

Recursive Learning of Feedforward and Compliance Compensation Parameters for Precision Motion Systems

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Abstract: To meet the stringent requirements of future motion systems exhibiting time-varying and/or position-dependent behavior, online data must be leveraged to improve control performance. This paper presents a recursive algorithm for simultaneous learning of feedforward and compliance compensation parameters. A multivariate regression formulation is proposed that jointly estimates friction, mass, jerk, and compliance compensation parameters while mitigating parameter coupling. Experimental results on a high-tech semiconductor metrology and inspection system demonstrate an order-of-magnitude improvement in servo performance.

Keywords: High-performance motion control systems, Extremum seeking and model free adaptive control, Iterative and repetitive learning control

1. INTRODUCTION

High-tech motion systems in semiconductor manufacturing equipment such as lithography, chip dicing, and wire bonding machines, combine extraordinary positioning accuracy with fast movements and extreme accelerations. To achieve the exceptional control performance, model-based feedforward plays a key role (Heertjes (2016)). Although exact system inversion in feedforward control would result in perfect tracking, in practice this inversion is typically approximated (Van Zundert and Oomen (2018)). Acquiring an inverse is challenging since the underlying system is unknown and may exhibit time-varying and/or position-dependent behavior (Voorhoeve et al. (2021)), which limits the effectiveness of approximate inversion. To address practical limitations such as modeling errors, the inversion problem is approximated by a low-frequency representation, typically expressed as a linear combination of the reference position and its derivatives up to the fourth order (snap feedforward), see Boerlage et al. (2004).

Compliance compensation counteracts quasi-static deformation during acceleration phases and was introduced in Colombi and Raimondi (1994), with further developments in Vervoordeldonk and Baggen (2012); Kontaras et al. (2016). Unlike snap feedforward, compliance compensation acts as a measurement correction in the feedback path. It is often preferred over snap feedforward, as snap feedforward may induce high-frequency amplification of the reference, which leads to higher settling times if the system contains lightly-damped resonances often associated with flexible modes (Heertjes et al. (2020)). As performance demands drive higher accelerations, these deformations during acceleration phases become more significant and require effective compensation strategies. Existing approaches rely on time-invariant models and therefore cannot fully cap-

ture time-varying and/or position-dependent behavior, motivating the use of control strategies that utilize data in an online setting.

The class of controllers that adapt in an online setting, so called adaptive controllers, have been extensively studied in the past, see Åström (1981) and Annaswamy and Fradkov (2021) for surveys. Most emphasis in the literature is on feedback control, whereas for high-tech motion systems, feedforward control is of key importance. Methods that focus on performance optimization through learning of feedforward control parameters include trial-based approaches (Van der Meulen et al. (2007); Bolder and Oomen (2015)). These methods assume a repetitive setpoint trajectory, which is a severe limitation in high-tech motion systems. Other methods that adapt the feedforward controller online are, for instance, Zhao and Tan (2005), and Butler (2013), where measurements of the input and output are utilized for updating the feedforward controller parameters. These methods suffer from bias in the estimates due to correlation between the regressor and measurement noise. This is a well-known problem in system identification, which can be mitigated by using the instrumental variable approach, see Söderström and Stoica (2002). The instrumental variable approach for feedforward parameter estimation, as used in a trial-based tuning method Boeren et al. (2015) or a recursive method as proposed in Mooren et al. (2023), are both limited in their effectiveness in capturing time-varying and/or position-dependent behavior.

In this paper, we build upon the work of Van Keulen et al. (2023), which uses instrumental variables in a finite moving-horizon framework to capture time-varying and position-dependent behavior for feedforward control, and extend it to incorporate compliance compensation.

Extending the framework is non-trivial due to the acceleration feedforward that is intrinsically linked to the deformation that compliance compensation is intended to correct leading to coupling effects in the parameters. To address the current limitations of the learning framework, we present the following contributions:

- (1) Extension of the framework in Van Keulen et al. (2023) to recursive learning of compliance compensation in addition to feedforward parameters;
- (2) Utilizing multivariate regression to negate coupling effects in the parameters; and
- (3) Experimental validation on a state-of-the-art industrial metrology inspection machine.

