Learning Contact Dynamics using Physically Structured Neural Networks

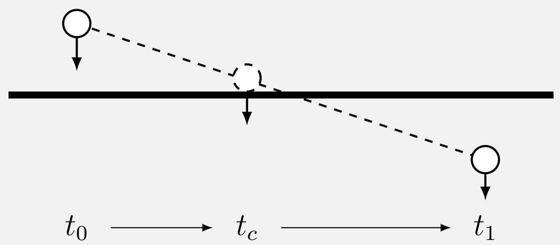
Andreas Hochlehnert[1] · Alexander Terenin[2] · Steindór Sæmundsson[2] · Marc Peter Deisenroth[1]

[1]Centre for Artificial Intelligence, University College London · [2]Imperial College London

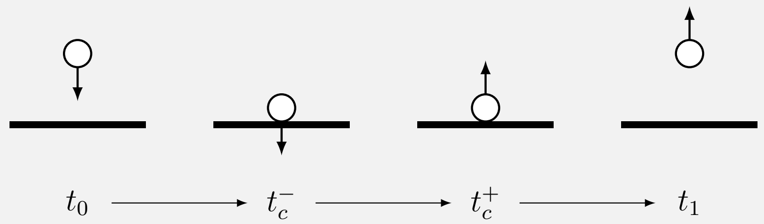
Abstract

Learning physically structured representations of dynamical systems that include contact between different objects is an important problem for learning-based approaches in robotics. In this work, we use connections between deep neural networks and differential equations to design a family of deep network architectures for representing contact dynamics between objects. We show that these networks can learn discontinuous contact events in a data-efficient manner from noisy observations in settings that are traditionally difficult for black-box approaches and recent physics inspired neural networks. Our results indicate that an idealised form of touch feedback—which is heavily relied upon by biological systems—is a key component of making this learning problem tractable.

Contact Dynamics

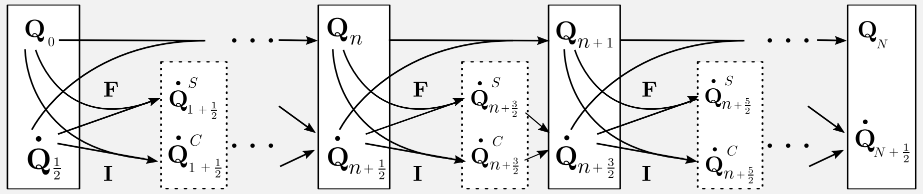


(a) Find the contact time t_c



(b) Calculate true trajectory

Central-Difference Lagrange Networks



Recurrent neural network architecture for contact dynamics

$$\dot{\mathbf{Q}}_{n+\frac{3}{2}} = \dot{\mathbf{Q}}^S_{n+\frac{3}{2}} + \dot{\mathbf{Q}}^C_{n+\frac{3}{2}},$$
$$\dot{\mathbf{Q}}^S_{n+\frac{3}{2}} = \dot{\mathbf{Q}}_{n+\frac{1}{2}} - h\mathbf{M}^{-1}\frac{\partial V(\mathbf{Q}_{n+1})}{\partial \mathbf{Q}_{n+1}},$$
$$\dot{\mathbf{Q}}^C_{n+\frac{3}{2}} = \mathbf{M}^{-1}\mathbf{I}(\mathbf{Q}_{n+1}, \dot{\mathbf{Q}}_{n+\frac{1}{2}}),$$

V Fully connected potential network
$\mathbf{I}$ Impulse (via physical laws)

Idealised Touch Feedback

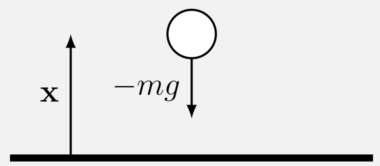
Contact signal $\boldsymbol{c} \in \{0,1\}^K$

$$c_n^k = \begin{cases} 1 & \text{if contact for body } k, \\ 0 & \text{otherwise.} \end{cases}$$

