From neurons to muscles: virtual musculoskeletal arm driven by sensorimotor cortex model

SUNY Downstate Medical Center

NEUROSIM LAB

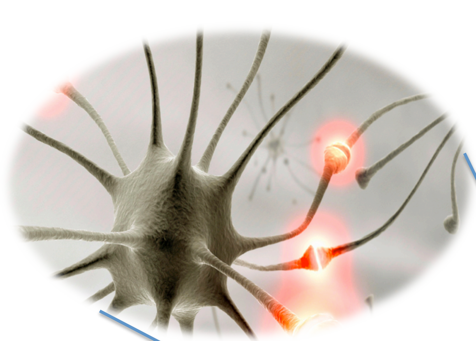
Salvador Dura-Bernal[1], Xianlian Zhou[2], Samuel A Neymotin[1], George L Chadderdon[1], Andrzej Przekwas[2], Joseph T Francis[1], William W Lytton[1,3]

[1] SUNY Downstate, Brooklyn, NY; [2] CFD Research Corp; [3]Kings County Hospital, Brooklyn, NY

CFDRC Delivering Breakthrough Solutions

NEURON MODEL

Individual neurons are efficiently modeled as rule-based dynamical units (event-driven), reproduces key features found in real neurons (adaptation, bursting, depolarization blockade, and voltage-sensitive NMDA conductance).



3 **types of cells**: excitatory (E), fast-spiking inhibitory (I), and low-threshold spiking inhibitory (IL), each with 3 **types of synaptic inputs** (AMPA, NMDA and GABA), all based on realistic physiological parameters.

NETWORK MODEL

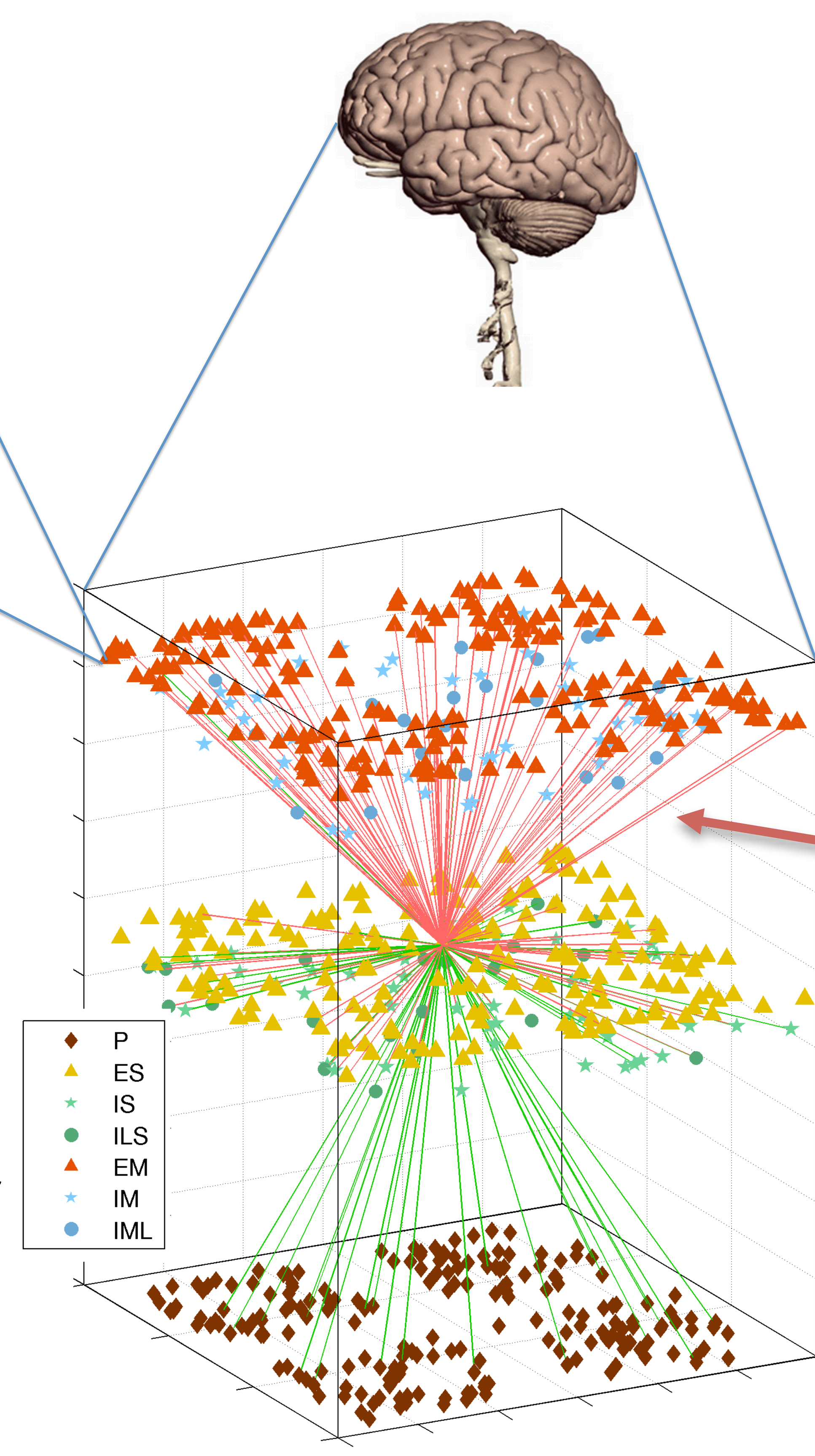
The **reinforcement learning system** is divided into an Actor, mapping perceptions to actions, and a Critic providing reward and punishment feedback to the actor.

