Spinal cord plasticity "solves" the sensorimotor loop

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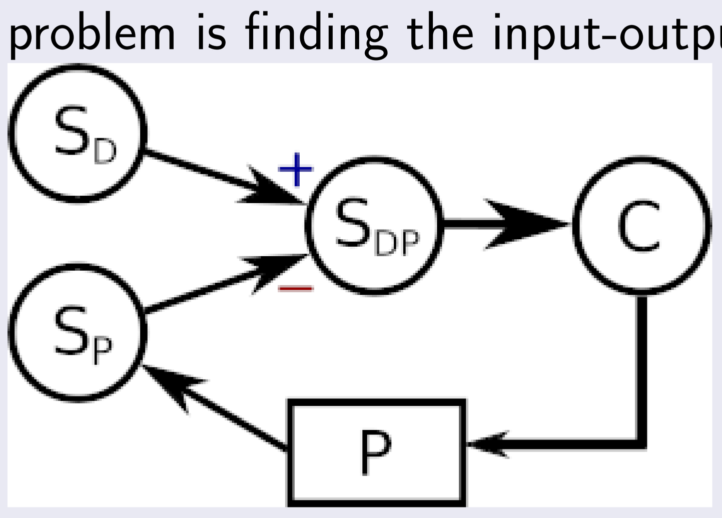
Introduction

- Mounting evidence shows that long-term spinal cord plasticity is involved in learning even simple behaviors.
- Corticospinal connections mainly target interneurons (not motoneurons).
- Plasticity in the spinal cord must coordinate with cortical plasticity.
- This is a big gap in our understanding of the sensorimotor loop.

A differential Hebbian learning framework

We developed a biologically-plausible motor control framework based on differential Hebbian learning.

- In a MIMO feedback control system a central problem is finding the input-output structure



- C contains N neurons with activity vector $\mathbf{c} = [c_1, \dots, c_N]$. The input to each of these units is an M-dimensional vector $\mathbf{e} = [e_1, \dots, e_M]$. Each unit in C has an output $c_i = \sigma\left(\sum_j \omega_{ij} e_j\right)$, where $\sigma(\cdot)$ is a positive sigmoidal function. The inputs are assumed to be errors, and to reduce them **we want e_j to activate c_i when c_i can reduce** e_j. One way this could happen is when the weight ω_{ij} from e_j to c_i is proportional to the negative of their sensitivity derivative:

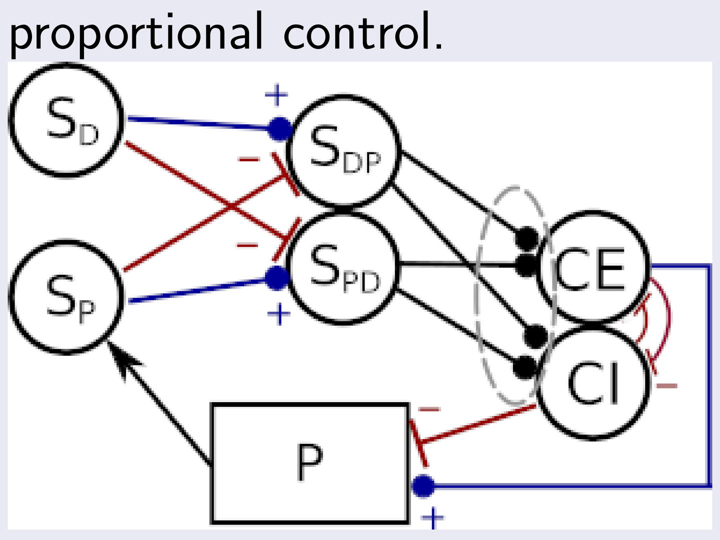
$$\omega_{ij} \propto -\frac{\partial e_j}{\partial c_i}.$$

- In turn, sensitivity derivatives can be approximated through a synaptic learning rule with 4 main characteristics:
  1. Obtains the correlation between input and output derivatives
  2. Incorporates time delays
  3. Heterosynaptic competition
  4. Weight normalization (sum of weights stays constant)

