Modeling force-field adaptation in speech motor control

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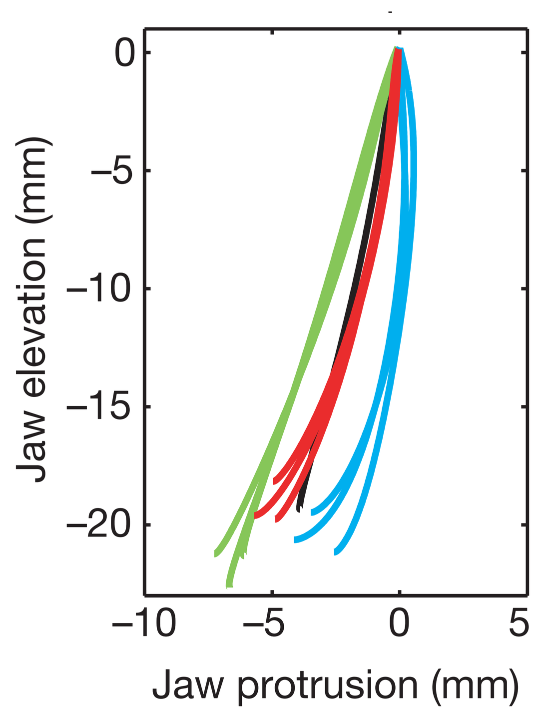
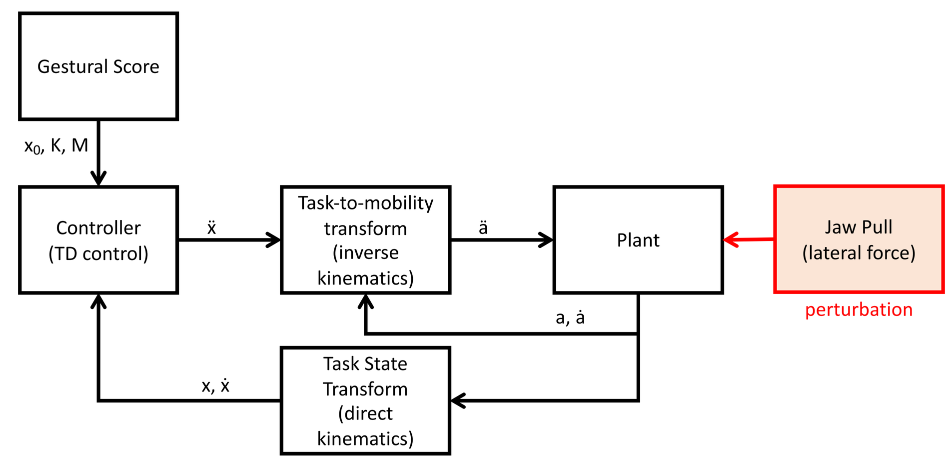
**equal contribution*

When a velocity-dependent forcefield is applied to the jaw during production of the vowel sequence /iæ/, humans **first show displacement** of jaw trajectories, but **adapt over time** to return to near **baseline** movements. When the forcefield is removed, large **aftereffects** are seen, indicative of learning [1].

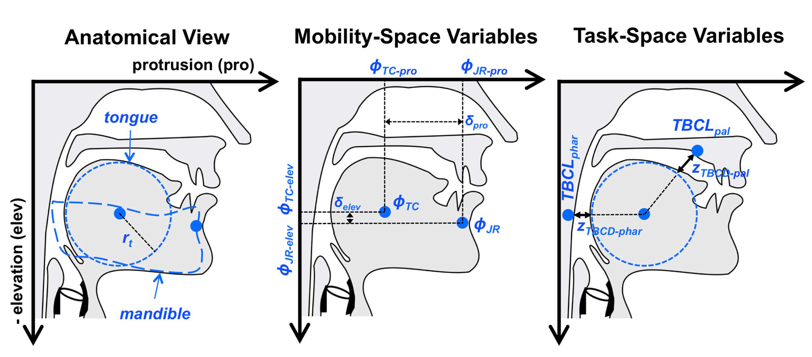


What computational changes allow the speech motor system to adapt to such dynamic perturbations?