The **neural network (Actor)** consists of proprioceptive (P) neurons, sensory (S) neurons, and motor (M) neurons.

Each P cell was tuned to fire for a narrow range of particular muscle lengths for one of the 4 muscles.

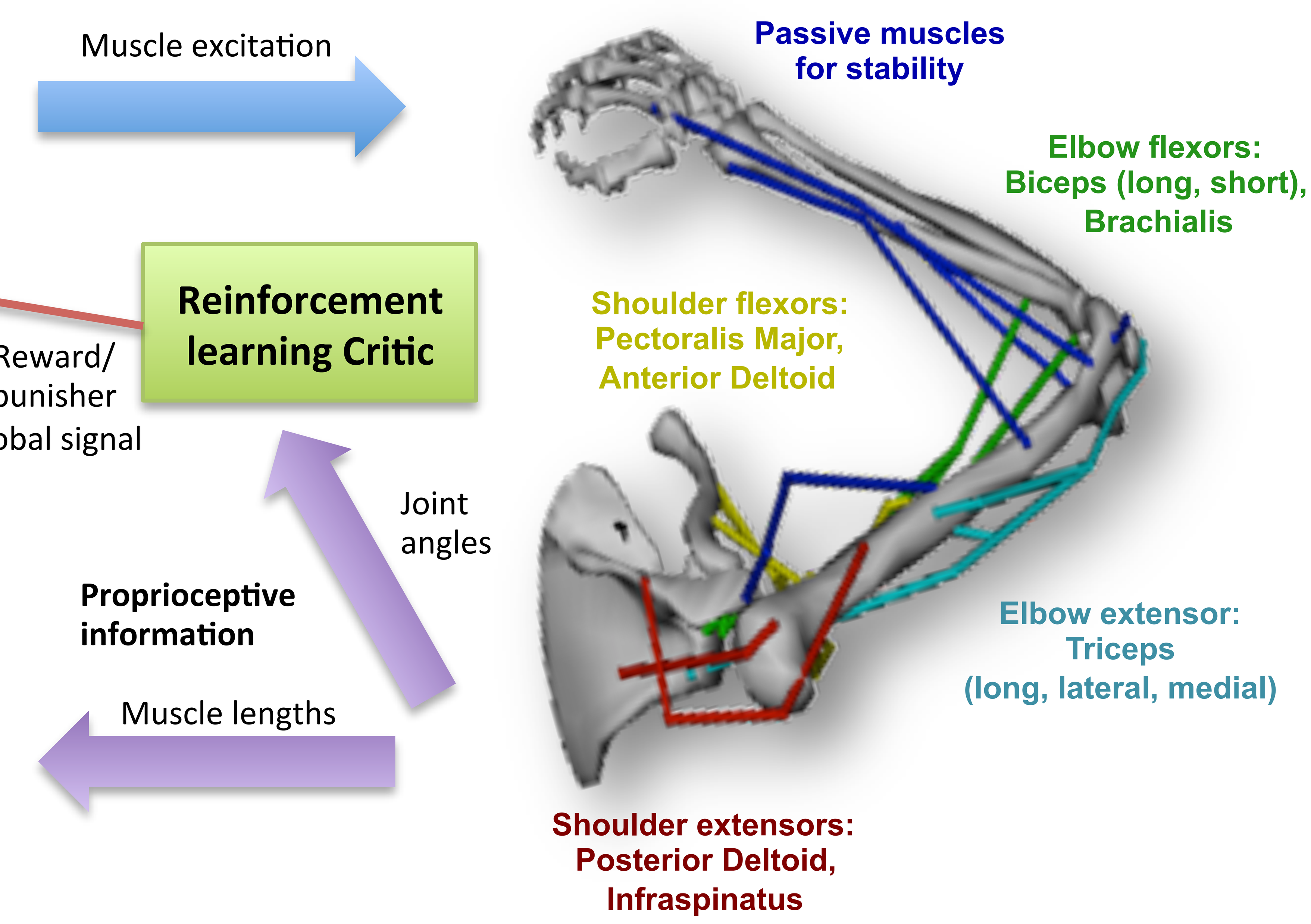
The window-averaged firing rate of M subpopulations was used to generate the muscle excitation.

