Feedforward Control for an Interventional X-ray: A Physics-Guided Neural Network Approach

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1 Background

Interventional X-ray systems (IXs) are a key technology in healthcare that improve treatment quality through visualization of patient tissue. This enables minimally invasive therapies, resulting in faster patient recovery. To guarantee both high imaging quality as well as patient and operator safety, accurate feedforward control is essential during operation of an IX. A typical IX is visualized in Fig. 1.

2 Problem Formulation

The tracking performance of feedforward controllers based on first-principles modeling is limited by hard-to-model dynamics in the IX, such as the configuration-dependent cable forces and nonlinear friction characteristics in the guidance.

Instead, the goal of this work is to learn these hard-to-model dynamics from input-output data of the IX through capturing their contributions to the equations of motion using neural networks as flexible function approximators.

3 Physics-Guided Neural Network Feedforward

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

$$f(\theta_d(k)) = M\ddot{\theta}_d(k) + mgh(\theta_d(k)) + g_\phi(T(\theta_d(k)), \quad (1)$$

where M and $mgh(\theta)$ represent the inertia and gravity contribution derived from first-principles, and

$$T(\theta_d(k)) = \begin{bmatrix} \theta_d(k) & \dot{\theta}_d(k) & \ddot{\theta}_d(k) & \mathrm{relay}(\theta_d(k)) \end{bmatrix}^T \quad (2)$$

represents is a physics-guided input transformation.

The parameters M, m, ϕ 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

$$\textstyle\sum_{k=1}^N (u(k) - f(y(k)))^2 + R(\phi). \quad (3)$$

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

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4 Results

The feedforward controller is validated experimentally on the IX setup of Fig. 1. 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.

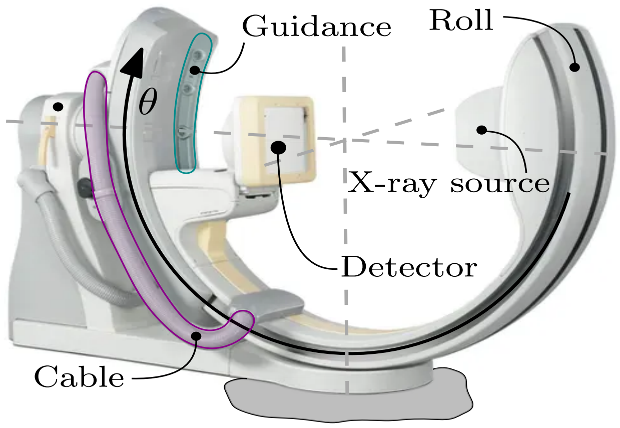

Figure 1: Interventional X-ray system positioning the X-ray source and detector through rotating, i.a., the roll axis.

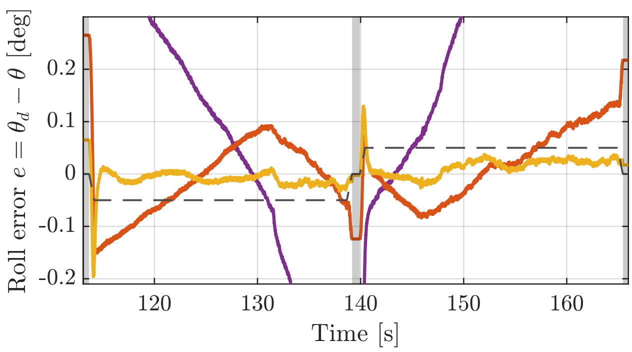

Figure 2: Error signals for proposed (—) and physical-model-based (—) feedforward controller compared to the feedback only case (—) with scaled velocity reference (- -).

References

[1] J. Kon, D. Bruijnen, J. van de Wijdeven, M. Heertjes, and T. Oomen, “Physics-guided neural networks for feedforward control: An orthogonal projection-based approach,” in *Proc. Am. Control Conf.*, 2022.