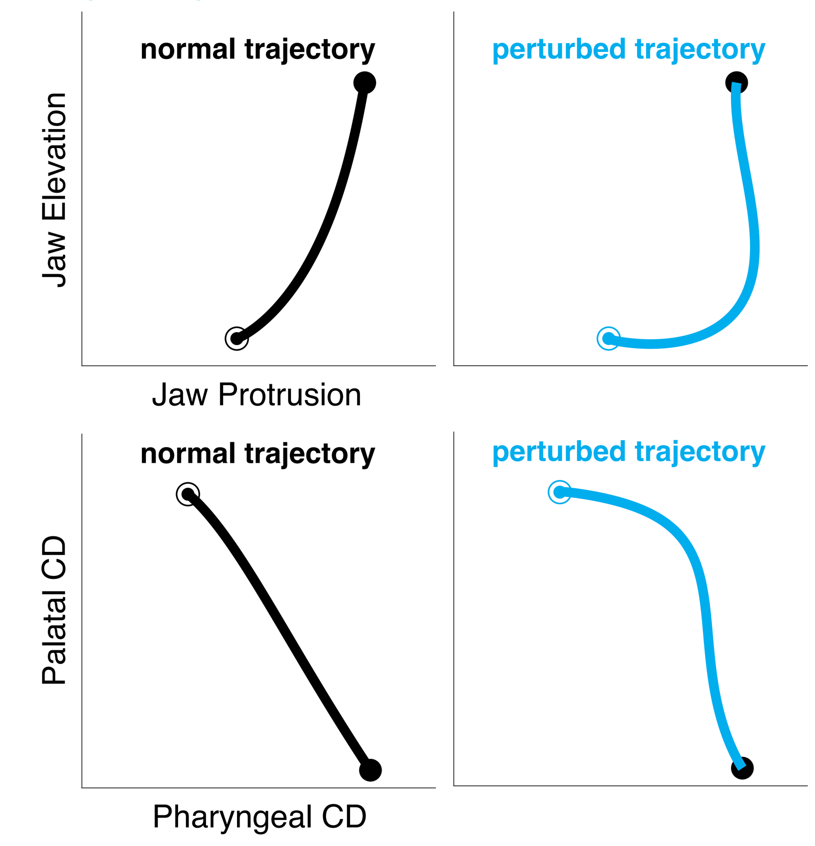
As our basic model, we use a Task-Dynamics [2] hierarchical feedback controller (below), with the addition of a velocity-dependent force field applied to the jaw.



We use a simplified model including two task-level tract constriction tasks (Palatal and Pharyngeal Constriction Degree) and two mobility-level dimensions relating to jaw movement (elevation and protrusion).



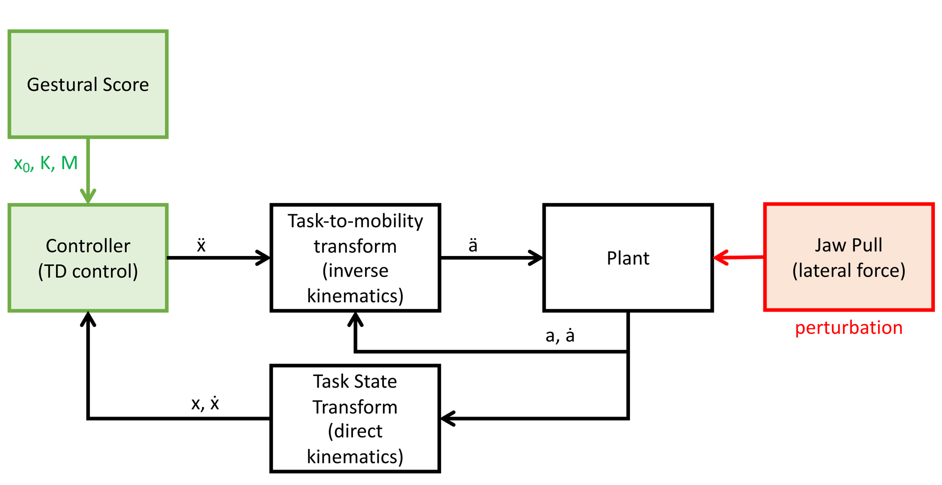
The Task Dynamics model produces **straight trajectories in task space** (bottom) and **slightly curved jaw trajectories** (top). Without any additional components, the Task Dynamics model **cannot correct for externally-applied jaw dynamics**.



