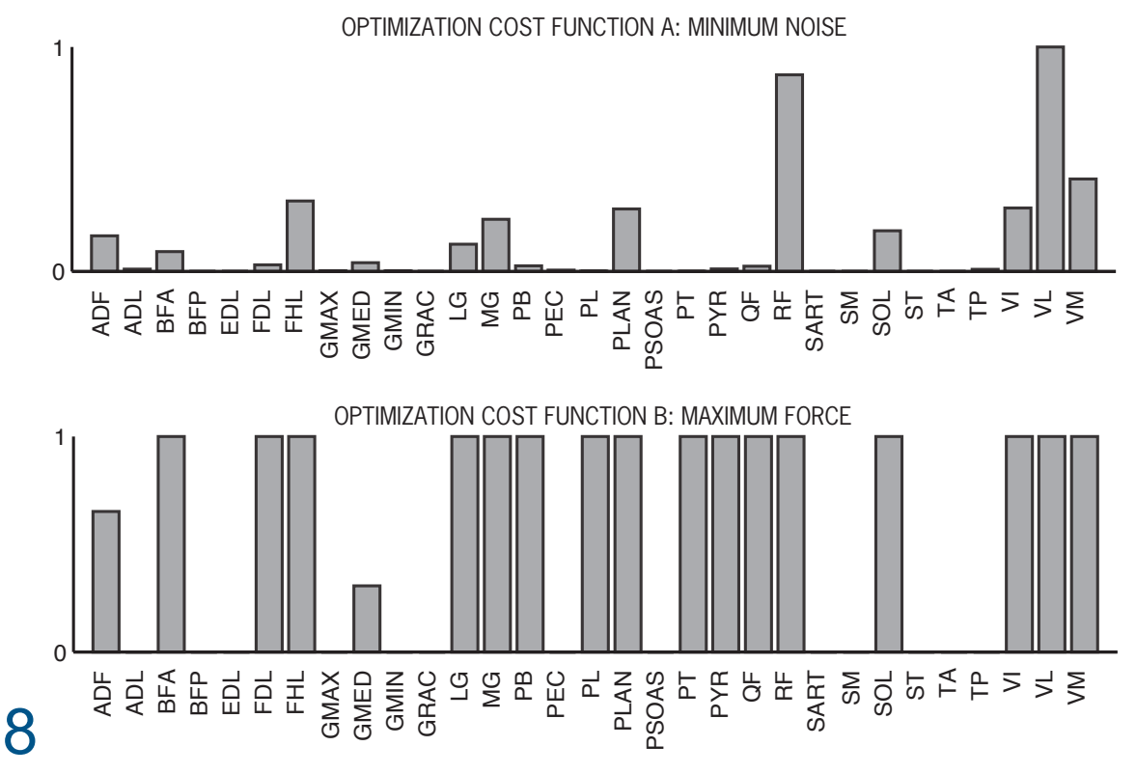
2. Apply the neural controllers to a 3D, static musculoskeletal model of the hindlimbs

- Relates muscle activation to endpoint force
- 62 muscles, 14 degrees of freedom at 6 anatomical joints
  - Burkholder and Nichols 2004; McKay et al. 2007
- Postures based on kinematic data of each cat in each stance distance.

