



Enhancing Machine Learning-Based Feedforward Control of 2-DOF Flexure Manipulator: Benefits of Time-Delay Embedding

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Enhancing Machine Learning-Based Feedforward Control of 2-DOF Flexure Manipulator: Benefits of Time-Delay Embedding

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1 Introduction

The rapid evolution of machine learning offers new opportunities to improve model-based control systems. Our research focuses on using these techniques to enhance a feedforward controller for a fully actuated 2 degrees of freedom (DOF) manipulator with flexure joints (Fig. 1).

Feedforward control is a powerful technique to improve the tracking performance of a manipulator. This study's feedforward controller is built solely based on data-driven techniques. The foundation of the controller is a combination of the Lagrangian Neural Network (LNN) and the Feedforward Neural Network (FNN), primarily introduced in [1]. We utilize the LNN to simulate the system's conservative forces, whereas the FNN is tasked with forecasting the variances between the total necessary forces and those generated by the LNN, particularly the non-conservative forces. It is essential to note the inherent limitation of both networks in precisely modeling the reproducible part of these forces.

To address this limitation, we introduce residual modeling as a secondary layer in the controller, enabling us to integrate forecasted errors into the controller's original output, as illustrated in Fig. 2. We call this approach the Data-Driven Inverse Dynamics (DID) error discovery as we use the weighted recursive least-squares method with regularization, which maps the system's configurations to the residue of control signals [2]. Its efficiency comes from rank-1 updates and the ability to outperform the NN-based part in updating.

One of the promising methods to improve these state-of-the-art results is Time-Delay Embedding (TDE), which has already seen applications in robotics modeling [3]. This study assesses whether TDE can enhance our DID error modeling and ultimately improve control performance.

2 Integrating Time-Delay Embedding into Data-Driven Inverse Dynamics

The DID method develops a linearized error model $\mathbf{D} \in \mathbb{R}^{2 \times 8}$. It maps from $\mathbf{z}_j = [\mathbf{x}_j^T \mathbf{r}_{j+1}^T]^T \in \mathbb{R}^8$, which comprises the current state of the system $\mathbf{x}_j \in \mathbb{R}^4$ (position and velocity for each degree of freedom) and the desired next state $\mathbf{r}_{j+1} \in \mathbb{R}^4$ to the residual error $\mathbf{e}_j = [e_{1,j} \ e_{2,j}]^T \in \mathbb{R}^2$ of the control signals, which drive the actuators moving the system's arms. This can be formulated as

$$\mathbf{e}_j = \mathbf{D}\mathbf{z}_j, \quad \text{where} \quad \mathbf{e}_j = \mathbf{F}_j - \tilde{\mathbf{F}}_j \quad \text{for} \quad j = 1, 2, \dots \quad (1)$$

Here, the residual is defined as the difference between the actual control signals \mathbf{F}_j delivered to the fully-actuated robotic system and the control forces $\tilde{\mathbf{F}}_j$ predicted by the combined action of the LNN and FNN.

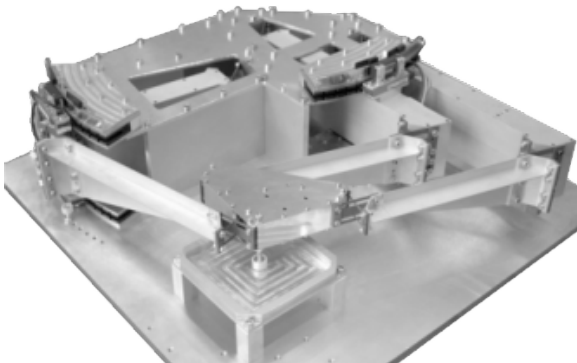


Figure 1: Photo of the 2 DOF manipulator with flexure joints (photo by Ger Folkersma).

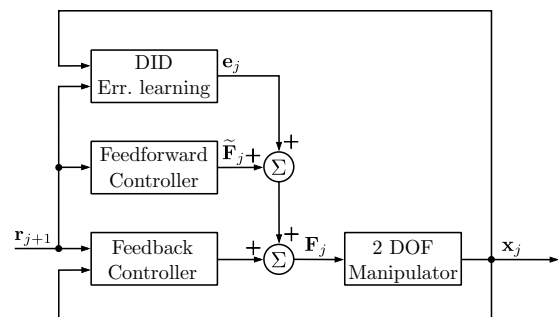


Figure 2: Control system structure with the DID learning error of the NN-based controller.