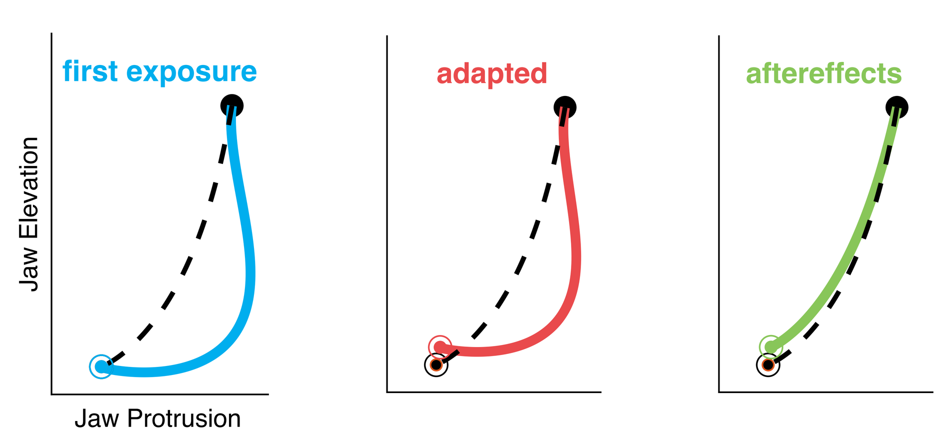
We explore three possible additions to the Task-Dynamics model that may enable learning of perturbed system dynamics.

Task Parameter Optimization

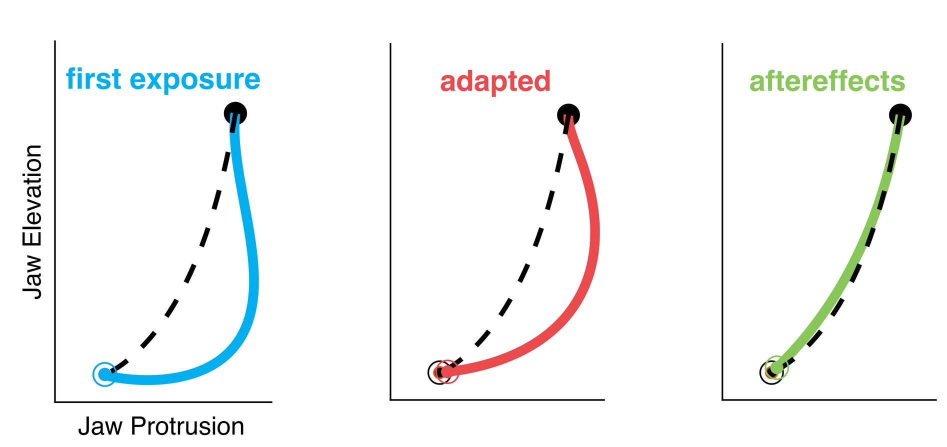
We iteratively optimize the gestural parameters of target location (x_0), mass (M) and stiffness (K) based on a cost function with penalties for target achievement and effort.



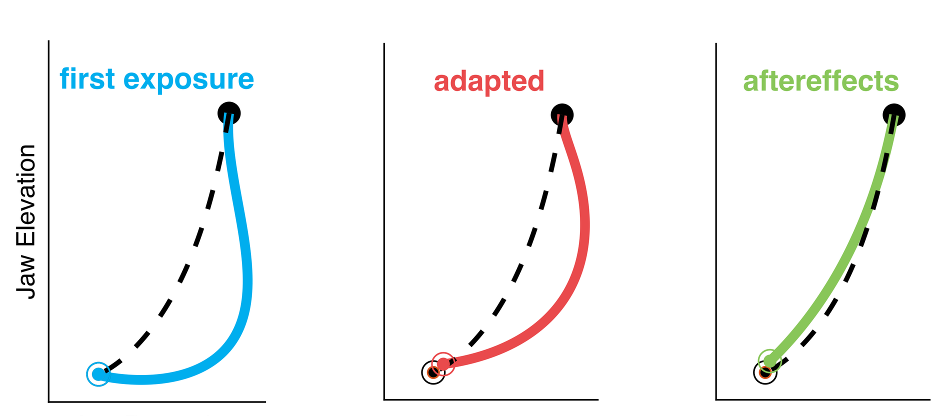
Optimizing palatal and pharyngeal constriction degree targets (x_0) minimally changes the trajectories.