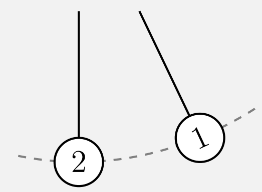
Train contact network $\hat{\boldsymbol{c}}(\mathbf{Q}_{n+1}, \dot{\mathbf{Q}}_{n+\frac{1}{2}})$

$$\left[\dot{\mathbf{Q}}^C_{n+\frac{3}{2}}\right]^k = \begin{cases} \left[\mathbf{M}^{-1}\mathbf{I}(\mathbf{Q}_{n+1}, \dot{\mathbf{Q}}_{n+\frac{1}{2}})\right]^k & \text{if } \hat{c}^k = 1, \\ \mathbf{0} & \text{otherwise.} \end{cases}$$

Experiments

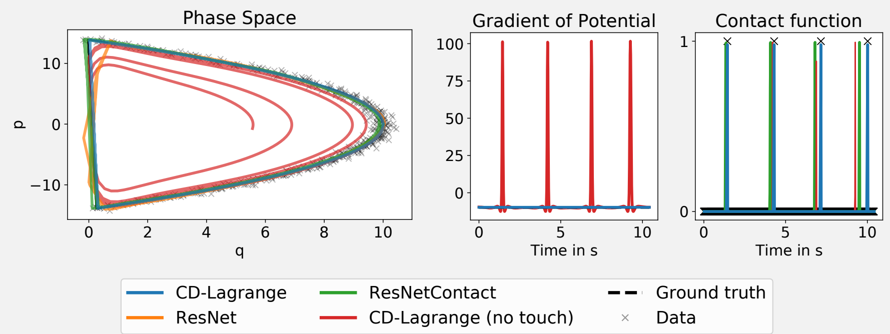


(a) Bouncing ball



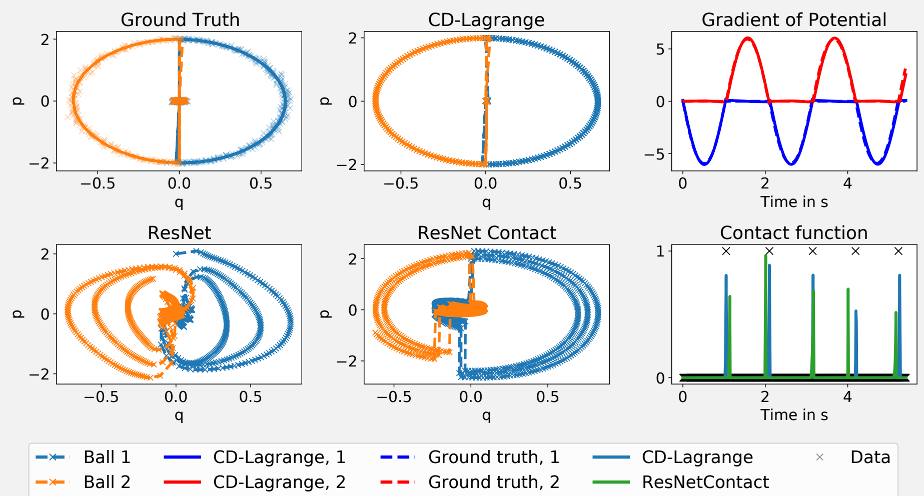
(b) Newton's cradle

Bouncing Ball



Touch feedback → accurate predictions
No touch feedback → confuse contacts with noise

Newton's Cradle



Accurate modelling of multi-body systems
Improved performance vs. residual network baseline

References

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[2] F.-E. Fekak, M. Brun, A. Gravouil, and B. Depale. A New Heterogeneous Asynchronous Explicit–implicit Time Integrator for Nonsmooth Dynamics. Computational Mechanics, 60(1):1–21, 2017.