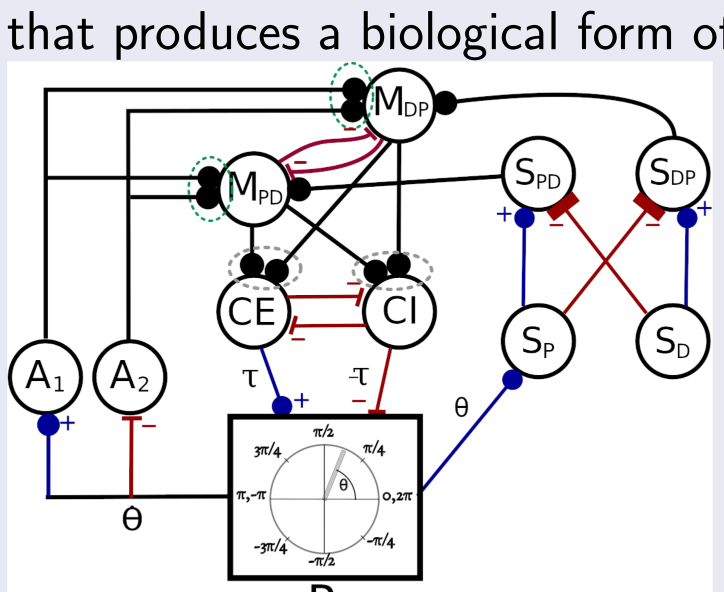
$$\dot{\omega}_{ij}(t) = -\left(\ddot{e}_j(t) - \langle \ddot{e}(t) \rangle\right)\left(\dot{c}_i(t-\Delta t) - \langle \dot{c}(t-\Delta t) \rangle\right),$$

where $\langle \ddot{e} \rangle \equiv \frac{1}{N_M}\sum_k \ddot{e}_k$.

- Along with this rule we use a biologically plausible network that performs closed-loop control. The result is a self-configuring MIMO proportional control.



- Proportional control can be unstable in a system with delays. Inspired by the long-loop reflex, we introduce a network architecture that produces a biological form of PD control.