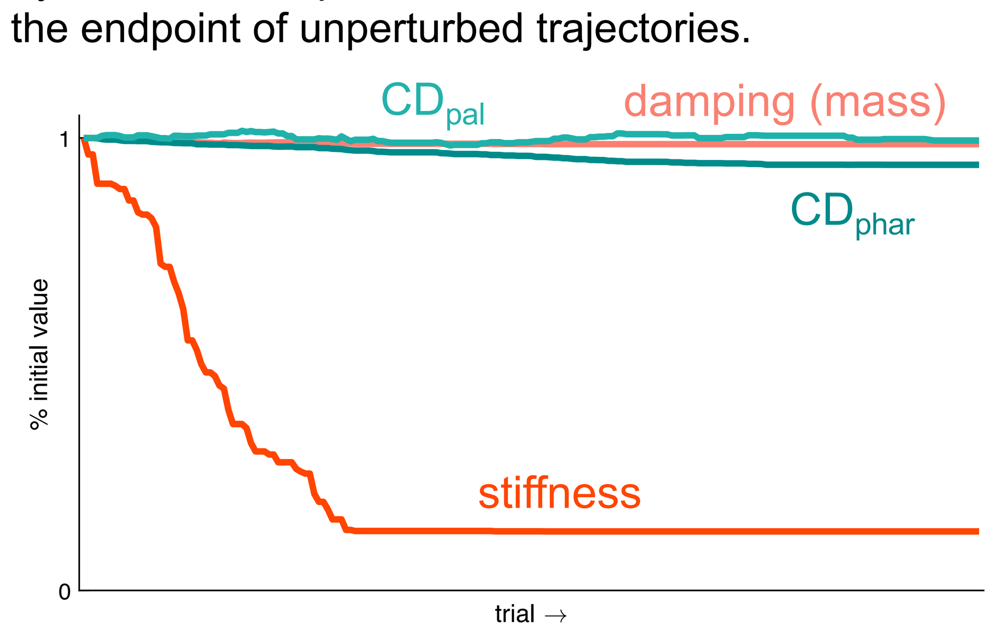
Optimizing stiffness (K,M) is minimally more effective.



Optimizing all parameter simultaneously produces similar results.

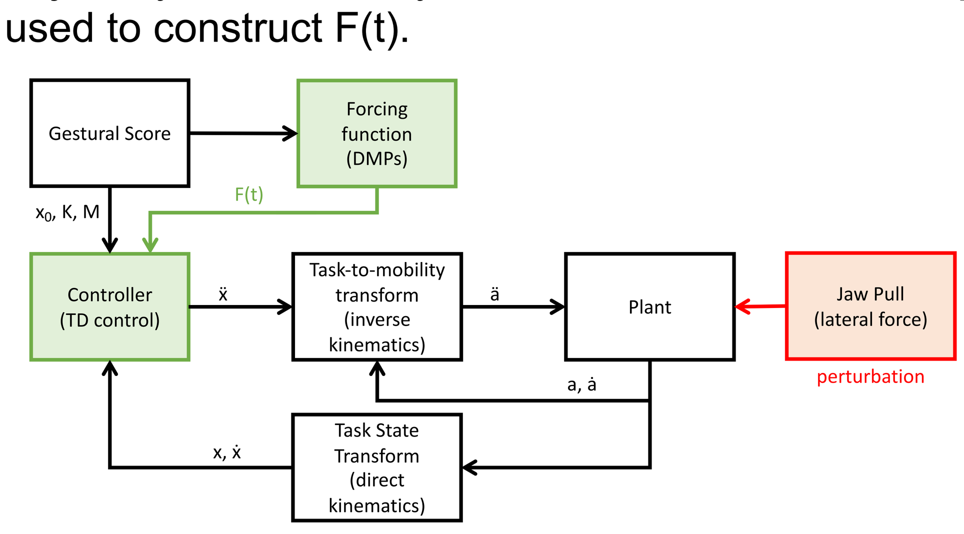


Stiffness optimization (K, M) has larger effects on parameter values than target optimization (CD_{pal}, CD_{phar}), likely due to the requirement that movements ended close to the endpoint of unperturbed trajectories.

