Physics Informed Neural Network for feedforward control of a 2-DOF manipulator with flexure joints

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May 22, 2024

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Abstract

Feedforward control can greatly improve the accuracy of a manipulator by computing a control input from the desired motion using an inverse dynamic model of the multibody system. The achievable performance gain from this feedforward depends heavily on the correctness and completeness of the model. In a *model-based* approach a *white-box* model with the equations of motion of the multibody system is derived of which the parameters are estimated. Assuming these parameters have a clear physical meaning, it is expected that the model can be used for a wide variety of trajectories. However, the "richness" of the model is obviously limited to features included in the model structure. Alternatively, in a *data-driven* approach a *black-box* model is estimated purely from data. E.g. using machine learning techniques a Feedforward Neural Network (FNN) can be trained that does not require any knowledge about the system dynamics and its parameters. However, care has to be taken to avoid overfit and incorrect model outputs are likely for operating conditions that were not sufficiently included in the training data.

In [2] we augmented the black-box FNN model with a Lagrangian Neural Network (LNN), or Deep Lagrangian Networks (DeLaN) [3], to improve the robustness of feedforward control for a manipulator with two degrees-of-freedom (2-DOF) where the motion is enabled using flexure joints, figure 1. In this manipulator the actuator forces are dominated by conservative forces arising from the accelerations of the links and the deformations of the compliant joints. It was shown that the physical structure of the equation of motion can be embedded in the DeLaN such that it can be trained robustly with a relatively small data set. In parallel a FNN was needed to represent the relatively small remaining residue.

In the present paper the physical structure of the DeLaN is extended to a more general Physics Informed Neural Network (PINN) such that no additional black-box model is needed anymore.

In the 2-DOF manipulator shown in figure 1, two actuators drive the rotation of two arms to achieve in-plane end-effector motion in two translation directions "X" and "Y". Due to the flexure joints, the manipulator shows rather smooth operation with low friction and hysteresis. Contributions from the link mass and joint stiffness result in well-defined terms in the non-linear equation of motion expressed in mass matrix $\boldsymbol{M}(\boldsymbol{q})$ and potential energy $V(\boldsymbol{q})$ that both are functions of the independent generalised coordinates $\boldsymbol{q}$. The wiring of the actuators and sensors results in some (small) damping that is assumed to combine linear viscous and Coulomb damping, both depending on the velocity $\dot{\boldsymbol{q}}$ and described with matrices $\boldsymbol{D}_{\mathrm{v}}(\boldsymbol{q})$ and $\boldsymbol{D}_{\mathrm{c}}(\boldsymbol{q})$, respectively. In the equation of motion for the forces $\boldsymbol{F}$ applied at the independent generalised coordinates $\boldsymbol{q}$ all contributions are combined into

$$\boldsymbol{F} = \boldsymbol{M}(\boldsymbol{q})\ddot{\boldsymbol{q}} + \dot{\boldsymbol{M}}(\boldsymbol{q})\dot{\boldsymbol{q}} - \frac{1}{2}\dot{\boldsymbol{q}}^{\mathsf{T}}\frac{\partial \boldsymbol{M}(\boldsymbol{q})}{\partial \boldsymbol{q}}\dot{\boldsymbol{q}} + \boldsymbol{D}_{\mathrm{v}}(\boldsymbol{q})\dot{\boldsymbol{q}} + \boldsymbol{D}_{\mathrm{c}}(\boldsymbol{q})\,\mathrm{sign}(\dot{\boldsymbol{q}}) + \frac{\partial V(\boldsymbol{q})}{\partial \boldsymbol{q}}. \tag{1}$$

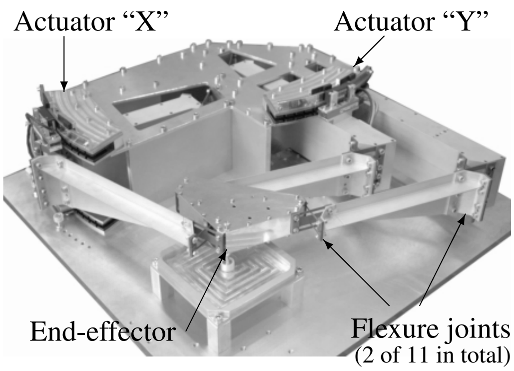

Figure 1: The 2-DOF manipulator with flexure joints [1] (photo by Ger Folkersma).

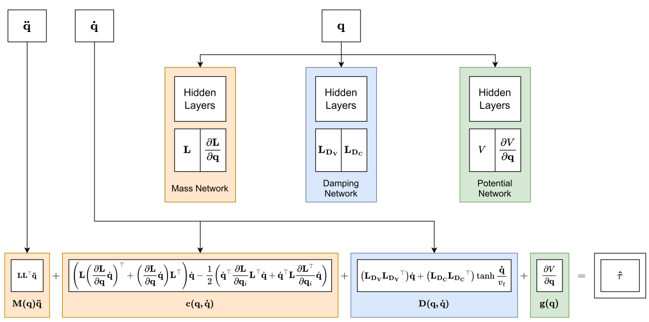

Figure 2: DeLaN+D-structure (detailed in full paper).