2. SYSTEM DESCRIPTION

To represent a broad system class of mechanical motion systems, we adopt the description used in Van Keulen et al. (2024), and for convenience, separate the quasi-static compliance $\gamma_0 \in \mathbb{R}$ from the resonant dynamics $\gamma(s)$ to obtain

$$G(s) = \frac{1}{ms^2 + \zeta s} + \gamma_0 + \gamma(s), \quad (1)$$

with m the mass, ζ the viscous friction. The static compliance captured by γ_0 represents the inverse of the overall stiffness of the mechanical system, mapping an applied force to the resulting static deformation. The transfer function $\gamma(s)$ captures the remainder of the flexible dynamics.

2.1 Reference and stabilizing feedback

The considered control structure is depicted in Fig. 1, where the reference r is the desired position and y is the measured position of the motion system. The reference consists of a sequence of point-to-point moves as described in Van Keulen et al. (2023).

Assumption 1. The reference trajectory r is a non-zero sequence of point-to-point moves bounded up to the fourth derivative subject to $\frac{d}{dt}r(0) = \frac{d}{dt}r(T_r) = 0$, $\frac{d^3}{dt^3}r(0) = \frac{d^3}{dt^3}r(T_r) = 0$ and $\frac{d^4}{dt^4}r(0) = \frac{d^4}{dt^4}r(T_r) = 0$, with T_r the duration of the trajectory.

The feedback control structure is a cascade of a second-order low-pass-filtered PID controller, to mitigate high-frequency noise, in combination with a series of notch filters:

$$C_{fb}(s) = C_{fb}^{PID}(s)C_{fb}^N(s), \quad (2)$$

with

$$C_{fb}^{PID}(s) = k_p \left(1 + \frac{\omega_i}{s} + \frac{s}{\omega_d} \right) \cdot \frac{\omega_{lp}^2}{s^2 + 2\beta_{lp}\omega_{lp}s + \omega_{lp}^2}, \quad (3)$$

where k_p is the proportional gain, ω_i and ω_d are the integrator, and derivative frequencies respectively. Furthermore, ω_{lp} is the cut-off frequency and β_{lp} is the damping of the low-pass filter. The notch filters are described as:

$$C_{fb}^N(s) = \prod_{i=1}^q \left(\frac{s^2 + 2\beta_{z,i}\omega_{z,i}s + \omega_{z,i}^2}{s^2 + 2\beta_{p,i}\omega_{p,i}s + \omega_{p,i}^2} \right), \quad (4)$$

where $\omega_{z,i}$ and $\omega_{p,i}$ are the zero and pole frequencies and $\beta_{z,i}$ and $\beta_{p,i}$ are the zero and pole damping coefficients.

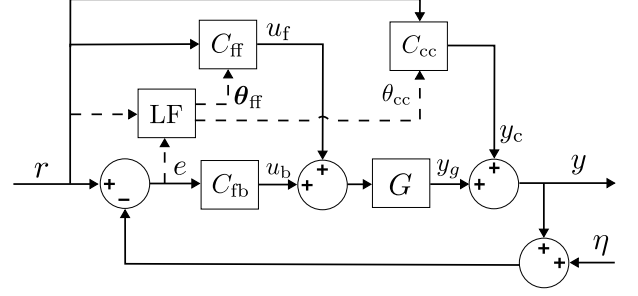


Fig. 1. Control diagram including feedback, feedforward, and compliance compensation, with the latter two adapted by the learning framework (LF).