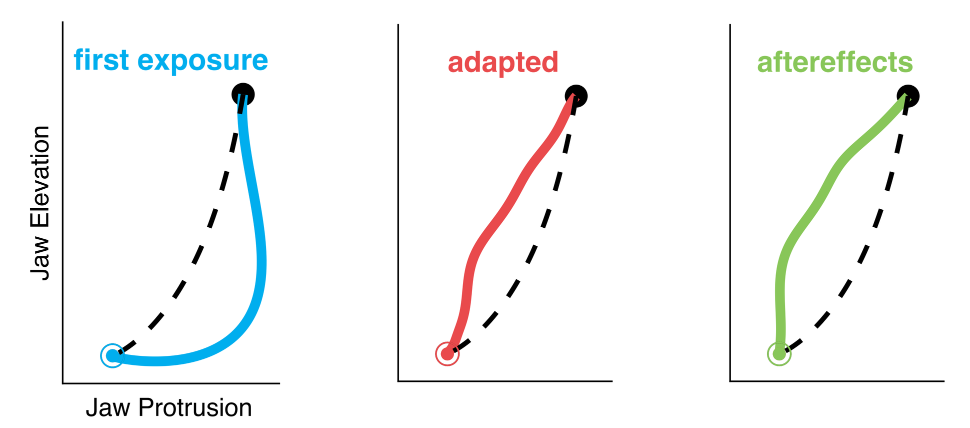


Dynamic Movement Primitives

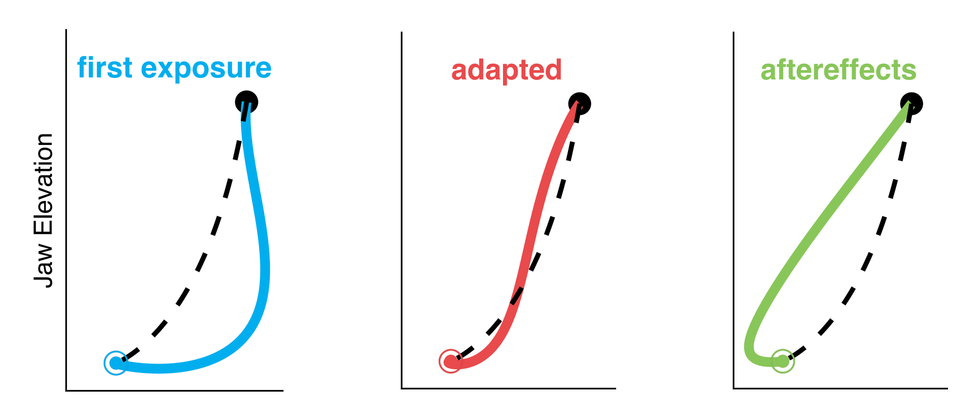
We iteratively optimize a time-varying forcing function, F(t), that alters task-level dynamics based on a cost function with penalties for target achievement and either effort or trajectory curvature. Dynamic Movement Primitives [3] are used to construct F(t).



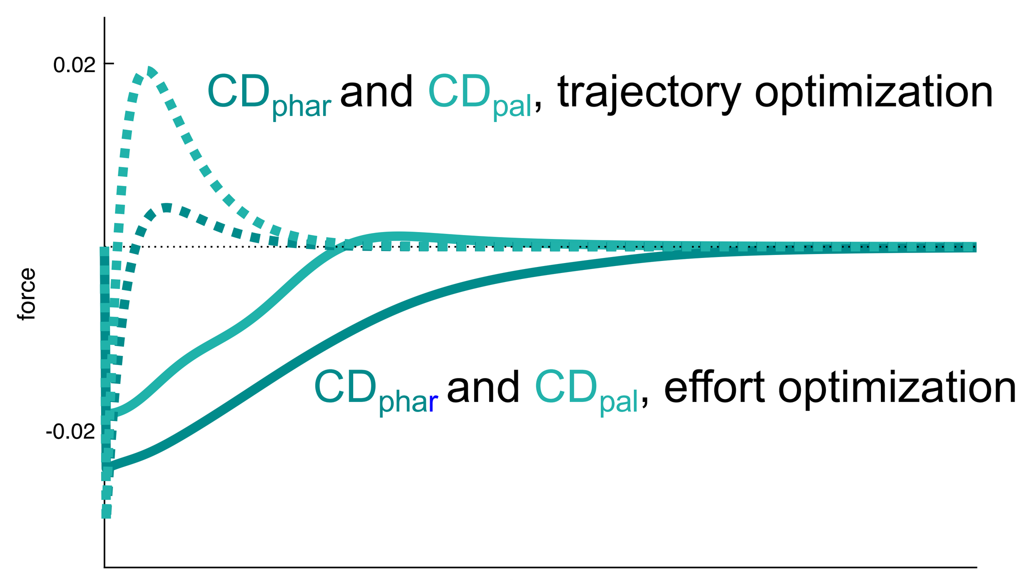
Optimizing for effort (mobility velocity) results in near-complete compensation for the force field.



