Repairing lesions via microstimulation in a spiking network model driving a virtual arm

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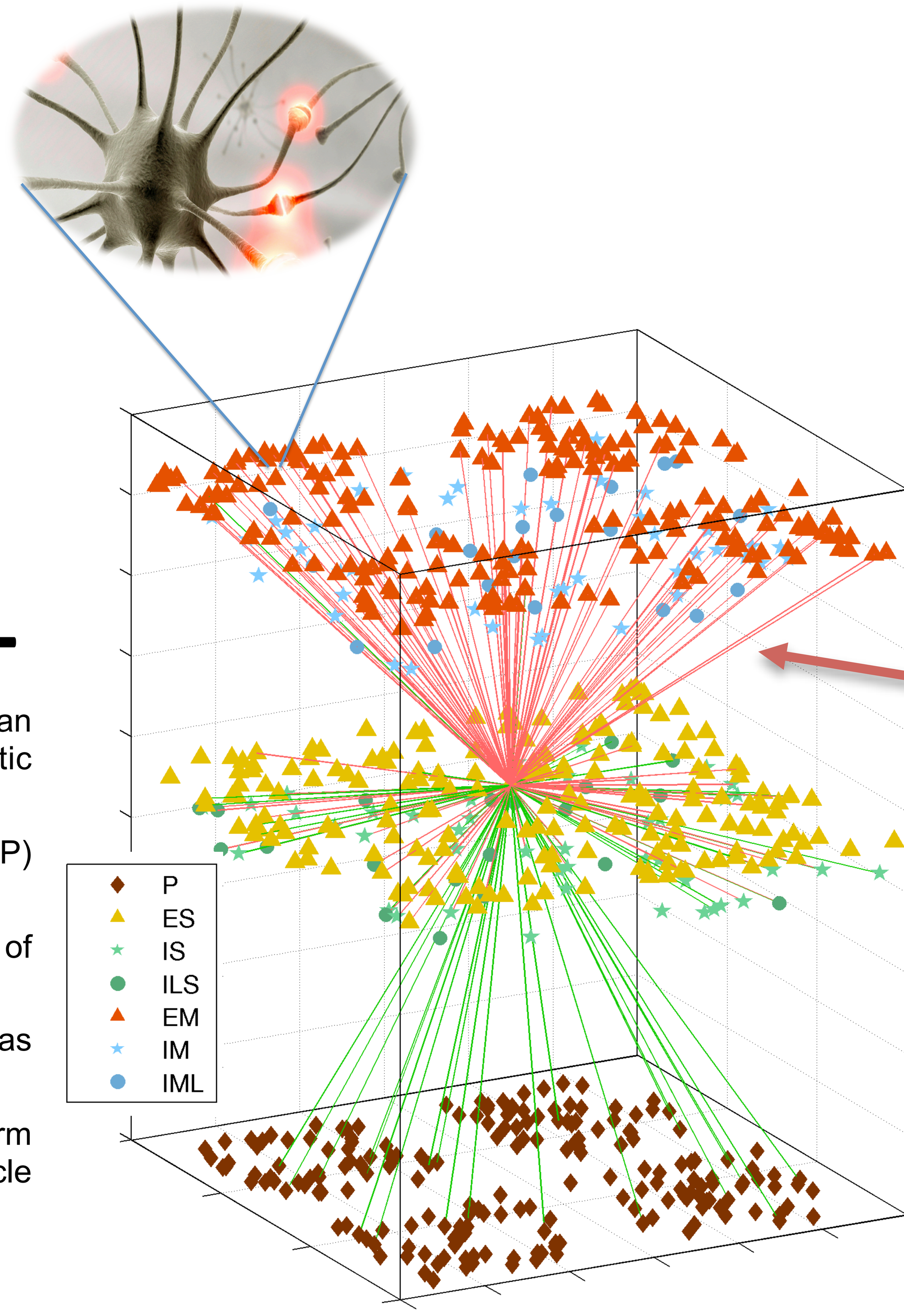
NEURON MODEL

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.

