Data-Driven Compensation of Unmodeled Dynamics for Complex Mechatronic Systems – Part I: Position-Dependent Feedforward through Gaussian Process Regression

Maurice Poot[1], Max van Haren[1], Dragan Kostić[2], Jim Portegies[3], Tom Oomen[1,4]

[1]Control Systems Technology, Eindhoven University of Technology, The Netherlands

[2]Center of Competency, ASMPT, The Netherlands

[3]Centre for Analysis, Scientific computing and Applications, Eindhoven University of Technology, The Netherlands

[4]Delft Center for Systems and Control, Delft University of Technology, The Netherlands

m.m.poot@tue.nl

Abstract

The requirements for high accuracy and throughput in data-intensive complex mechatronic systems lead to situations where unmodeled dynamics can not be neglected. For example, nonlinearities caused by cable connections, or position-dependent dynamics due to changing flexible dynamics as function of position, or position-dependency caused by force ripple in actuators can limit the positioning accuracy if they remain unmodeled in the feedforward.

This research aims to develop systematically tunable and interpretable position-dependent feedforward for systems that are approximated well by a linear time-invariant system for motion tasks that stay close to a fixed position, e.g., a wire bonder or wafer scanner. To achieve a systematically tunable and interpretable position-dependent feedforward that is also flexible to varying motion tasks, the feedforward is chosen as a function of the reference r with position-dependent feedforward parameters, e.g.,

$$f(p,r,t) = K_{mfc}(p)\left(k_{fa}(p)\ddot{r}(t) + k_{fs}(p)\ddddot{r}(t) + k_{fc}(p)\mathrm{sign}\big(\dot{r}(t)\big)\right).$$

Here, $K_{mfc}(p)$ is a position-dependent motor force constant, and $k_{fa}(p), k_{fs}(p), k_{fc}(p)$ are position-dependent feedforward parameters corresponding to, respectively, acceleration feedforward parameter to compensates Newton's first law, snap feedforward parameter corresponding to the low-frequency contribution of the flexible modes, and the parameter for the sign of the reference velocity to compensate Coulomb friction. Note that traditional feedforward is recovered in case $k_{fa}(p), k_{fs}(p), k_{fc}(p)$ are position independent. Moreover, the motor force constant is often already calibrated by well-established calibration methods, see, e.g., [1].

To find the position-dependent parameters in the feedforward signal, estimation methods such as iterative learning control with basis functions [2] can be applied for references that stay close to a fixed position. The key idea is then to interpolate the learned parameters for a few fixed positions using Gaussian process regression, where prior knowledge about the smoothness of the parameters as function of position can be specified in a kernel [3]. To optimally distributed the fixed learning positions, the variance of the estimation of the Gaussian process is utilized in a mutual information optimization procedure.

Experimental results on a wirebonder by ASMPT, see Figure 1, show that in case the motor force constant is not calibrated well, position-dependency may cause possibly additional position dependency in the feedforward parameters. The acceleration feedforward parameter that is modelled by the Gaussian process, see Figure 2, captures the variation in the motor force constant. The systematically tunable position-dependent feedforward framework using Gaussian processes significantly outperforms the position-independent feedforward methods, as shown in Figure 3, for six random test positions.

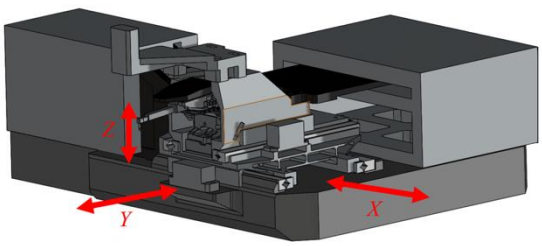

Figure 1. Wirebonder by ASMPT consisting of a stacked xyz-stage with position-dependent actuators.

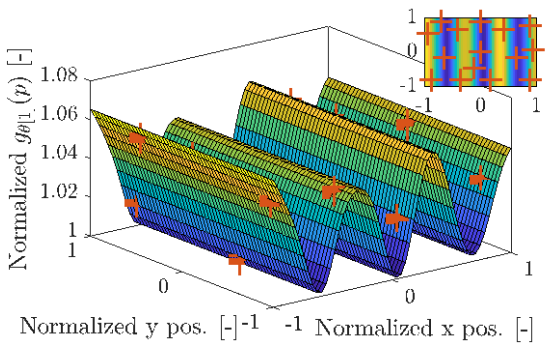

Figure 2. Gaussian process of the acceleration feedforward parameter as function of x and y position for optimally distributed training data (red).

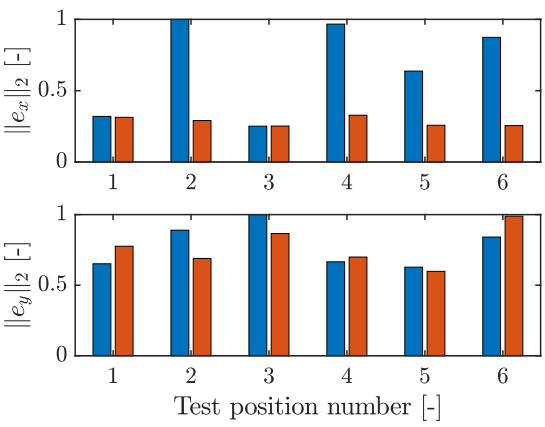

Figure 3. Normalized error 2-norm for position-independent feedforward and the developed position-dependent feedforward approach with optimally distributed learning positions.

[1] Röhrig C and Jochheim A 2001 Identification and compensation of force ripple in linear permanent magnet motors *Proceedings of the American Control Conference* vol 3 pp 2161–2166

[2] van der Meulen S, Tousain R and Bosgra O 2008 Fixed Structure Feedforward Controller Design Exploiting Iterative Trials: Application to a Wafer Stage and a Desktop Printer *Journal of Dynamic Systems, Measurement, and Control* vol 130 no 5 pp 0 510 061–05 100 616

[3] Rasmussen C and Williams K 2006 Gaussian Processes for Machine Learning (Cambridge, Massachusetts: MIT Press)