Optimizing for trajectory curvature returns trajectories closer to baseline.

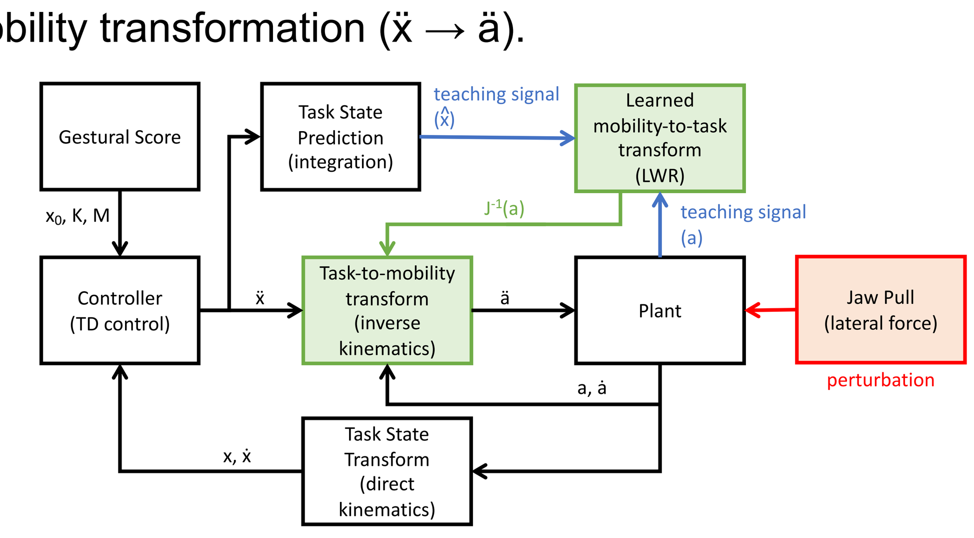


The forcing functions generated through the two methods are very different.