2.2 Feedforward control

The feedforward controller is parameterized as:

$$C_{ff}(s) := [s \ s^2 \ s^3] \theta_{ff}^{tot}, \quad (5)$$

where $\theta_{ff}^{tot} := \theta_{ff}^{nom} + \theta_{ff} \in \mathbb{R}^{3 \times 1}$ with

$$\theta_{ff}^{nom} = [\theta_v^{nom} \ \theta_a^{nom} \ \theta_j^{nom}]^T, \quad \theta_{ff} = [\theta_v \ \theta_a \ \theta_j]^T, \quad (6)$$

where $(\theta_v, \theta_a, \theta_j)$ denote the velocity, acceleration, and jerk parameters, respectively. The vector θ_{ff}^{nom} represents nominal offline-calibrated values which are useful for the implementation and enable a linear, rather than an affine parameterization of the regressors, as shown in Sec. 3.

2.3 Compliance compensation

As illustrated in Fig. 1, the compliance compensation $C_{cc}(s)$ acts on the output y_g by means of a measurement adjustment, and not on the input signal u_b as in feedforward control. In particular, it aims to remove quasi-static deformations during acceleration phases from the servo error e , which depends on the compliance of the system γ_0 in (1), so that the feedback controller dynamics do not respond to quasi-static deformation.

From Hooke's law and Newton's second law, the quasi-static deformation induced by acceleration due to the reference is $y_{qs} = \gamma_0 m \ddot{r}$, which motivates defining the ideal compliance compensation term as $y_c = -y_{qs}$. If we parameterize $C_{cc}(s)$ as

$$C_{cc}(s) := (\theta_{cc}^{nom} + \theta_{cc})s^2, \quad (7)$$

with θ_{cc}^{nom} denoting the nominal offline calibrated term, we separate $C_{cc}(s)$ from $C_{ff}(s)$ and lump the mass m and compliance γ_0 , yielding the parallel branch as depicted in Fig. 1. This separation avoids nonlinear coupling between the acceleration θ_a and the compliance θ_{cc} parameters.

The parameters subject to learning and the nominal parameters are stacked as follows:

$$\theta := \begin{bmatrix} \theta_{ff} \\ \theta_{cc} \end{bmatrix} \in \mathbb{R}^{4 \times 1}, \quad \theta^{nom} := \begin{bmatrix} \theta_{ff}^{nom} \\ \theta_{cc}^{nom} \end{bmatrix} \in \mathbb{R}^{4 \times 1}. \quad (8)$$

The control goal is to minimize the servo tracking error e , which is the mapping $H(s) : r \mapsto e$ given by

$$H(s) = S(s)(1 - G(s)C_{fb}(s) - C_{cc}(s)), \quad (9)$$

with $S(s) := (1 + G(s)C_{fb}(s))^{-1}$ the sensitivity function.

2.4 Problem statement

The current state of practice is $\theta = 0_{4 \times 1}$ and $\theta^{nom} = [0 \ \hat{m} \ 0 \ -\hat{m}\hat{\gamma}_0]^T$ where $\hat{m}$ and $\hat{\gamma}_0$ may deviate from the

true mass $m(t, x)$ and compliance $\gamma_0(t, x)$ that can be time-varying and/or position-dependent. This motivates the development of an adaptive framework that adjusts θ over a moving-horizon of length T . The objective is to find the optimal time-dependent parameter set θ in the sense that it minimizes the squared servo error e , *i.e.*,

$$\theta^*(t) = \arg \min_{\theta} \int_{t-T}^t e^2(\tau, \theta) d\tau. \quad (10)$$

As such, the aim is to continuously update $\theta(t)$ to improve the performance online, while taking into account the specific feedforward structure defined in (5) and compliance compensation defined in (7).

3. LEARNING FRAMEWORK

This section extends the learning framework proposed in Van Keulen et al. (2023) by incorporating adaptive compliance compensation in addition to learning velocity, acceleration and jerk parameters.