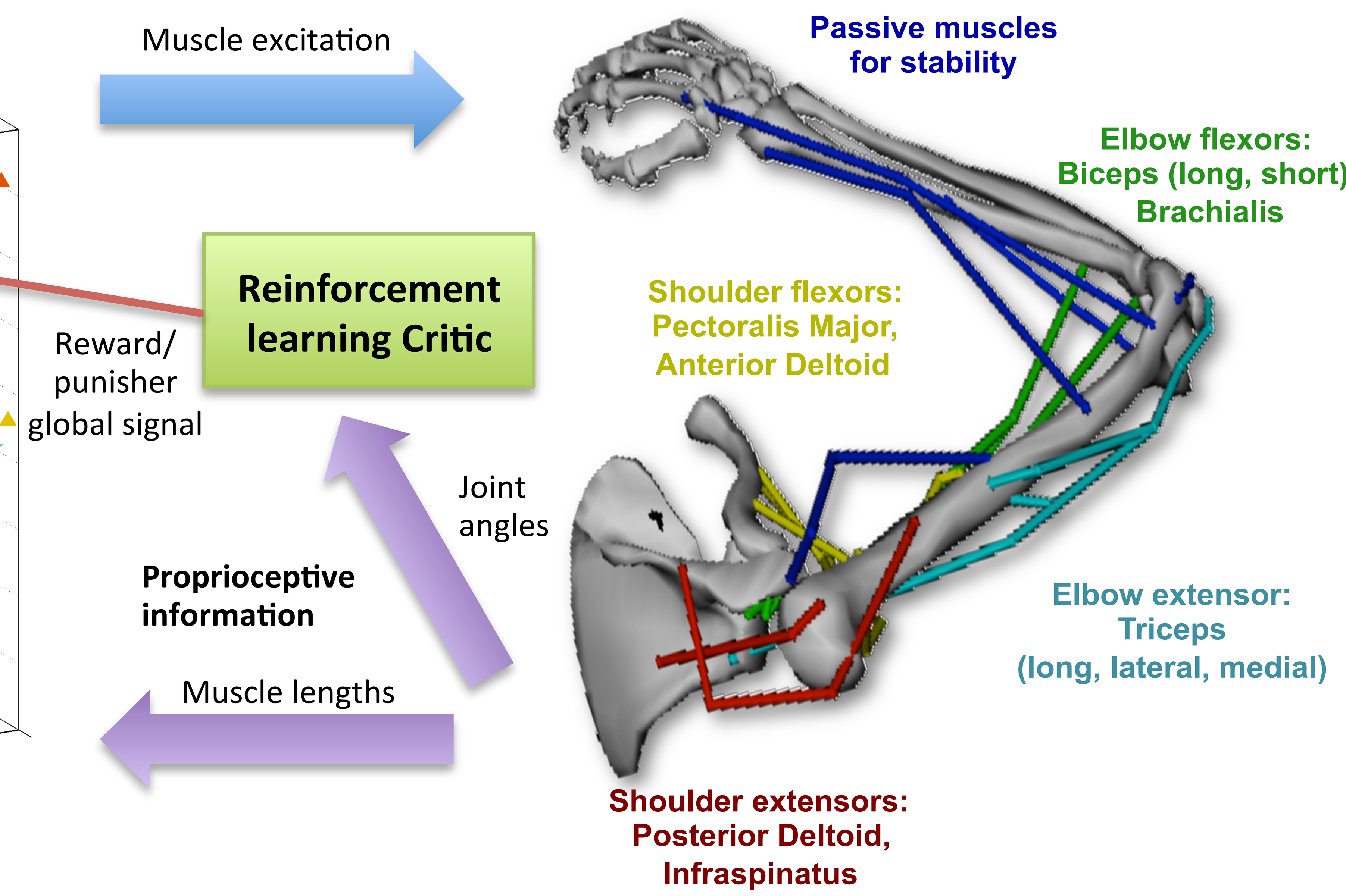
The window-averaged firing rate of M subpopulations was used to generate the muscle excitation.