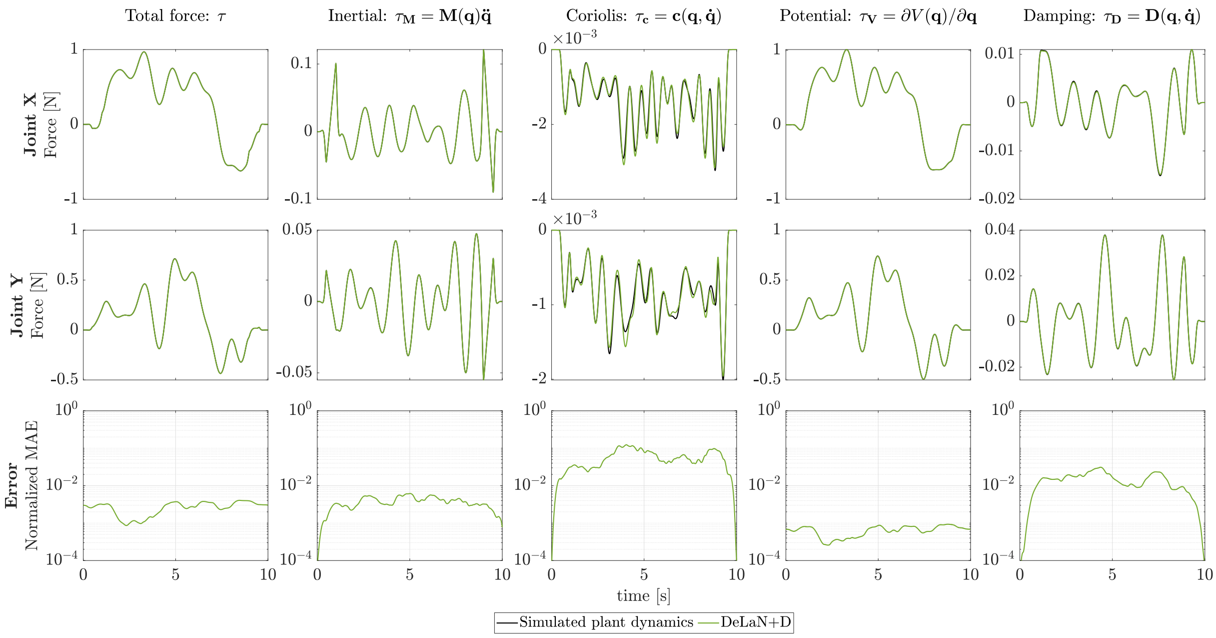

Figure 3: Comparison between simulated 2-DOF manipulator dynamics and DeLaN+D force estimates for the total force (leftmost plots) as well as split into four components (other plots). In case of a (near) perfect agreement the simulated data are hidden and the plots in the bottom row confirm the small error.

This equation of motion for the inverse dynamics of the manipulator is implemented in a PINN that effectively extends the previously used DeLaN [2] with the viscous-Coulomb damping terms into a “DeLaN+D” network, figure 2. The damping terms are added similarly to the mass term, where the mass, viscous and Coulomb matrices are guaranteed to be symmetric and positive definite.

The performance of the DeLaN+D network has been evaluated with simulated and experimental data. In the leftmost plots of figure 3 the total predicted actuator forces in both directions “X” and “Y” are compared to the simulated plant dynamics and show an agreement of approximately 99.8%. The other plots show this comparison for four separate components that contribute to the total force in agreement with Eq. (1), i.e. the first term, the second and third terms, the stiffness term, and the damping terms, respectively. It can be seen that most mean square errors (MSE) are small with a relatively larger misfit only in the small contribution of the Coriolis terms.

The closed-loop tracking accuracy in both “X” and “Y” directions has been evaluated experimentally as will be detailed in the paper. The joint position errors are compared using only feedback, i.e. no feedforward, and adding the feedforward force estimated with a white-box model or the DeLaN+D network, respectively. Both feedforward estimates show similar performance, reducing the mean absolute error (MAE) with 92%. Furthermore, the effectiveness of the DeLaN+D feedforward action is confirmed by comparing it with the remaining feedback control. It appears that the DeLaN+D estimate accounts for on average 86% of the total control force.

These results demonstrate that the feedforward control generated by the trained DeLaN+D network can be applied successfully for the considered manipulator. The robustness and more general applicability of this approach will be investigated in future work.

References

[1] Brouwer, D.M.; Folkersma, K.G.P.; Boer, S.E.; Aarts, R.G.K.M.: Exact constraint design of a two-degree of freedom flexure-based mechanism. Journal of Mechanisms and Robotics, Vol. 5, No. 4, pp. 041011:01–10, 2013.

[2] Heerze, E.; Rosic, B.; Aarts, R.: Feedforward Control for a Manipulator with Flexure Joints Using a Lagrangian Neural Network. In K. Nachbagauer and A. Held (Eds.) IUTAM Symposium on Optimal Design and Control of Multibody Systems 2022, IUTAM Bookseries 42, 12 pages, Springer, 2024.

[3] Lutter, M.; Peters, J.: Combining Physics and Deep Learning to learn Continuous-Time Dynamics Models. arXiv:2110.01894, 2023.