To circumvent bias in the parameter estimates in (10) we introduce an auxiliary signal φ that is correlated with the servo error e but uncorrelated with the measurement noise η that can be taken for comparison in the parameter optimization. Such a setting is also known as an instrumental variable setting, see *e.g.*, Söderström and Stoica (2002). For a mechanical system as given in (1), we select this auxiliary signal φ as the output of an approximate control system that reflects an approximate servo-error. To be specific, the approximated control system is described by the transfer function $\hat{H} : r \mapsto \varphi$ given by

$$\hat{H}(s) := \hat{S}(s)(1 - \hat{G}(s)\hat{C}_{ff}(s) - \hat{C}_{cc}), \quad (11)$$

where

$$\hat{S}(s) := (1 + \hat{G}(s)C_{fb}^{PID}(s))^{-1}, \quad (12)$$

$$\hat{C}_{ff}(s) := [s \ s^2 \ s^3] \hat{\theta}_{ff}^{\text{tot}}, \quad (13)$$

$$\hat{C}_{cc}(s) := (\theta_{cc}^{\text{nom}} + \theta_{cc}^{\text{IV}})s^2, \quad (14)$$

and $\hat{\theta}_{ff}^{\text{tot}} := \theta_{ff}^{\text{nom}} + [\theta_v^{\text{IV}} \ \theta_a^{\text{IV}} \ \theta_j^{\text{IV}}]^T$ with $\theta_v^{\text{IV}}, \theta_a^{\text{IV}}, \theta_j^{\text{IV}}$ and θ_{cc}^{IV} fixed non-zero parameters. Moreover, $\hat{G}$ represents an approximation of the system G . Now if we take

$$\hat{G}(s) = \frac{1}{\hat{m}s^2}, \quad \theta^{\text{nom}} = [0 \ \hat{m} \ 0 \ 0]^T \quad (15)$$

with $\hat{m}$ being the mass parameter in the nominal, offline tuned, feedforward, then $\hat{H}$ as given in (11) simplifies to

$$\hat{H}(s) = -\frac{1}{\hat{m}}\hat{S}(s) \left([1/s \ 1 \ s \ s^2] \theta^{\text{IV}} \right), \quad (16)$$

where

$$\theta^{\text{IV}} := \begin{bmatrix} \theta_{ff}^{\text{IV}} \\ \theta_{cc}^{\text{IV}} \end{bmatrix} \in \mathbb{R}^{4 \times 1} \quad (17)$$

denotes the vector with fixed non-zero parameters. Observe that for $\hat{G}$ as given in (15), the transfer function $\hat{H}$ depends linearly on θ^{IV} .

To match the approximated control system $\hat{H}$ with the true control system H , the parameters in θ^{IV} are scaled. To streamline the exposition, we first introduce the transfer functions $\hat{H}_i : r \mapsto \varphi_i$, $i \in \{1, 2, 3, 4\}$, given by

$$\hat{H}_i(s) = -\frac{1}{\hat{m}}\hat{S}(s) (s^{i-2}\theta_i^{\text{IV}}). \quad (18)$$

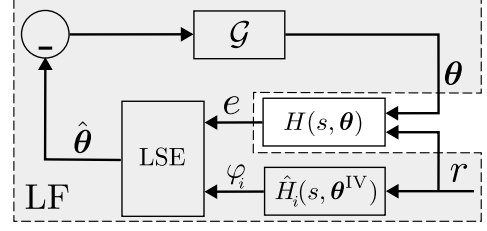


Fig. 2. System representation of the feedback interconnection of the parameter adaptation $\mathcal{G}$ with the parameter estimation.