The model \mathbf{D} is derived from $\mathbf{D} = \mathbf{E}\mathbf{Z}(\mathbf{Z}\mathbf{Z}^T + \alpha\mathbf{I})^{-1}$, where \mathbf{E} , \mathbf{Z} constitute the training dataset and α is the regularization parameter. This dataset is constructed to mimic ideal tracking. Specifically, it is created from measurements assuming the desired state $\mathbf{r}_{i+1} \leftarrow \mathbf{x}_j$ is precisely reached from the current state $\mathbf{x}_i \leftarrow \mathbf{x}_{j-1}$ (accordingly $\mathbf{e}_i \leftarrow \mathbf{e}_{j-1}$). If we build the model with such snapshot pairs $(\mathbf{e}_i, \mathbf{z}_i)$ from steps $i = 1, \dots, k$, these matrices are formed as follows

$$\mathbf{E}_k = [\mathbf{e}_1 \quad \mathbf{e}_2 \quad \dots \quad \mathbf{e}_{k-1}], \quad \mathbf{Z}_k = \begin{bmatrix} \mathbf{x}_1 & \mathbf{x}_2 & \dots & \mathbf{x}_{k-1} \\ \mathbf{x}_2 & \mathbf{x}_3 & \dots & \mathbf{x}_k \end{bmatrix}. \quad (2)$$

The TDE involves augmenting the matrices \mathbf{E}_k , \mathbf{Z}_k with time-shifted copies of the measurements, transforming them into Hankel matrices. This process can be represented as follows

$$\hat{\mathbf{E}}_k = \begin{bmatrix} \mathbf{e}_1 & \mathbf{e}_2 & \dots & \mathbf{e}_{k-N_{TDE}-1} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{e}_{N_{TDE}+1} & \mathbf{e}_{N_{TDE}+2} & \dots & \mathbf{e}_{k-1} \end{bmatrix}, \quad \hat{\mathbf{Z}}_k = \begin{bmatrix} \mathbf{x}_1 & \mathbf{x}_2 & \dots & \mathbf{x}_{k-N_{TDE}-1} \\ \mathbf{x}_2 & \mathbf{x}_3 & \dots & \mathbf{x}_{k-N_{TDE}} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{x}_{N_{TDE}+2} & \mathbf{x}_{N_{TDE}+3} & \dots & \mathbf{x}_k \end{bmatrix}, \quad (3)$$

where N_{TDE} is the number of embeddings. The TDE elevates the dimensionality of the space in which the system is analyzed. This dimensional change is hypothesized to improve the precision of the linear model in representing phenomena, which, seen in a lower dimension, would be perceived as nonlinear.

3 Reducing the Feedforward Control Error

Fig. 3 presents the outcome of incrementally adding embeddings. The left plot reveals that the error in residue prediction for e_1 decreases across the entire range. However, in the error for e_2 , after an initial reduction by an order of magnitude, the trend does not persist. This could be attributed to the worsening conditioning of matrices as N_{TDE} increases. The right plot includes standard deviation information, exhibiting an exponential-like decrease for both signals.

Nonetheless, there is a trade-off to consider – as the number of embeddings grows, so does the computational cost of updating the DID model ($\mathcal{O}(n^2)$). Despite the modest improvements in numbers, the results are optimistic and pave the way for further research. Additionally, it is essential to investigate the relationship between the embeddings used in this study and the Koopman operator theory.

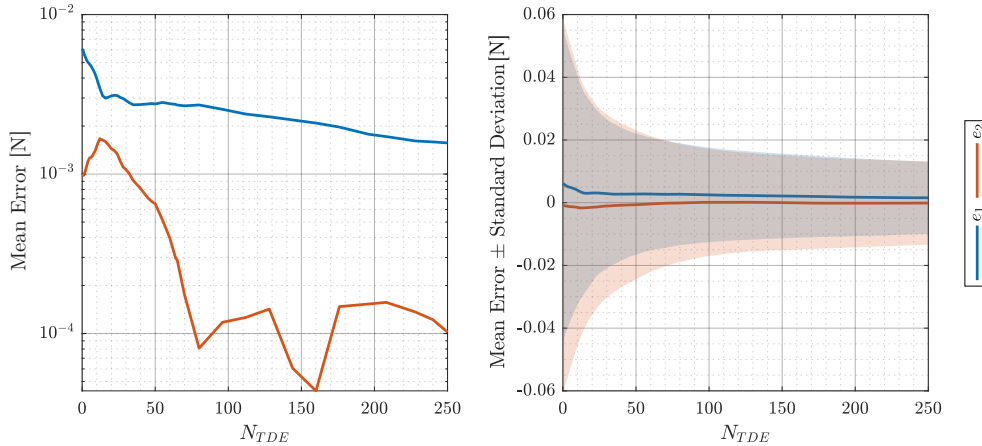


Figure 3: Mean error (left) and representation of its standard deviation (right) as a function of N_{TDE} .

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