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.

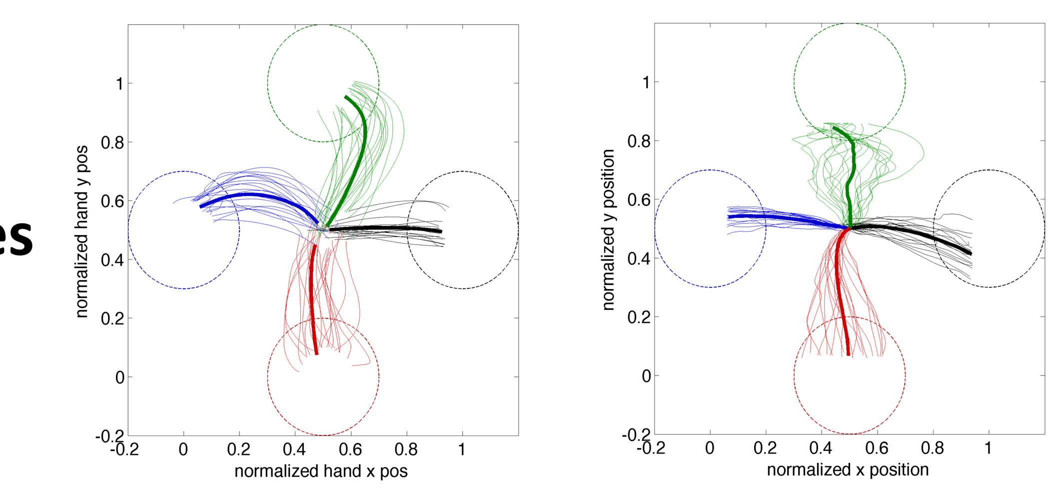
At every time step, given the input excitation to each muscle, the model calculates the muscle activation, fiber and tendon lengths, force, contraction velocity, and the position and velocity of each of the joints.