Consequently, the output of the *scaled* approximate control system, also referred to as the predictor model, is given by

$$\tilde{e}(t, \lambda) = \lambda^T \Phi(t), \quad (19)$$

where $\Phi(t) := [\varphi_1(t) \ \varphi_2(t) \ \varphi_3(t) \ \varphi_4(t)]^T$ and $\lambda := [\lambda_1 \ \lambda_2 \ \lambda_3 \ \lambda_4]^T$ with the scaling factors $\lambda_1, \lambda_2, \lambda_3$, and λ_4 selected such that the square integrated prediction error $e(t, \theta) - \tilde{e}(t, \lambda)$ is minimal. To be specific, the optimal scaling λ minimizes

$$V(t, \lambda) = \int_{t-T}^t (e(\tau, \theta) - \tilde{e}(\tau, \lambda))^2 d\tau, \quad (20)$$

$$= \int_{t-T}^t (e(\tau, \theta) - \lambda^T \Phi(\tau))^2 d\tau. \quad (21)$$

Given the optimal scaling $\lambda^*(t)$ at time $t \in \mathbb{R}_{\geq 0}$, *i.e.*

$$\lambda^*(t) = \arg \min_{\lambda \in \mathbb{R}^4} V(t, \lambda), \quad (22)$$

the estimated parameter mismatch that caused the remaining servo error is given by

$$\hat{\theta}(t) = \lambda^*(t) \odot \theta^{\text{IV}} \in \mathbb{R}^{4 \times 1}, \quad (23)$$

where $\odot$ denotes element-wise multiplication. Closed-form expressions for $\lambda^*(t)$ are given in Sec. 4.

Since the estimated parameter mismatch $\hat{\theta}(t)$ describes the remaining servo error, it justifies to slowly adjust the parameters $\theta(t)$ in the opposite direction of $\hat{\theta}(t)$ through an adaptation system given by

$$\mathcal{G} := \begin{cases} \dot{x}_{\theta_i}(t) &= -B_i \hat{\theta}_i(t), \\ \theta_i(t) &= x_{\theta_i}, \end{cases} \quad (24)$$

for $i \in \{1, 2, 3, 4\}$, where B_i is chosen sufficiently small such that $\theta(t)$ is constant within the moving-horizon of length T to enforce time-scale separation, and where $\hat{\theta}_i$ and θ_i denote the i -th element of $\hat{\theta}$ and θ , respectively.

4. COUPLING IN THE PARAMETERS AND MULTIVARIATE REGRESSION

We consider two cases, namely, i) the case in which the regressors φ_i are orthogonal, which allows to use a univariate regression, and ii) the case in which the regressors φ_i are not orthogonal, which requires the formulation of a multivariate regression for the extended learning framework. For orthogonality, we adopt the following definition.

Definition 2. Two signals $(f_i(t), f_j(t))$ defined over a moving-horizon of length T , are *orthogonal*, if $\langle f_i(\tau), f_j(\tau) \rangle := \int_{t-T}^t f_i(\tau) f_j(\tau) d\tau = 0 \quad \forall t$.

4.1 Univariate regression

In case the regressors φ_i , $i \in \{1, 2, 3, 4\}$, are orthogonal, the scaling $\lambda^*(t) = [\lambda_1^*(t) \lambda_2^*(t) \lambda_3^*(t) \lambda_4^*(t)]^\top$ that minimizes (20) is given by

$$\lambda_i^*(t) = \left(\int_{t-T}^t \varphi_i^2(\tau) d\tau \right)^{-1} \int_{t-T}^t \varphi_i(\tau) e(\tau, \theta) d\tau, \quad (25)$$

where $\int_{t-T}^t \varphi_i^2(\tau) d\tau$ must be non-zero. As such, each i -th element can be computed individually based on the regressor φ_i .

In our case, we show that the regressors are not orthogonal, which implies that the univariate regression cannot be decoupled into independent scalar estimation problems. Note that $\varphi_j(t) = \alpha \dot{\varphi}_a(t)$, with $\alpha = -\frac{\theta_a^{IV}}{\ddot{m}}$. We evaluate the moving-horizon integral via substitution:

$$u = \varphi_a(t), \quad du = \dot{\varphi}_a(t) dt, \quad (26)$$

$$\begin{aligned} I(t) &= \alpha \int_{t-T}^t u du, \\ &= \frac{\alpha}{2} \left(\varphi_a^2(t) - \varphi_a^2(t-T) \right). \end{aligned} \quad (27)$$

Hence, $I(t) = 0$ if and only if $\varphi_a^2(t) = \varphi_a^2(t-T)$, i.e., $\varphi_a(t) = \pm \varphi_a(t-T)$ which only holds true when $\varphi_a(t)$ is periodic with period length T . By Assumption 1, the regressor φ_a does not reach steady-state which implies it is not T -periodic, and therefore $(\varphi_a(t), \varphi_j(t))$, is not orthogonal over the moving-horizon. This observation motivates to extend the algorithm in Van Keulen et al. (2023) to a multivariate regression formulation.