Control of simple systems

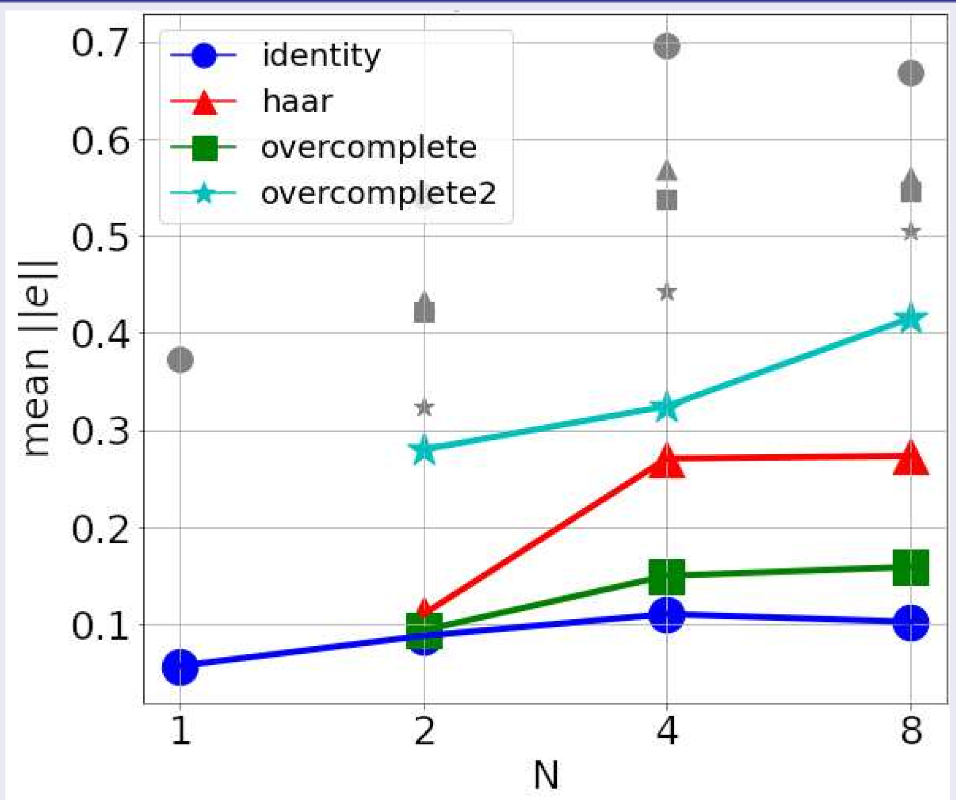


Figure: Linear redundant MIMO systems

