Naturalistic Movement Generalization under Perturbations using MotorNet

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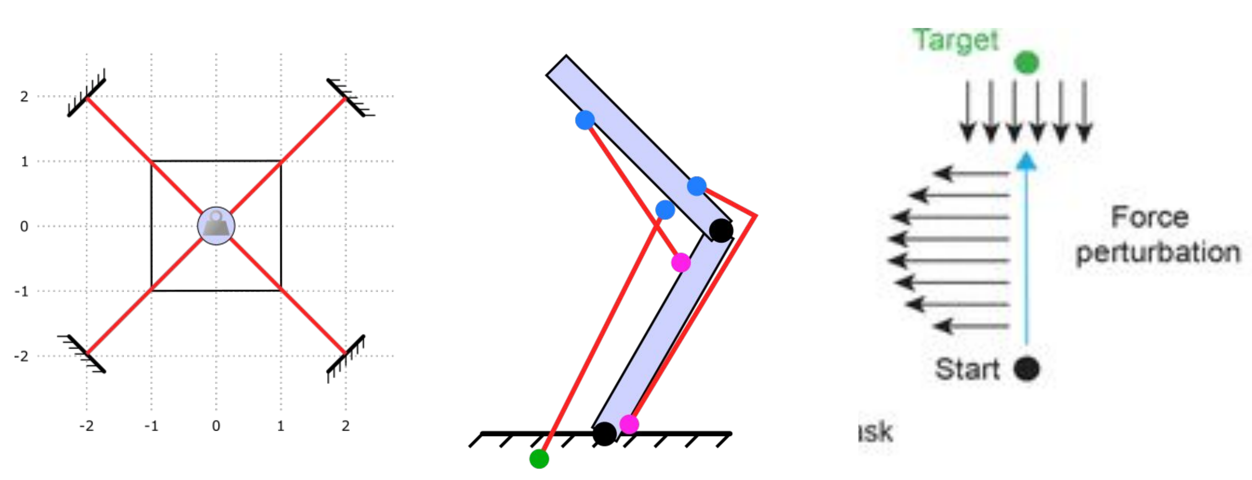
Research Motivations

Motor control is essential concept for understanding how biological systems move. However, traditional biomechanical models are often non-differentiable, which limits their integration with modern deep learning techniques.

MotorNet solves this issue by providing differentiable effectors using pytorch framework. This innovation enables faster and stable learning compared to traditional reinforcement learning approaches.

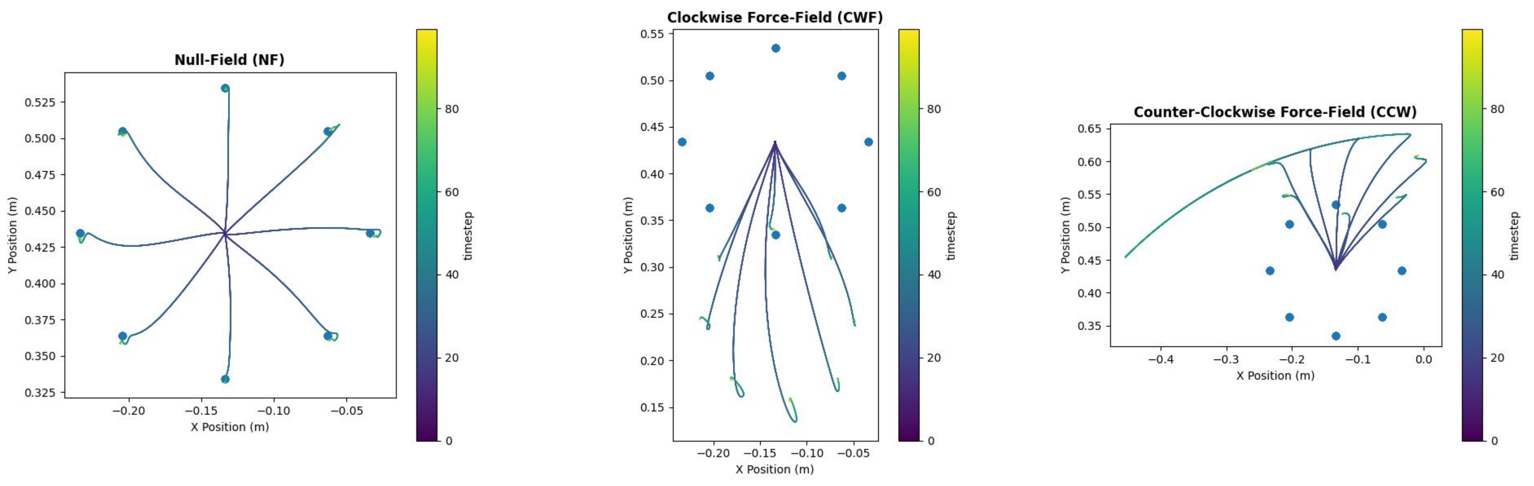
This project aimed to examine how neural networks can learn motor control under biomechanical constraints. We assessed MotorNet's ability to learn natural movements and adapt to external force.

