Neural networks for feedforward control

Citation for published version (APA):

Document license:
CC BY-NC-ND

Document status and date:
Accepted/In press: 01/01/2023

Document Version:
Accepted manuscript including changes made at the peer-review stage

Please check the document version of this publication:
• A submitted manuscript is the version of the article upon submission and before peer-review. There can be important differences between the submitted version and the official published version of record. People interested in the research are advised to contact the author for the final version of the publication, or visit the DOI to the publisher’s website.
• The final author version and the galley proof are versions of the publication after peer review.
• The final published version features the final layout of the paper including the volume, issue and page numbers.

Link to publication

General rights
Copyright and moral rights for the publications made accessible in the public portal are retained by the authors and/or other copyright owners and it is a condition of accessing publications that users recognise and abide by the legal requirements associated with these rights.

• Users may download and print one copy of any publication from the public portal for the purpose of private study or research.
• You may not further distribute the material or use it for any profit-making activity or commercial gain
• You may freely distribute the URL identifying the publication in the public portal.

If the publication is distributed under the terms of Article 25fa of the Dutch Copyright Act, indicated by the “Taverne” license above, please follow below link for the End User Agreement:
www.tue.nl/taverne

Take down policy
If you believe that this document breaches copyright please contact us at:
openaccess@tue.nl
providing details and we will investigate your claim.
Neural networks for feedforward control

Johan Kon\textsuperscript{1}, Dennis Bruijnen\textsuperscript{2}, Jeroen van de Wijdeven\textsuperscript{3}, Marcel Heertjes\textsuperscript{1,3}, Tom Oomen\textsuperscript{1,4}

I. RESEARCH OVERVIEW

Hard-to-model dynamics limit the performance of current feedforward approaches as it is hard to describe these dynamics as a mathematical function. For example, consider the inability of a polynomial basis function feedforward to compensate nonlinear friction characteristics. This work focuses on developing more advanced feedforward controllers based on neural networks to instead learn these dynamics from data. Relevant topics within this research are i) how to combine neural networks with prior knowledge in the form of models, ii) how to guarantee stability, and iii) how to obtain consistent estimates when working with closed-loop data.

Everything that can be explained by a physical model, should be explained by this model [1], [2].

When employing neural networks for feedforward, it is common practice to ignore all prior knowledge about the systems dynamics. However, physical models are usually a very efficient representation of the dynamics, such that a purely neural network approach can introduce unnecessarily big networks. In [1] and [2], a parallel physical-model and neural-network feedforward controller is developed to utilize prior knowledge and learn unmodelled dynamics simultaneously. Through regularization, it is ensured that the neural network does not learn anything that can be captured by the physical model. The figure shows that the combined feedforward of the parallel combination (---) can learn the required input (----). However, the neural network (---) can learn parts of the physical model (---) without changing the combined feedforward (right). The proposed regularization ensures that the contributions of the physical model and neural network are complementary (left).

\textbf{LPV feedforward control for position dependent zeros [3]}

Position-dependent dynamics are omnipresent in mechatronic systems, possibly necessitating an LPV feedforward controller with 'shifting poles' to compensate for the shifting antiresonances of the position-dependent system. To learn any position-dependent function, the dependency of the controller coefficients on the scheduling variable is learned through a parallel physical model and neural network. Analytical gradient expressions combined with a second order solver allow for significantly faster optimization compared to a standard implementation in an automatic differentiation framework.

The figure shows an example system with a resonance that has a position-varying damping (left). The LPV feedforward controller (---) is able to generate the required input for perfect tracking (----) up to the approximation capabilities of the neural network, whereas a rational transfer function feedforward controller (---) cannot capture the effects of the position-dependent resonance. Current research is aimed at guaranteeing that the LPV feedforward controller is stable.

\textbf{Instrumental variables for consistent estimation [4].}

Input-output data for learning a feedforward controller is often obtained from a closed-loop experiment for safety concerns. Consequently, unmeasured disturbances entering the control loop end up in both input and output, creating correlations that result in inconsistent parameter estimates, degrading control performance. To obtain consistent parameter estimates, an instrumental variable neural network optimization criterion is developed. The figure shows the validation error, i.e., the norm of the predicted input and the actual input, for both a standard least-square criterion (---) and the proposed IVNN criterion (---). This validation error is shown for multiple noise realizations in the input output data (crosses and circles) and for a range of noise levels. It can clearly be seen that the bias worsens the quality of the LS estimate.

