High-Precision Mechatronics: from Experiment Design to Point of Interest Control

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I. RESEARCH OVERVIEW

The performance of future high-precision mechatronics relies on advanced control strategies that can cope with the increasing system complexity, e.g., due to pronounced flexible dynamics, unmeasurable performance variables, and a large number of actuators and sensors. The availability of high-quality identified dynamic models that accurately describe these complex systems is indispensable for precision control. This research is focused on advanced identification and control of complex precision mechatronics.

Exploiting input directions enables effective identification \cite{1}.

Good design of identification experiments is crucial to obtain high-quality models, especially for complex motion systems with a large number of actuators. In classical optimal input signal design approaches, such MIMO systems are treated as a multiple of SIMO systems, leading to non-optimal model quality. In \cite{1}, it is shown that optimality is achieved by exploiting the multiplicity of the actuators, resulting in directional input signals. Optimal directional inputs significantly reduce the uncertainty region (\textcircled{2}) compared to classical optimal input design strategies (\textcircled{1}).

Addressing control purpose in experiment design and identification improves robust performance \cite{2}.

Addressing the control goal during the system identification procedure is crucial to ensure that the model achieves high control performance. In \cite{2}, a framework is developed for the identification of model sets for high-performance robust control. The key approach is to connect the criteria for robust control, identification, and experiment design through a specific robust-control-relevant (rcr) coprime factorization. Using a rcr excitation spectrum design (\textcircled{3}), a significantly tighter model set (\textcircled{2}) is identified, compared to the set (\textcircled{1}) resulting from classical excitation design. This enables improving robust control performance.

Controlling the point that matters via inferential control \cite{3}.

In many motion systems, the point of interest \(z\) cannot be measured directly, but must be estimated from sensory data \(y\) in combination with a dynamic system model. The inferential aspect has large implications on the structure, the dynamics, and the design of the controller. In addition, the required inferential controller is inherently model-based, which emphasizes the need for addressing model uncertainty. In \cite{3}, a robust multivariable control design framework is developed for positioning the point of interest explicitly. Experimental results show that the inferential controller (\textcircled{4}) suppresses the disturbance (\textcircled{5}) significantly better than the classical control approach (\textcircled{1}).
II. Seminar Topic - Exploiting Wavelets for FRF Identification with Missing Samples [4]

Frequency Response Function (FRF) identification of complex systems typically requires collecting a large data amount. In practice, corrupted or missing samples in the data often occurs, which complicates FRF identification. In this section, a method is presented to accurately identify FRFs in the presence of missing samples.

A. Problem formulation

The aim is to identify the FRF model \( G(\Omega_k) \) from measured input and output data \( u, y^m \) where \( y^m \) contains missing samples. The input-output relation is exactly represented in the frequency domain by

\[
Y(k) = G(\Omega_k)U(k) + T(k) + V(k), \\
Y^m(k) = Y(k) + \Delta(k),
\]

where \( U(k), Y(k) \) is the Discrete Fourier Transform (DFT) of the signals \( u, y \) at frequency bin \( k \), term \( T(k) \) denotes the transient and \( V(k) \) the DFT of the measurement noise. Term \( \Delta(k) \) is the global and non-smooth perturbation due to the missing samples, which affects \( Y^m(k) \) as shown in Fig. 1.

![Fig. 1. Y (→) and Y^m (→). Missing samples introduce a global perturbation.](image)

B. Approach: Wavelet-based Local Polynomial Method

The key idea is to project out the effect of the missing samples \( \Delta(k) \) via a matrix \( M \), such that

\[
Y^m M = (Y + \Delta) M = Y M.
\]

To achieve (2), matrix \( M \) is selected as a bank of wavelets over a frequency grid. This enables transforming the time-domain data \( y^m \) to the time-frequency plane, in which the effect of the missing samples is local. This is shown in Fig. 2 for the same data as used in Fig. 1.

![Fig. 2. Time-frequency plane representation of y^m, in which the effect of the missing samples (•) is local.](image)

To identify the FRF \( G(\Omega_k) \) from the time-frequency plane data in (●), the classical Local Polynomial Method (LPM) [5] is extended to incorporate the wavelet-based transform. The FRF estimate is obtained from the minimization problem

\[
\hat{\Theta} = \arg\min_{\Theta} \|Y^m - K \Theta M\|_2,
\]

where \( K \) parametrizes \( G \) and \( T \) by local polynomials as in the LPM, and \( \Theta \) denotes the estimation variables.

C. Results

The developed method is applied for the identification of the simulated system with FRF in (→) in the figure below from noisy data with missing samples. The estimated FRF (→) accurately reflects the true system. In contrast, the classical LPM approach (→) fails to deliver an accurate model as a result of the missing samples.

![Graph showing FRF results.](image)

D. Conclusions and ongoing work

The presented wavelet-based identification approach enables achieving accurate FRF models from data that is corrupted by missing samples. Future work includes uncertainty quantification, closed-loop extensions, and experimental validation.

REFERENCES


Nic Dirkx received the MSc. degree in control systems from the Eindhoven University of Technology, in 2011. Currently, he is researcher at ASML Research Mechatronics & Control, while pursuing a Ph.D. degree at the department of mechanical engineering at the Eindhoven University of Technology. His research interests include advanced identification and control of high-precision mechatronics.