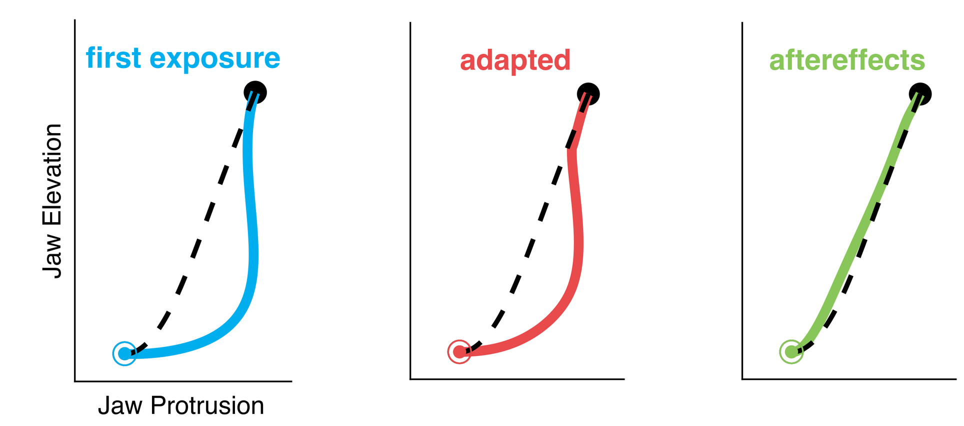


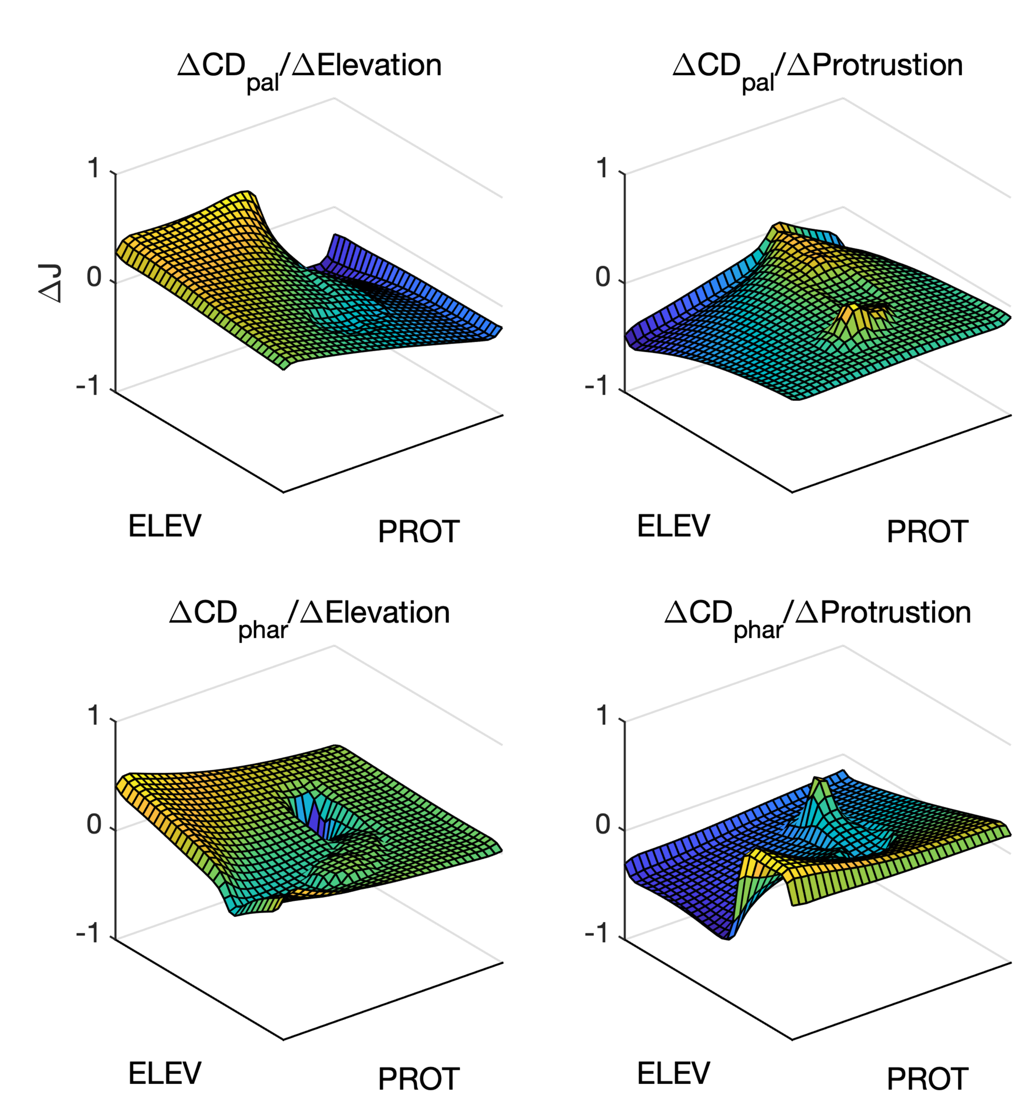
Jacobian Learning with LWR

We continuously update a learned mobility to task transformation (a → x) using Locally Weighted Regression. This mapping is used to generate the Jacobian, J(a), whose inverse, $J^{-1}(a)$, is used in the task to mobility transformation ($\ddot{x} \rightarrow \ddot{a}$).



Updating J(a) minimally changes the trajectories, despite changes in the Jacobian (bottom).





References

[1] Tremblay, S., D. Shiller, and D. Ostry. “Somatosensory Basis of Speech Production.” *Nature* 423 (2003): 866–69.

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[3] Ijspeert, A., J. Nakanishi, H. Hoffmann, P. Pastor, and S. Schaal. “Dynamical Movement Primitives: Learning Attractor Models for Motor Behaviors.” *Neural Computation* 25, no. 2 (2013): 328–73.

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