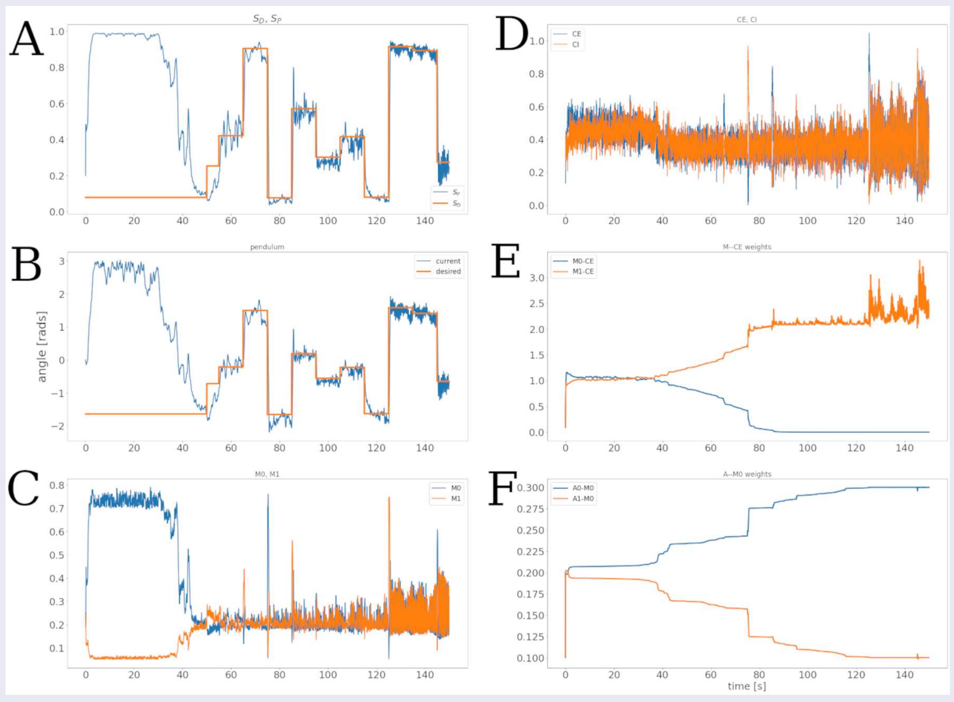
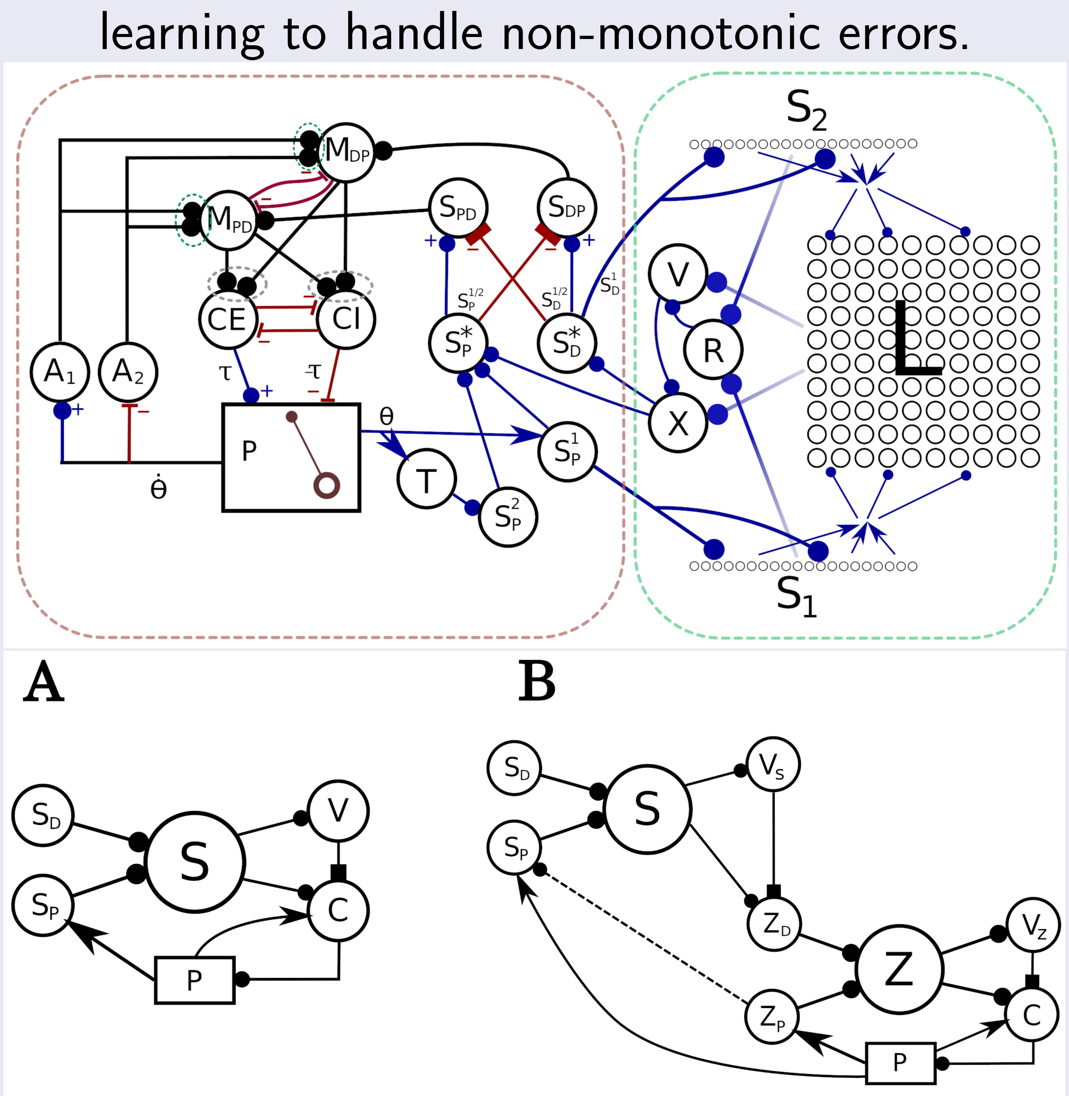


