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Neural networks for feedforward control

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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.

\textit{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).

\textit{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.

\textit{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.

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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 \( \sigma \) and nonlinear friction characteristics that are dependent on the normal force on the rollers in the guidance \( \phi \). These hard-to-model dynamics are only qualitatively known, and thus the aim is to learn them from data using neural networks.

![Interventional X-ray system](image)

Fig. 1. Interventional X-ray system positioning the X-ray source and detector through rotating 3 axes, among which the roll axis with angle \( \theta \).

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

\[
f(\theta_d(k)) = M\dot{\theta}_d(k) + H(\theta_d) + g_\phi(T(\theta_d(k)), \text{with } \dot{d} \text{ the viscous damping coefficient and}
\]

\[
M = m(g^2 + z^2) + J_{ax} \in \mathbb{R}_{\geq 0}, \\
H(\theta) = mg(y\cos(\theta) - z\sin(\theta))\cos(\zeta) \in \mathbb{R},
\]

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.

![Error signals](image)

Fig. 2. Error signals for proposed \( (\_\_\_\_\_\_\_) \) and physical-model-based \( (\_\_\_\_\_\_\_) \) feedforward controller compared to the feedback only case \( (\_\_\_\_\_\_\_) \) with scaled velocity reference \( (\_\_\_\_\_\_\_) \).

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 Mechnanical Engineering at Eindhoven University of Technology. His main research interest is the combination of feedforward control and inverse system identification with neural networks applied to high-precision mechatronic systems.