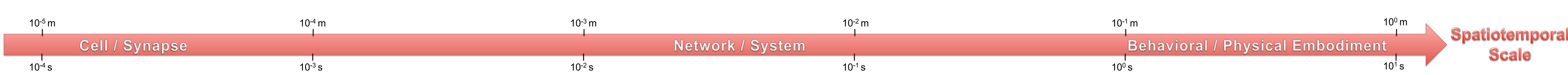
The network effectively performes a mapping between arm state, as measured by muscle length, and the muscle excitation required to drive the arm to the target.



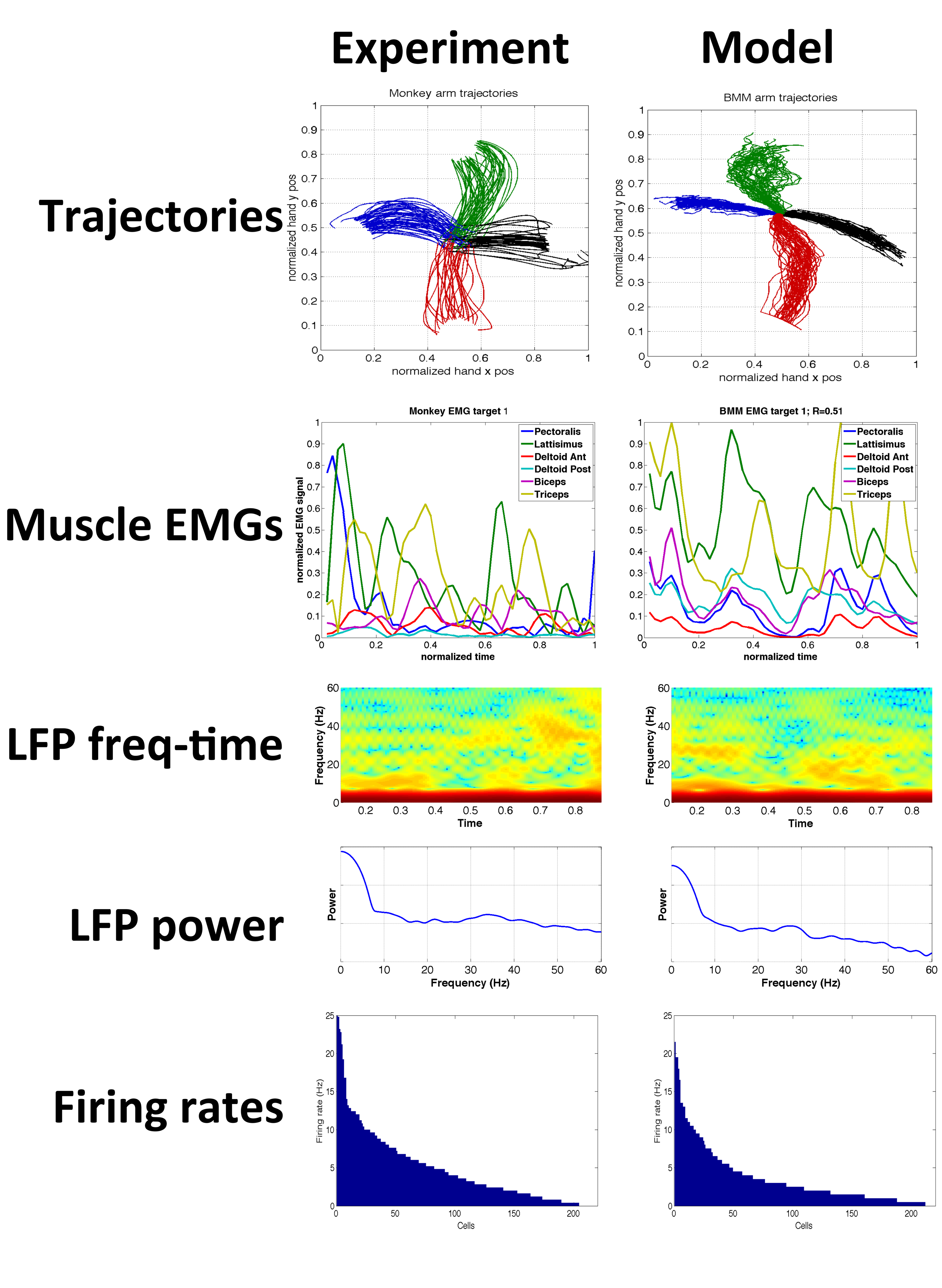
MUSCULOSKELETAL ARM MODEL

The **musculoskeletal model** includes 8 rigid bodies, 7 joints, 14 muscle branches divided into 4 muscle groups, leading to 2 degrees of freedom.Muscles are an extension of Hills muscle model.
Excitation is provided as a normalized value between 0 and 1, and can be interpreted as the EMG. At every time step, given the input excitation to each muscle, the model calculates the muscle activation, fiber and tendon lengths, force, contraction velocity, and the position and velocity of each of the joints.



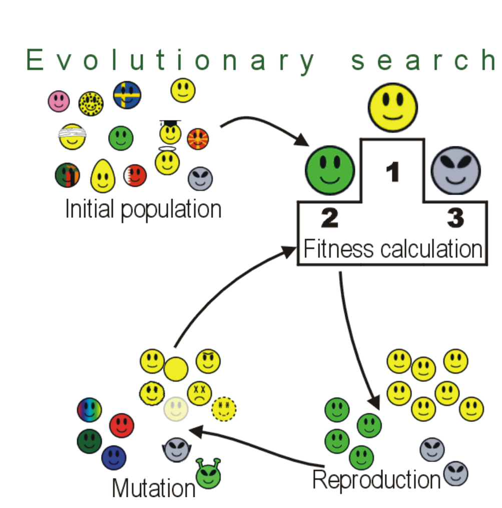


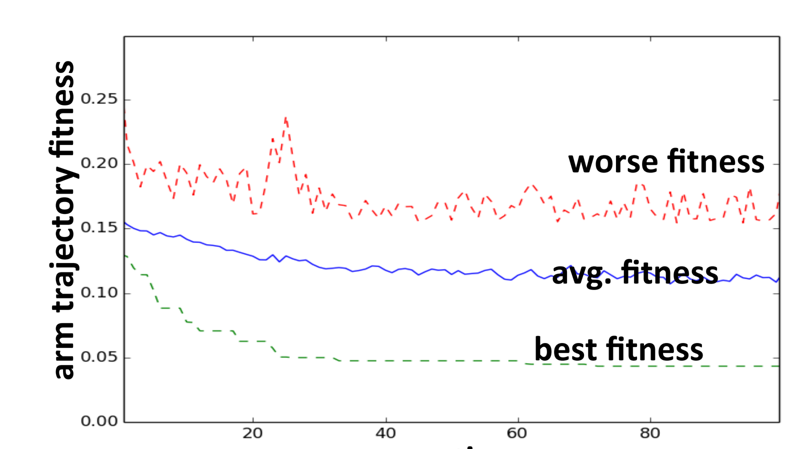
MODEL RESULTS



AUTOMATED PARAMETER TUNING

- **Evolutionary algorithm** with tournament selection, weak-elitism generational replacement, 40% Gaussian mutation, 50% crossover, and a population of 200 individuals.
- Parallel implementation using 500-core HPC (cluster)
- Synaptic weights are NOT directly optimized; instead we evolved the learning/training metaparameters of the model (indirect encoding), such as the learning rate.