Method

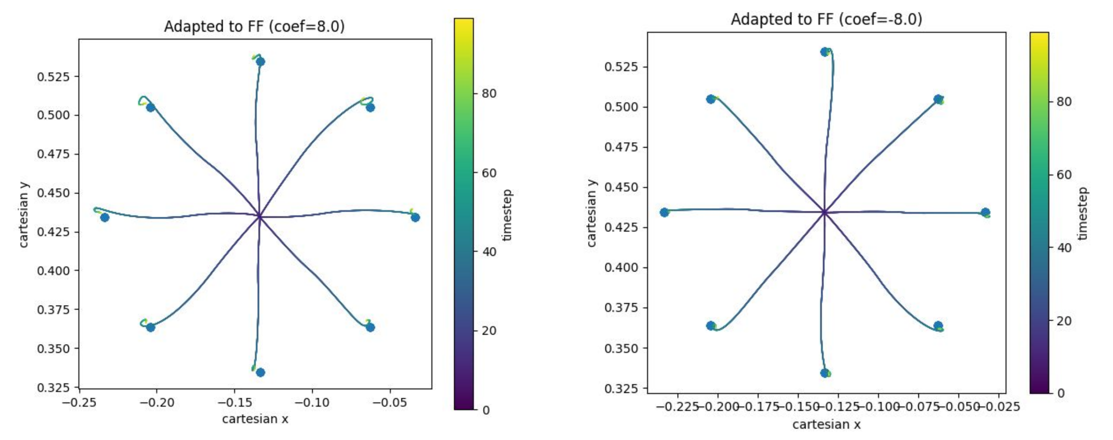


- Point-mass, 2-dof arm 26
- Differentiability, Euclidean Distance-based Endpoint Position Error, Backpropagation
- Training reaching task in each Null field, Force field environment. (clockwise, counter clockwise)

