Learning for Precision Motion of Mechatronic Systems: Add-on Physics-Guided Neural Network Feedforward Control

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Short abstract

Accurate feedforward control is essential for achieving future performance specifications in mechatronic systems, including wafer stages and interventional X-rays. Feedforward control parametrizations based on physical models, such as mass, friction, or snap feedforward have seen many successful implementations in the high-tech industry. They are physically interpretable and can compensate most dynamics with a few parameters. However, the performance of these physical-model-based feedforward controllers is limited by hard-to-model nonlinear parasitic dynamics.

To compensate these nonlinear parasitic dynamics, a feedforward framework is developed where a neural network component is added onto an existing physical model, creating a parallel physics-guided neural network (PGNN) feedforward structure. In this parallel structure, the neural network component can learn and subsequentially compensate hard-to-model parasitic dynamics not included in the physical model, increasing performance. Additionally, the neural network is regularized in such a way that it only learns and compensates dynamics that cannot already be captured by the physical model component. As a consequence, the physical model can be used as a baseline and has interpretable parameters, and the neural network only compensates deviations from the physical model, allowing for a neural network with fewer parameters and smaller outputs compared to a full neural network feedforward parametrization. The developed PGNN framework is validated in two use-cases in precision mechatronics.

1) **An ASML wafer stage**: in an ASML wafer stage, more specifically, in its short-stroke, the contribution of each flexible mode to the system dynamics varies as a function of the position on the wafer, resulting in position-varying dynamics. The developed framework is able to learn and compensate these varying dynamics through a neural network snap gain, increasing tracking performance by a factor 5.

2) **A Philips interventional X-ray experimental setup**: an interventional X-ray consists of three rotating axis coupled through cables and rolled-based guidance. The resulting position-varying friction characteristics and cable forces are hard-to-model, but are successfully learned from data by a PGNN feedforward controller, increasing the tracking performance by a factor 4.75 in a recent case-study [1].

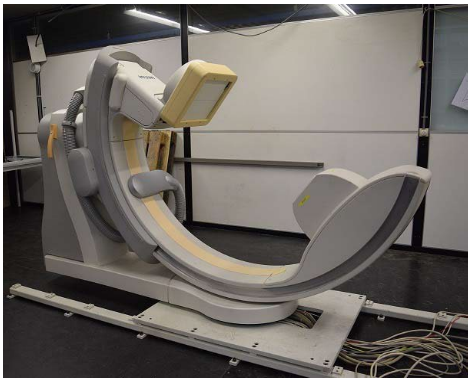

Figure 1: *Interventional X-ray.*

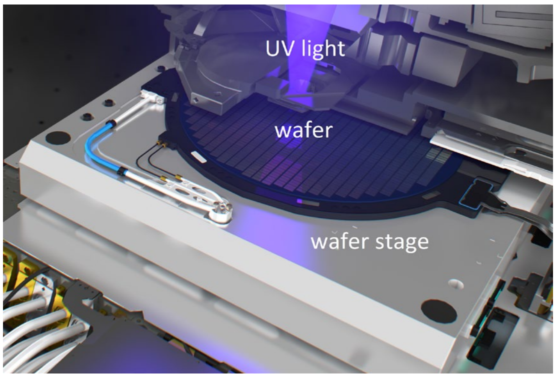

Figure 2: *ASML wafer stage.*

References

[1]: J. Kon, D. Bruijnen, Jeroen van de Wijdeven, Marcel Heertjes, Tom Oomen, “Feedforward Control for an Interventional X-ray: A Physics-Guided Neural Network Approach”, 42nd Benelux Meeting on Systems and Control, Elspleet, The Netherlands, 2023.

Keywords: Feedforward control, neural networks, data-driven learning