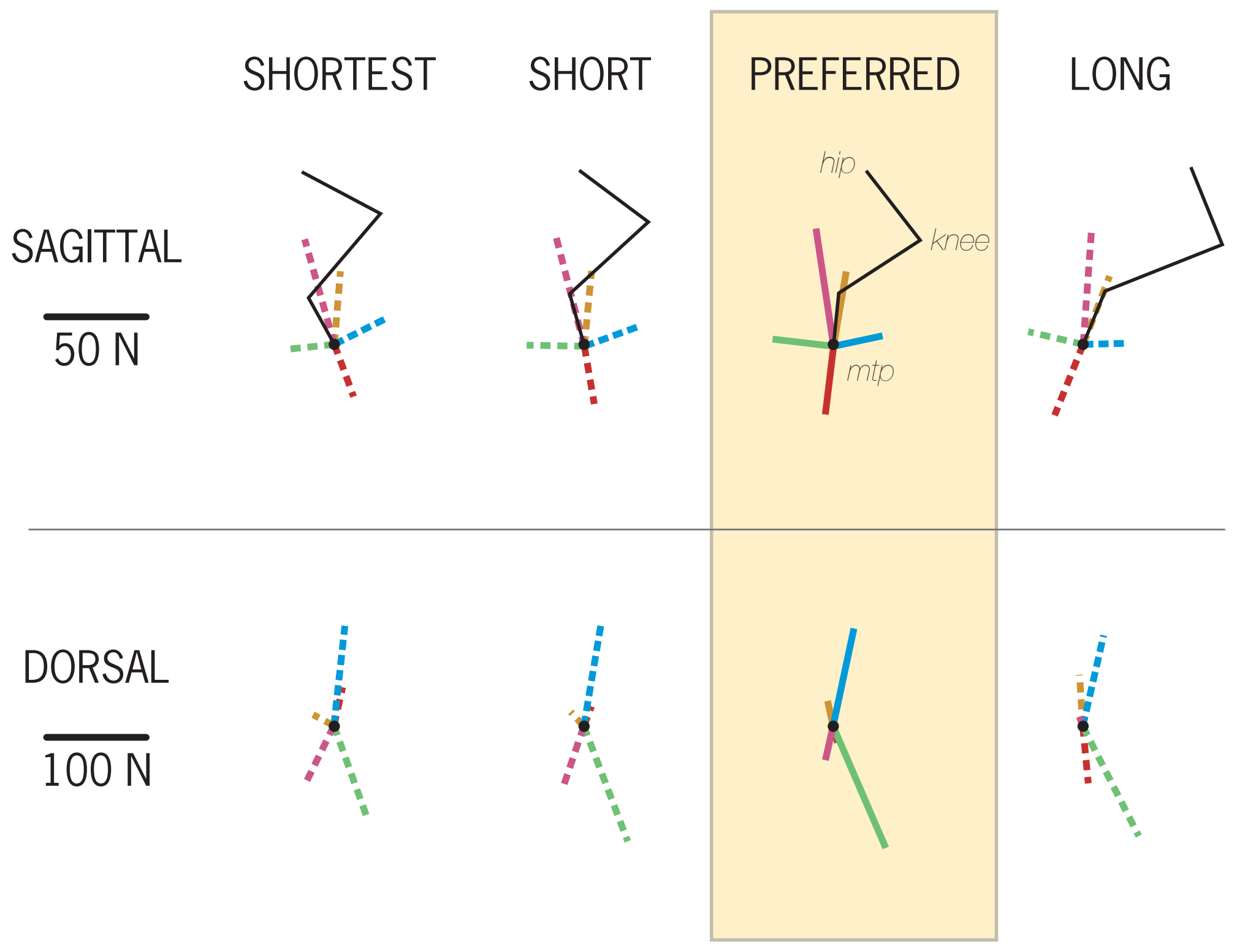
$$\vec{F}_R = \left(J_R\left(\vec{q}\right)^T\right)^+ R\left(\vec{q}\right) F_O F_{AFL}\left(\vec{q}\right)\vec{e}_R$$
$$\vec{F}_{NET} = \vec{F}_R + \vec{F}_L$$
$$0 \le e_i \le 1,\ i = 1,2,\ldots,N_{MUS}$$
$$\vec{e} = W\vec{c},\ \ 0 \le c_k,\ k = 1,2,\ldots,N_{SYN}$$

3. Synergy controller: muscle patterns are optimal combinations of synergies

- Minimize total synergy activation while achieving the postural task, F_{net}.
- Calculate muscle synergies numerically based on experimentally-measured synergy force vectors
- Cross-validate results with two different criteria
  - "Minimum-noise" Harris and Wolpert 1998
  - "Maximum-force" Valero-Cuevas et al. 1998



- Resulting synergy force vectors rotate with limb axis, as predicted by Torres-Oviedo et al. (2006)
  - McKay and Ting *in review*

