Mutual information-based feature selection for the inverse mapping parameter updating method

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Bas Kessels, TU/e*
b.m.kessels@tue.nl

Adarsh Subrahamanian, TU/e*
a.subrahamanian.moosath@student.tue.nl

Rob Fey, TU/e*
r.h.b.fey@tue.nl

Nathan van de Wouw, TU/e*
n.v.d.wouw@tue.nl

1 Introduction

A digital twin of a (controlled) physical system allows engineers to efficiently optimize the design of the physical system and both optimize its performance and monitor its health in real-time. Since a model (i.e., a digital twin) is typically not an exact representation of a measured physical system, the digital twin cannot be exploited to its full potential. Therefore, model (parameter) updating is employed to minimize the mismatch between the model and the measured system. To make model parameter updating generally applicable in an online, digital twin context, the updating method should be: 1) applicable in (near) real-time, 2) applicable to nonlinear models, and 3) physically interpretable. To satisfy these requirements, the Inverse Mapping Parameter Updating (IMPU) method is proposed [1] which maps a set of features to corresponding parameter values. Since many distinct features can be extracted and using too many features may lead to deteriorating accuracy and computational efficiency, Feature Selection (FS) is applied.

2 Inverse mapping parameter updating

In this research, the IMPU method is used to update physically interpretable parameter values $\boldsymbol{p}$ of a first-principles (nonlinear dynamics) parametric (forward) model. This is achieved by using the inverse relation between $\boldsymbol{p}$ and a set of features $\boldsymbol{\psi}$ as extracted from output responses that are obtained for user-defined initial conditions and excitation signals, see Figure 1. This inverse relation is captured in an Inverse Mapping Model (IMM):

$$\hat{\boldsymbol{p}} = \mathcal{I}(\bar{\boldsymbol{\psi}}). \tag{1}$$

The IMM is constituted by an ANN that is trained offline using simulated training data $\{\boldsymbol{p}_s, \boldsymbol{\psi}_s\}$, where $n_s = 1, \ldots, n_s$, such that it learns an accurate mapping. Then, in an online phase, measured sets of features are used as input to the already trained ANN such that parameter estimates are typically obtained in approximately 5 milliseconds, allowing for real-time updating. In this method, features describe the transient output response of the system. As many different features can be extracted from output data, see [1],

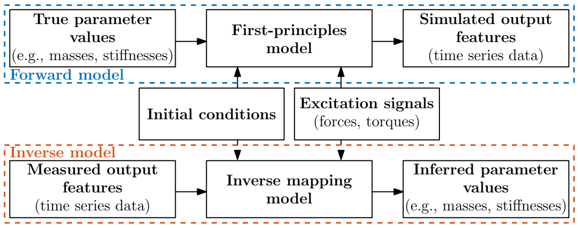

Fig. 1: Comparison of a first-principles forward model and an inverse mapping model and their inputs and outputs.

and too many features may deteriorate accuracy and training/inference time, FS is be applied to obtain a more informative subset.

3 Feature selection using mutual information

To select a subset of features, the Mutual Information (MI) [2] between the different features and the different parameter values is used. Here, MI can be regarded as the entropy that represents the information contained within a variable (feature or parameter value). By calculating a MI score for each combination of features and parameters in the training data, the features are ranked and the features with highest MI score are selected. By employing a subset of selected features as inputs to the ANN, it is observed that accuracy of the parameter estimates is maintained or improved with respect to the use of the entire set of features.

4 Conclusions

Using an IMM, constituted by an offline trained ANN, physically interpretable parameter values of nonlinear dynamics models can be updated in (near) real-time. To decrease training and inference time, and potentially increase accuracy of the estimated parameter values, MI-based FS is employed.

References

[1] B.M. Kessels, R.H.B. Fey, and N. van de Wouw, "Real-time parameter updating for nonlinear digital twins using inverse mapping models and transient-based features," *Nonlinear Dynamics* (Submitted for review), 2022.

[2] B. C. Ross, "Mutual information between discrete and continuous data sets," *PloS one*, vol. 9, no. 2, 2014.

*Eindhoven University of Technology, Department of Mechanical Engineering, Dynamics & Control Group