Figure: Pendulum control

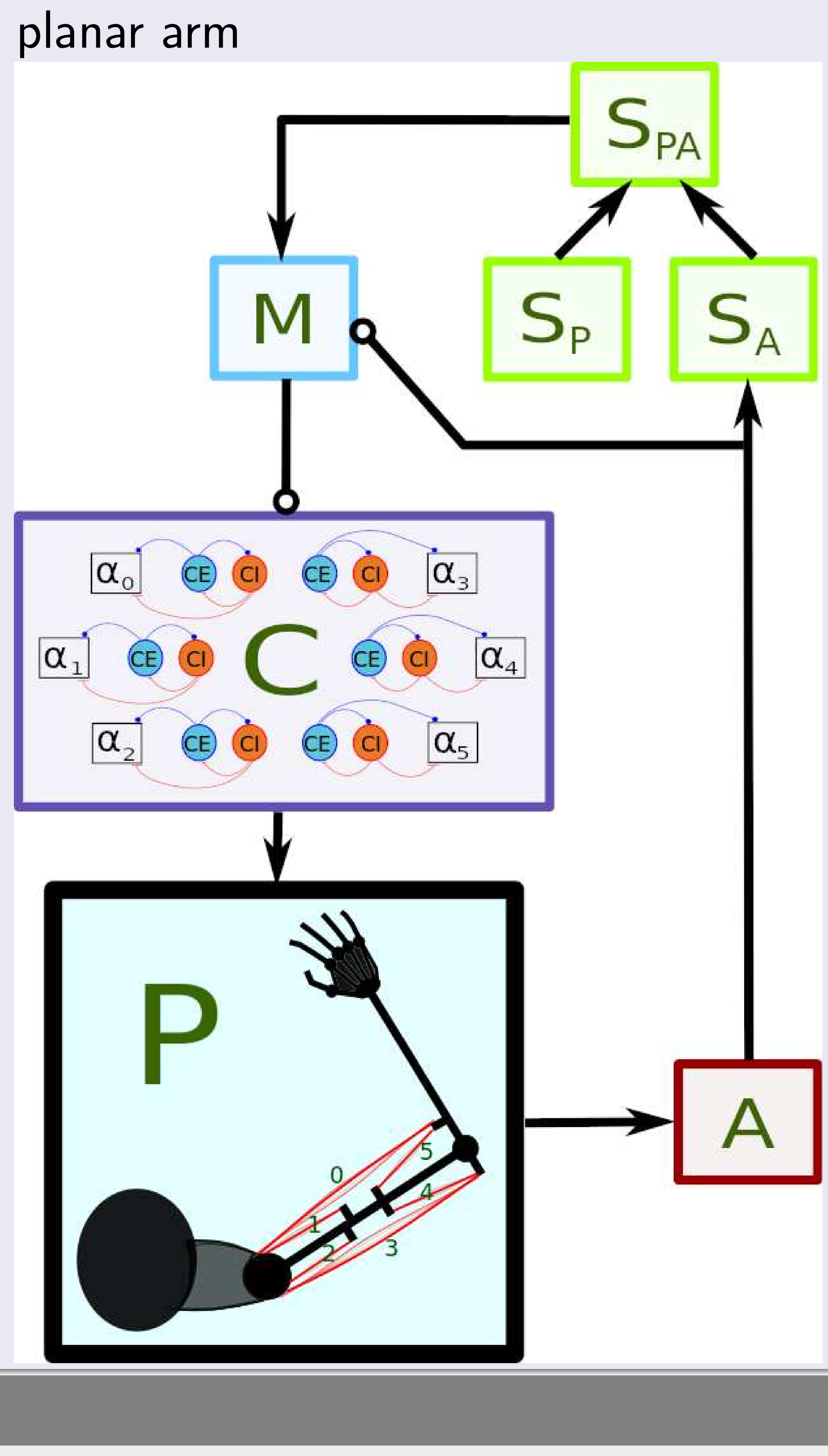
Non-monotonic control

The basic framework can incorporate reinforcement learning to handle non-monotonic errors.