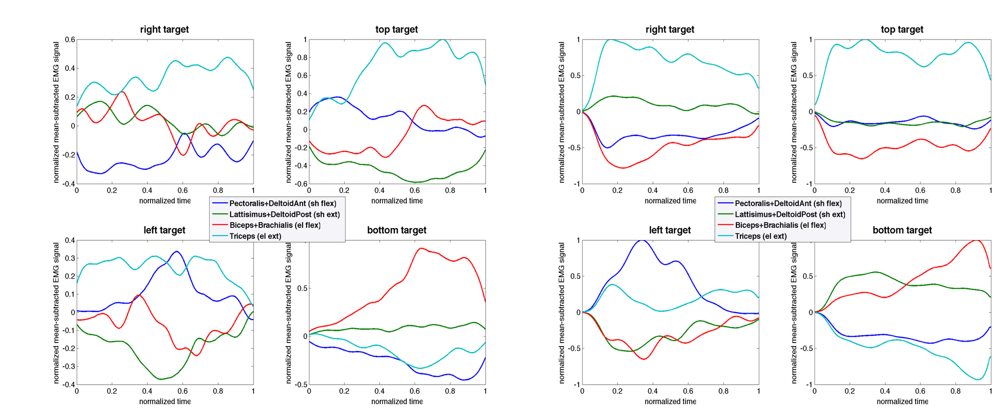
MODEL RESULTS

Experiment | **Model**

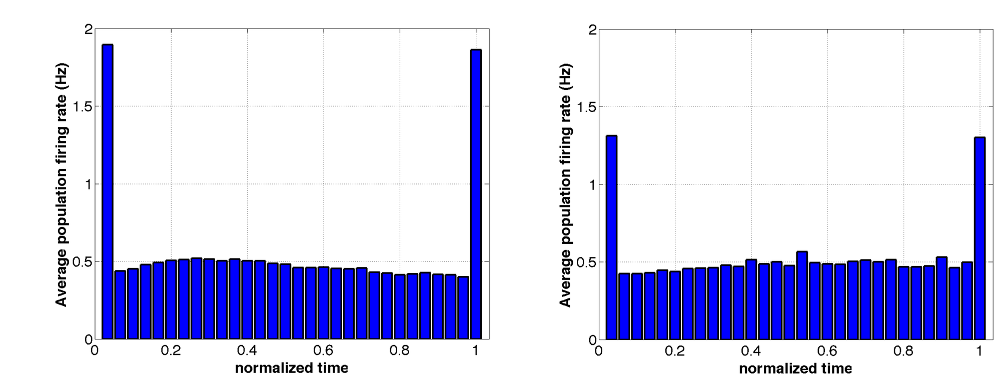
Trajectories



Muscle EMGs



Firing rates



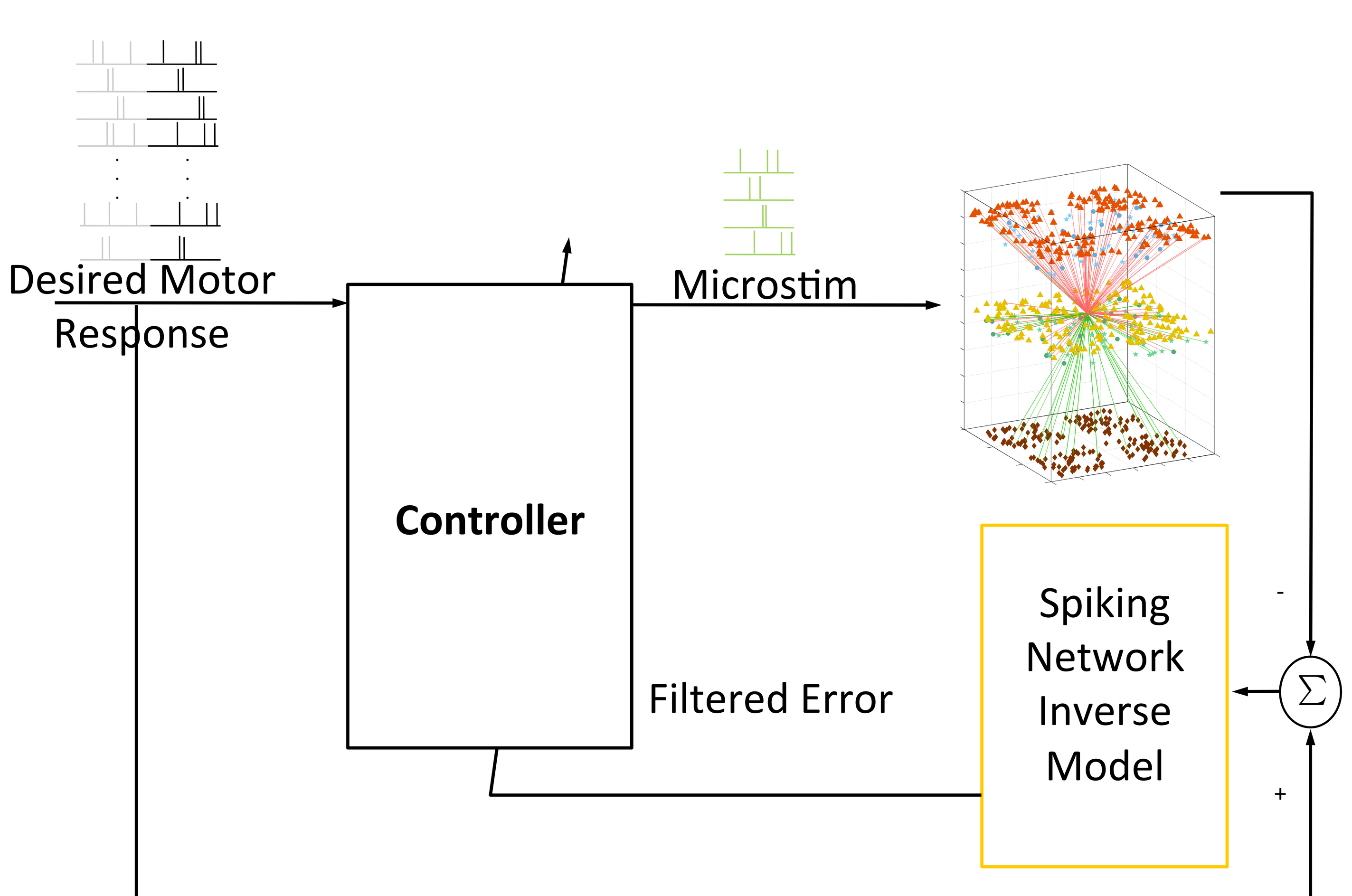
NEURAL CONTROLLER

Adaptive Inverse Control for Spike Trains

From desired neural activity (pre-perturbation), optimize a set of microstimulation