This work is supported by Topconsortia voor Kennis en Innovatie (TKI), and ASML and Philips Engineering Solutions.

\textsuperscript{1}: Control Systems Technology Group, Departement of Mechanical Engineering, Eindhoven University of Technology, Eindhoven, The Netherlands, corresponding e-mail: j.j.kon@tue.nl.
\textsuperscript{2}: Philips Engineering Solutions, Eindhoven, The Netherlands.
\textsuperscript{3}: ASML, Veldhoven, The Netherlands.
\textsuperscript{4}: Delft University of Technology, Delft, The Netherlands.
II. SEMINAR TOPIC - LEARNING FOR PRECISION MOTION OF AN INTERVENTIONAL X-RAY SYSTEM

This section illustrates research topic 1, i.e., parallel physical model and neural network feedforward control, through an experimental case study on an interventional X-ray (IX).

A. Problem Formulation

IXs are a key technology in healthcare that improve treatment quality through visualization of patient tissue. To guarantee both high imaging quality as well as patient and operator safety, accurate feedforward control is essential during operation of an IX. However, the mechanical design, constrained by the use around medical personnel, introduces nonlinear dynamics such as configuration-dependent cable forces and nonlinear friction characteristics that are dependent on the normal force on the rollers in the guidance. These hard-to-model dynamics are only qualitatively known, and thus the aim is to learn from data using neural networks.

B. Feedforward Parameterization

To compensate the hard-to-model dynamics, the feedforward controller is parametrized as a parallel combination of a physical model and neural network $g_\phi$ such that the feedforward $f$ for reference $\theta_d$ is given by

$$f(\theta_d(k)) = M \ddot{\theta}_d(k) + H(\theta_d) + g_\phi(T(\theta_d(k))),$$

with $d$ the viscous damping coefficient and

$$M = m(y^2 + z^2) + J_{xx} \in \mathbb{R}_{\geq 0},$$

$$H(\theta) = mg(y \cos(\theta) - z \sin(\theta)) \cos(\zeta) \in \mathbb{R},$$

the inertia and gravity contribution. Coordinates $y, z$ represent the offset of the center of mass with respect to the point of rotation, and $\zeta$ the known orientation of the roll axis out of the vertical plane. The neural network $g_\phi$ is given by

$$g_\phi(x) = W^L \sigma(W^{L-1} \sigma(\cdots \sigma(W^0 x + b^0) \cdots + b^{L-1}) + b^L),$$

with $\sigma$ an elementwise activation function, $\phi = \{W^i, b^i\}_{i=0}^L$ weight and bias matrices. $g_\phi$ acts on a physics-guided input

$$T(\theta_d(k)) = [\theta_d(k) \ \dot{\theta}_d(k) \ \ddot{\theta}_d(k) \ \text{relay}(\theta_d(k))]^T,$$

which encodes the prior knowledge that the required feedforward depends not only on position, but also on velocity, and the history of the direction for static friction.

The parameters $m, y, z, \phi$ are learned from input-output data $\{u(k), y(k)\}_{k=1}^N$ through inverse system identification, i.e., by regressing the feedforward output $f(y(k))$ on $u(k)$ as

$$\min_{m, y, z, \phi} \sum_{k=1}^N (u(k) - f(y(k)))^2 + R(\phi).$$

$R(\phi)$ represents orthogonal projection-based regularization [1] to ensure that $g_\phi$ does not learn modeled effects, such that the physical model remains interpretable.

C. Results

The feedforward controller is validated experimentally on the IX setup. Fig. 2 shows the resulting tracking errors. The proposed feedforward controller ( ) compensates almost all dynamics, resulting in a tracking error of a few encoder counts. In contrast, the physical-model-based feedforward controller ( ) improves upon the feedback only case ( ), but still contains predictable errors from uncompensated dynamics. Overall, the tracking error is reduced from 0.095 to 0.020 deg in mean absolute sense by the inclusion of a neural network.

REFERENCES


Johan Kon received the BSc. degree (2018) and MSc. degree (2021, cum laude) in control systems from the Eindhoven University of Technology. Currently he is pursuing a Ph.D. degree at the department of Mmechanical Engineering at Eindhoven University of Technology. His research interests include feedforward control and inverse system identification with neural networks applied to high-precision mechatronic systems.