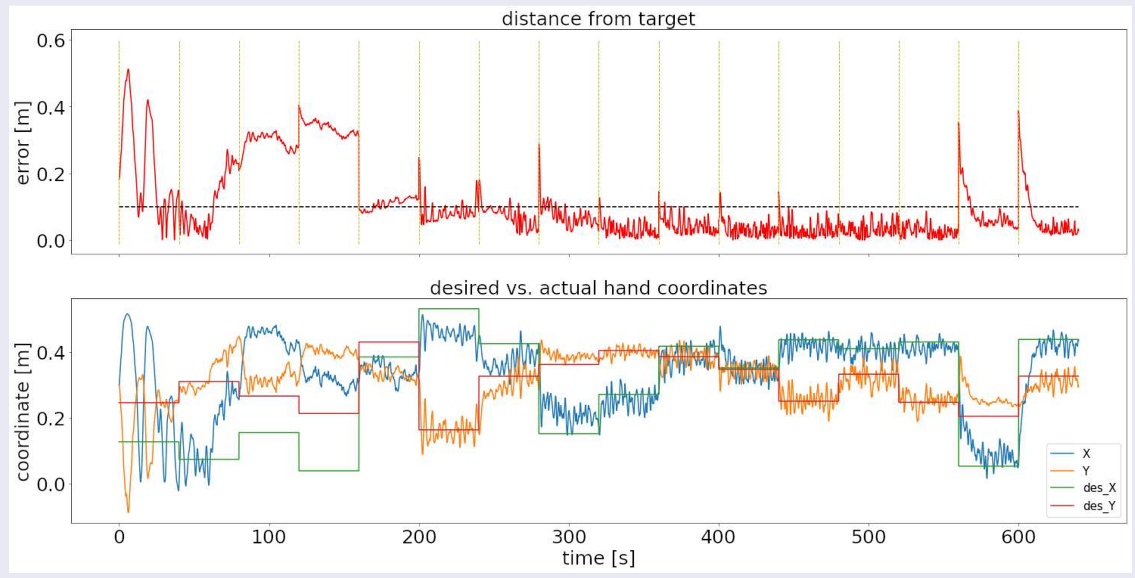


Planar arm control

The framework was also applied for the control of a realistic planar arm

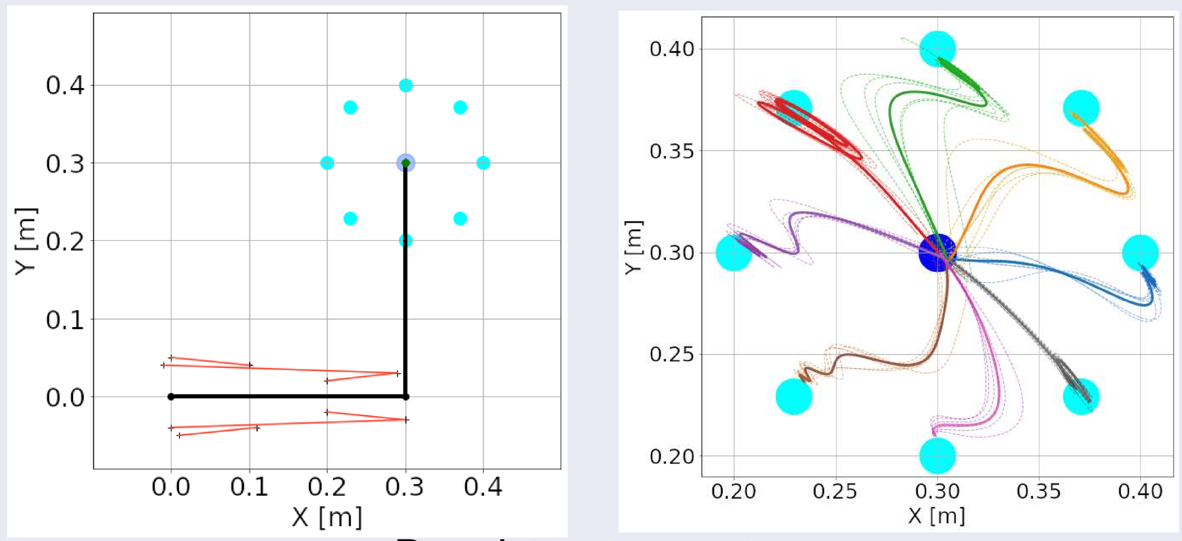


Learning to reach

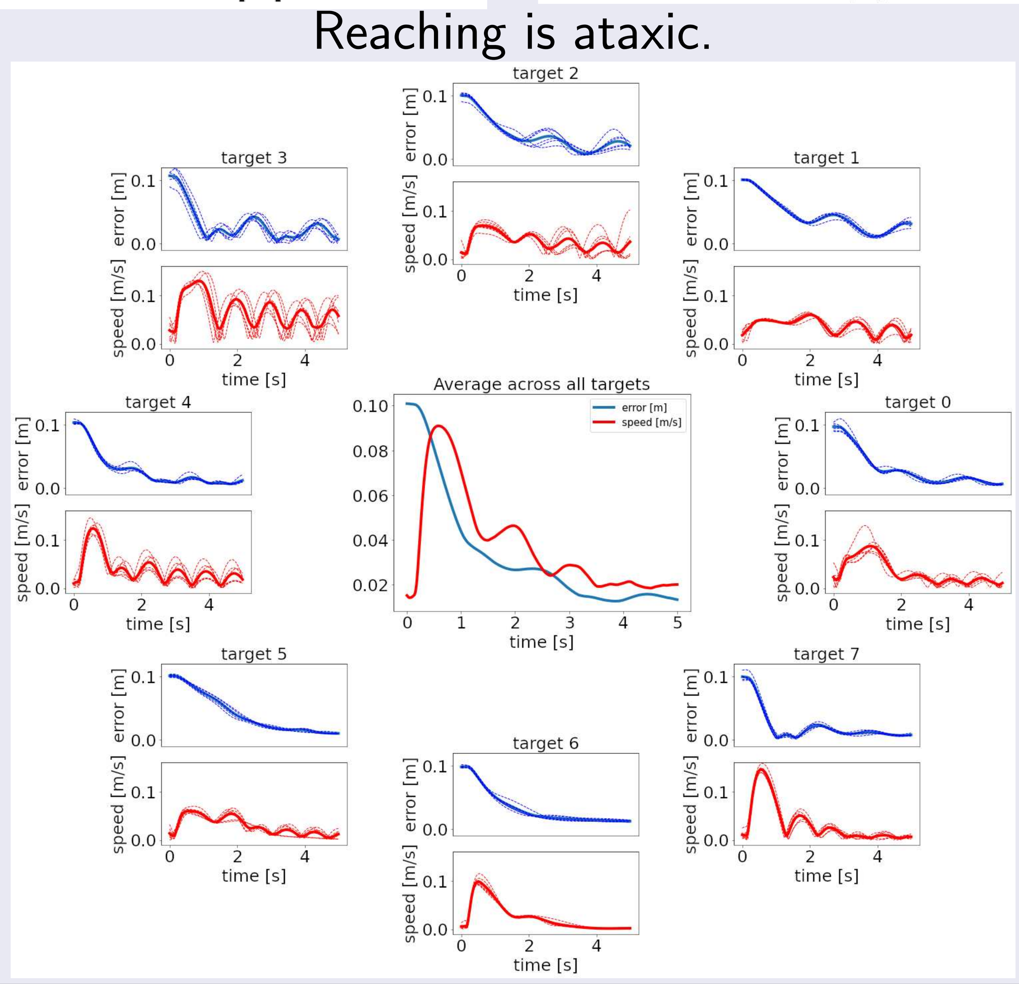