- Fitness function aimed at minimizing arm trajectory error after training





CONCLUSIONS

- Reinforcement learning allows the system to learn the appropriate mappings between neural populations required for the virtual arm to reach different targets.
- The modeled arm trajectories, muscle activations (EMG), and neural dynamics validated against data recorded during arm-reaching experiments.
- MSM can potentially be used to study motor system disorders, TBI, etc.
- MSM also paves the way towards a full closed-loop biomimetic brain-effector learning system that can be incorporated in a neural decoder for real-time prosthetic control.

References

- Neymotin SA, Chadderdon GL, Kerr CC, Francis JT, Lytton WW. *Reinforcement learning of 2-joint virtual arm reaching in a computer model of sensorimotor cortex.* **Neural Computation** (2013)
- Dura-Bernal S, Chadderdon GL, Neymotin SA, Francis JT, Lytton WW. *Towards a real-time interface between a biometic model of sensorimotor cortex and a robotic arm.* **Pattern Recognition Letters** (2013)
- Dura-Bernal S, Chadderdon GL, Neymotin SA, Xianlian Z, Przekwas A, Francis JT, Lytton WW. *Virtual musculoskeletal arm and robotic arm driven by a biomimetic model of sensorimotor cortex with reinforcement learning.* **IEEE Signal Processing in Medicine and Biology Symposium**, SPMB13 (2014)