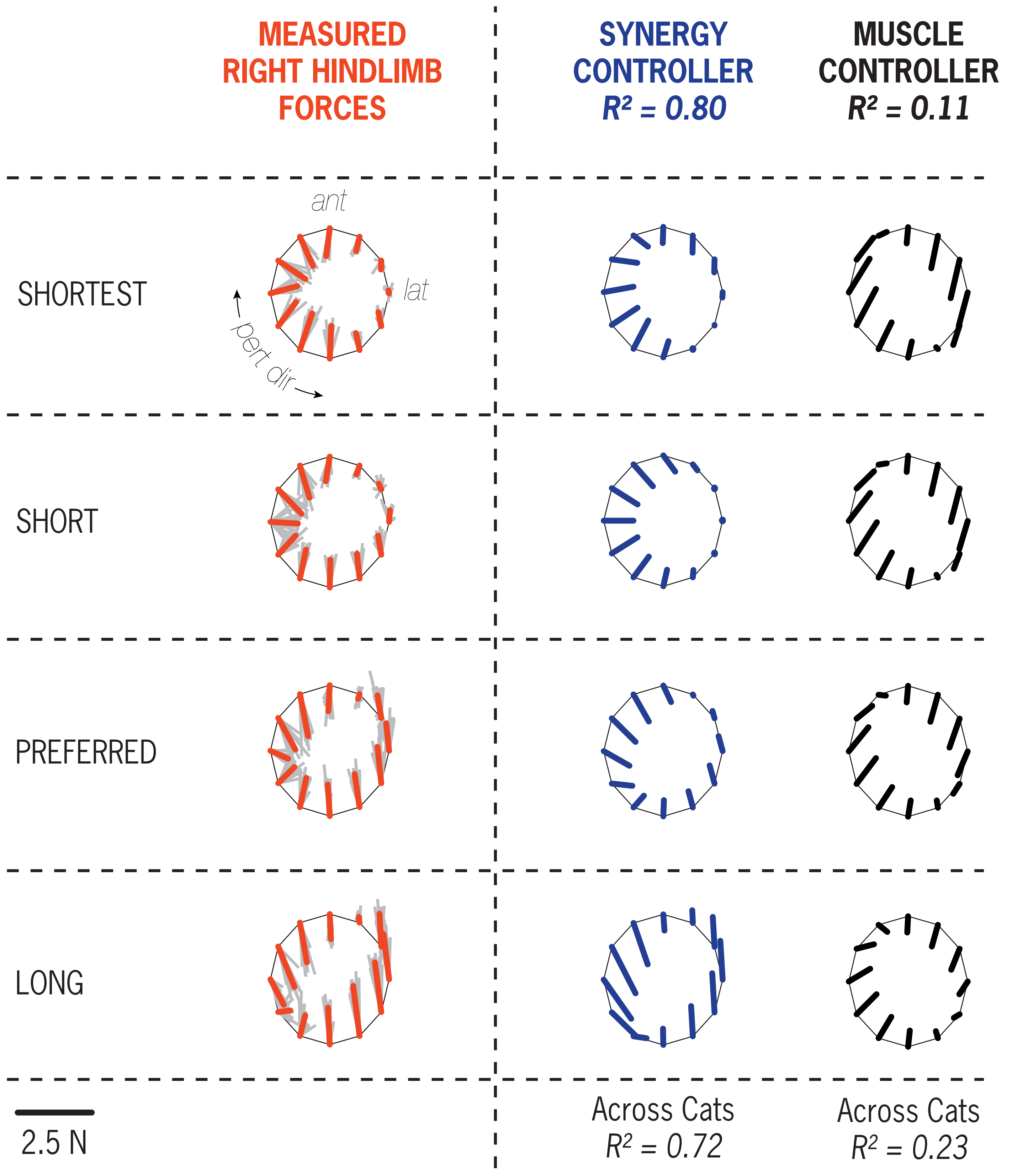


Source Data

4. Muscle controller: muscle patterns based on minimizing energetic expenditure

5. Compare predicted force patterns to experimentally-measured postural forces.

Results



Synergy Controller

- **Predicts average postural forces well** in all postural configurations and perturbation directions, particularly Long stance.
- Predicts changes with stance distance associated with "force constraint" behavior.
- Regions where the limb is not used are also predicted (i.e., directly lateral in Shortest stance)

Muscle Controller

- **Predicts average postural forces poorly** throughout the workspace.
- Predicts little or no change with stance distance.
- Predicts "opposite" diagonal axis in Shortest stance - a fundamentally different postural strategy.

Interpretation

- Muscle activation patterns, force coordination patterns are not completely determined by task mechanics – different neural coordination strategies result in markedly different coordination patterns.
- Is the synergy coordination strategy non-"optimal?"
  Optimally coordinating synergies results in more energetic expenditure than optimally coordinating muscles. Is there a cost for control?
- What is the role of homeostatic mechanisms?
  Should the synergy coordination solution converge to the muscle coordination optimum, e.g., Hoyt and Taylor 1981?
- Proprioceptive reference frames for sensory information may underlie synergy organization.
  Length and orientation of the limb are important variables (Bosco et al. 2000); synergy force vectors are fixed in this frame and may aid in computation.

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