α units may also stimulate 2 muscles (synergies)

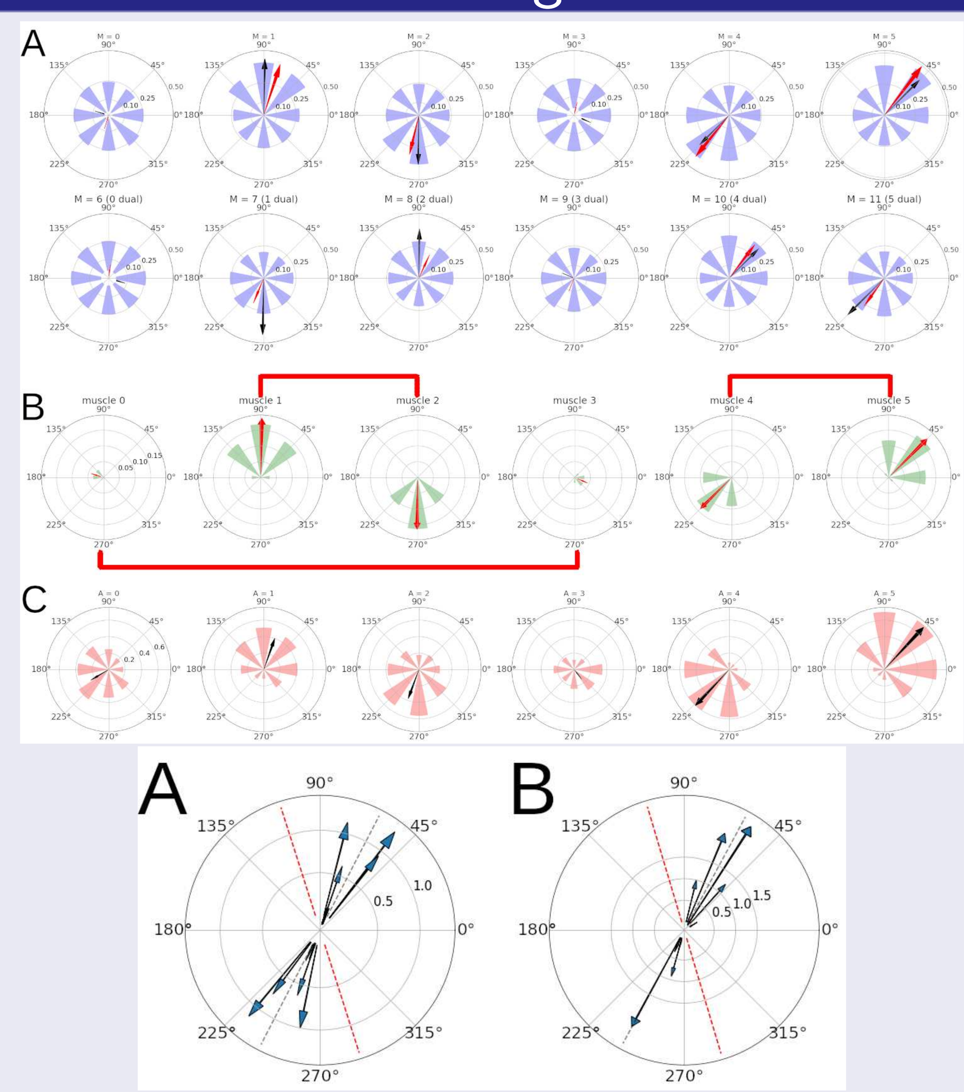
Planar arm reaching



Reaching is ataxic.



Preferred direction tuning



Additionally, PD vectors drift, and motor cortex activity shows rotational dynamics.

Convergent force fields