that aid the perturbed spiking model in driving the virtual arm to its target.

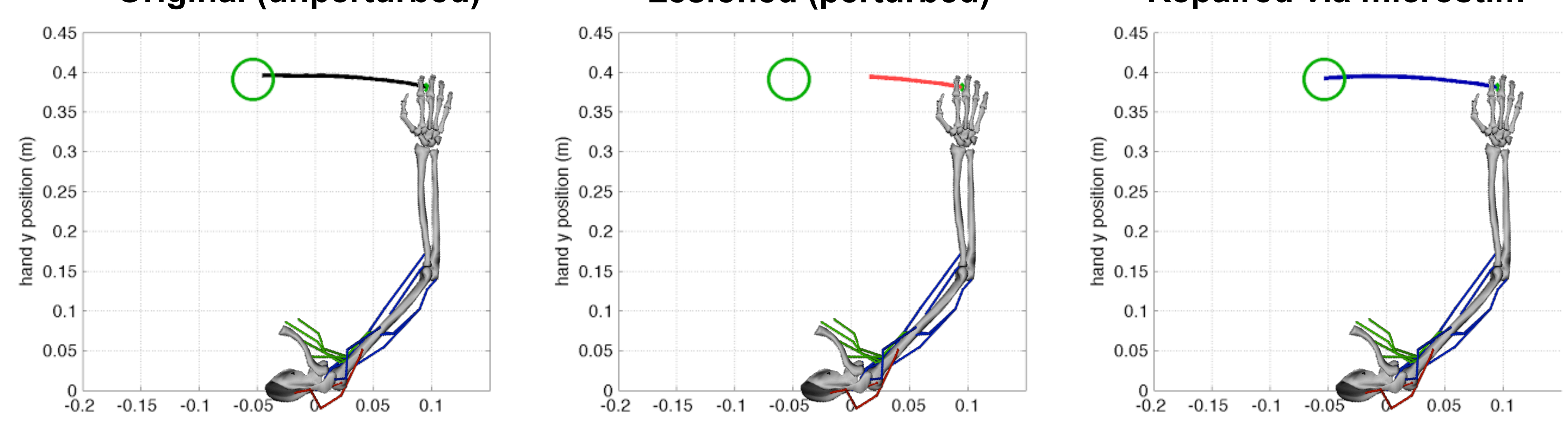
Optimizing microstimulation sequences requires repeatedly stimulating the neural system to obtain enough probing data to construct an inverse model. We tested over 700 microstim probing sequences to derive the inverse model.