Reaching Trajectories

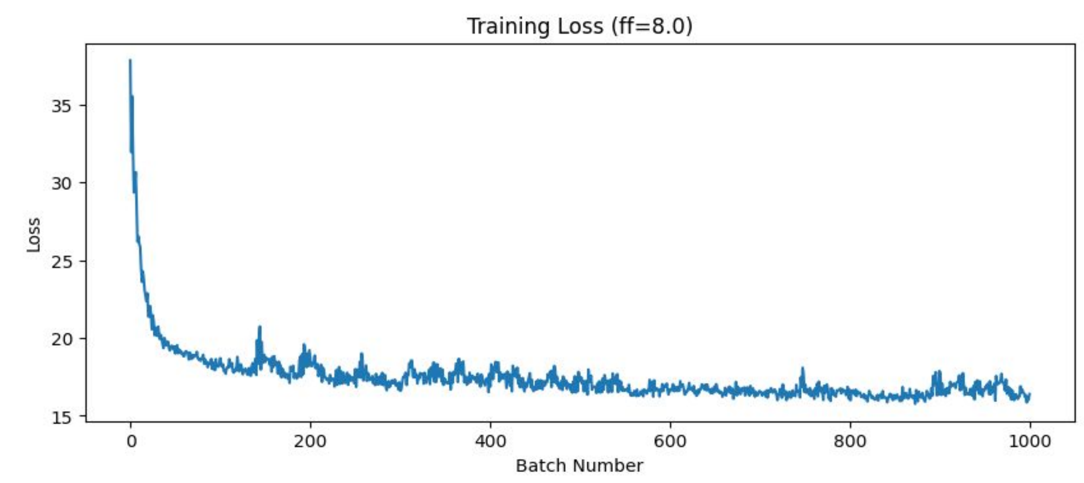


- Result of learning in nullfield environment

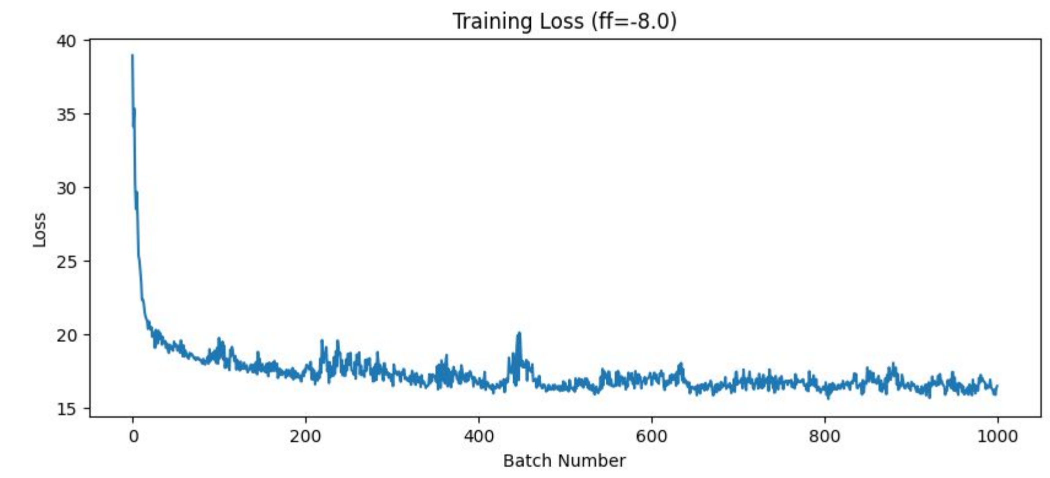


- Result of after learning in force field environment (clockwise, counterclockwise)

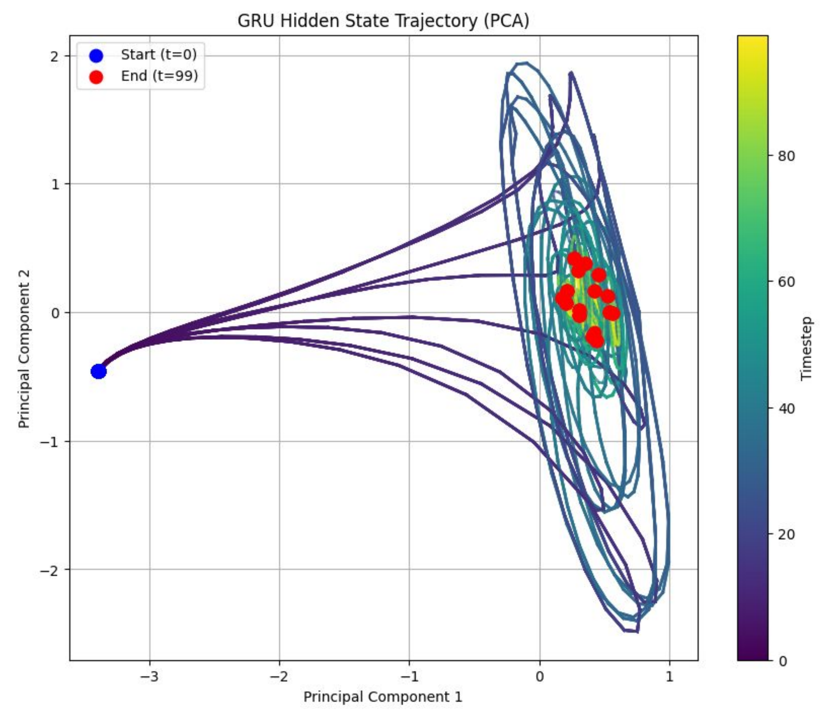
Results



- Loss graph of clockwise reaching task



- Loss graph of counter clockwise reaching task
- Both CW and CCW adaptations exhibits stable and decreasing training loss



- PCA for hidden states: Dimensionality reduction reveals trajectories of neural activity during 8-direction reaching

Conclusion

We demonstrated that a recurrent neural network trained with MotorNet can generate stable reaching trajectories and adapt to external force-field perturbations.
Improvements in learning when trained with higher batch values are observed.
Hidden state trajectories start from a common point, explore a complex path, and converge near the target at the end of each reach.

Future Work

As this study is conducted in a simulation-based environment, future work may explore motor control mechanisms by directly manipulating neural network hidden states.
By intervening in internal representations, we aim to investigate how changes in neural dynamics influence motor adaptation and control.