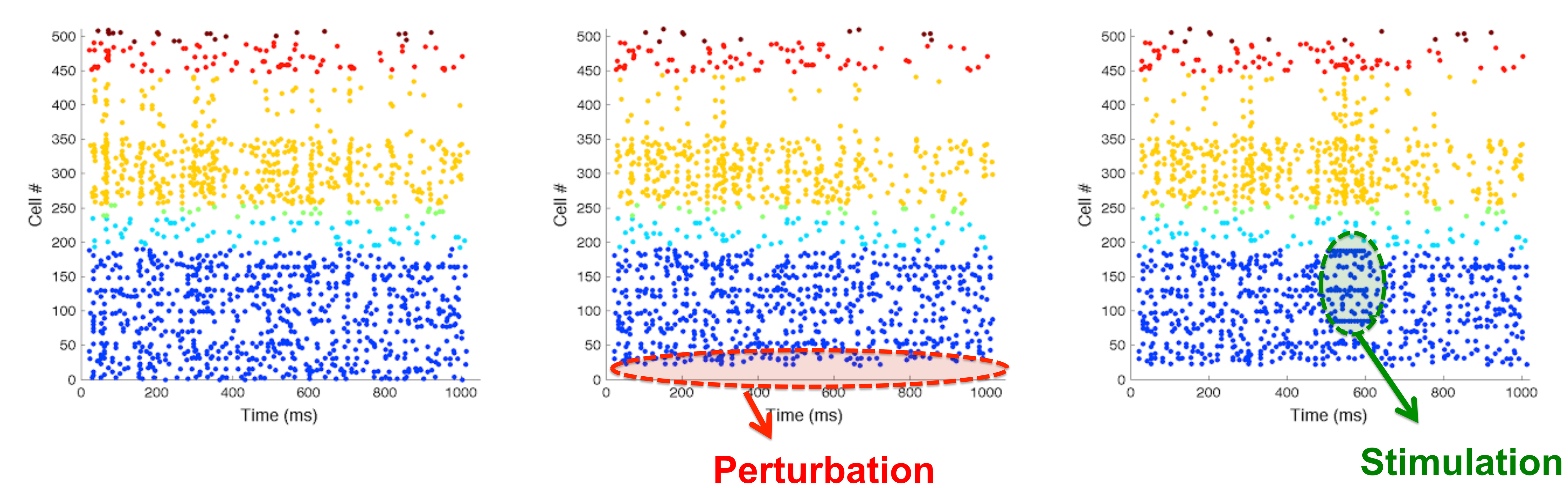
Schoenberg kernel maps the spike train to a Reproducible Kernel Hilbert Space (RKHS) allowing a linear algorithm to control the nonlinear neural system with convex optimization.



NEURAL CONTROLLER RESULTS

Original (unperturbed) | **Lesioned (perturbed)** | **Repaired via microstim**





CONCLUSIONS

- A biomimetic brain model can learn to control a virtual arm using reinforcement learning.
- Synthetic data from the brain model and virtual arm can be used as a test-bed to evaluate neural control methods e.g. to repair of motor lesions (M1).
- Unlike real brain, model can be probed extensively and precisely, and provides access to detailed information of all elements in the system (neurons, synapses, muscles, etc).
- Microstim pattern obtained via adaptive inverse controller manages to restore pre-lesion motor spike train and arm trajectory.
- Useful for rehabilitation by inducing long-term plasticity.

REFERENCES

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- Lin Li, Il Memming Park, Austin Brockmeier, Badong Chen, Sohan Seth, Joseph T. Francis, Justin C. Sanchez, and Jose C. Principe , *Adaptive Inverse Control of Neural Spatiotemporal Spike Patterns with a Reproducing Kernel Hilbert Space (RKHS) Framework.* **Trans. on Neural Systems and Rehabilitation Engineering**, Vol. 21, No. 4, pp. 532-543, (2013) DOI:10.1109/TNSRE.2012.2200300