Remark 3. As demonstrated in Section 5, even if the regressors φ_i , $i \in \{1, 2, 3, 4\}$ are not orthogonal, using the univariate regression as presented in (25) can still lead to converging parameter estimates.

4.2 Multivariate regression

In case the regressors φ_i , $i \in \{1, 2, 3, 4\}$, are *not* orthogonal, the analytical solution to (22) is given by

$$\lambda^*(t) = \left(\int_{t-T}^t \Phi(\tau) \Phi(\tau)^\top d\tau \right)^{-1} \int_{t-T}^t \Phi(\tau) e(\tau, \theta) d\tau, \quad (28)$$

when $\int_{t-T}^t \Phi(\tau) \Phi(\tau)^\top d\tau \in \mathbb{R}^{4 \times 4}$ is non-singular. By considering the linear combination of all regressors Φ simultaneously, parameter coupling is implicitly taken into account. This results in superior parameter estimation properties, at the cost of having to compute a matrix inverse online.

Remark 4. In case the regressors φ_i , $i \in \{1, 2, 3, 4\}$, are orthogonal, the matrix $\int_{t-T}^t \Phi(\tau) \Phi(\tau)^\top d\tau$ is diagonal and thus the result in (25) is recovered.

5. EXPERIMENTAL CASE STUDY

In this section, the extended learning framework is validated in simulation and with experiments on a high-tech metrology inspection system. Two separate experiments have been conducted, one experiment ($\mathcal{D}_1$) showcases the

effectiveness of learning individual parameters, the other experiment ($\mathcal{D}_2$) focuses on the effectiveness of utilizing multivariate regression to reduce parameter coupling. Both experiments are compared with simulation results ($\mathcal{D}_s$). The considered system in simulation is a non-collocated mass-spring-damper system consisting of two rigid masses.

5.1 System description and setting

The objective of the industrial machine is to measure overlay, a metric that quantifies the alignment accuracy between different layers of a microchip. Overlay is obtained by illuminating predefined targets on the wafer and analyzing the resulting diffraction patterns. The wafer stage positions each target such that it lies within the field of view of the optical sensor. A schematic representation of the wafer stage is shown in Fig. 3. The stage consists of two orthogonal beams, each driven by actuators on both sides, which position a wafer carrier.

Assume that a stabilizing feedback is achieved by means of geometric decoupling that maps control forces in logical degrees of freedom (x, y) to physical actuator forces. For the current case study, only the x -direction is considered. Note that viscous friction is present, and the compliance in the x -direction depends on the y -position. We consider a total of 500 point-to-point moves in (x, y) and a reference trajectory satisfying Assumption 1, shown in Fig. 4.

5.2 Experimental results

The approximate sensitivity $\hat{S}(s)$ is tuned such that is close to the sensitivity of the true system in low frequency regimes. Furthermore, a similar discretization and delay compensation is adopted as in Butler (2013). We use $\theta^{\text{nom}} = [0 \ \hat{m} \ 0 \ -\hat{m}\hat{\gamma}_0(y)]^\top$, where $\hat{\gamma}_0(y)$ is a look-up table for y -position-dependent compliancy. Fig. 6 shows the effectiveness of the extended learning framework for experiment $\mathcal{D}_1$, in terms of the cumulative power spectral density of the servo error for different parameter sets after parameter convergence. Observe that the servo error is improved by a factor of 7 when all parameters are included

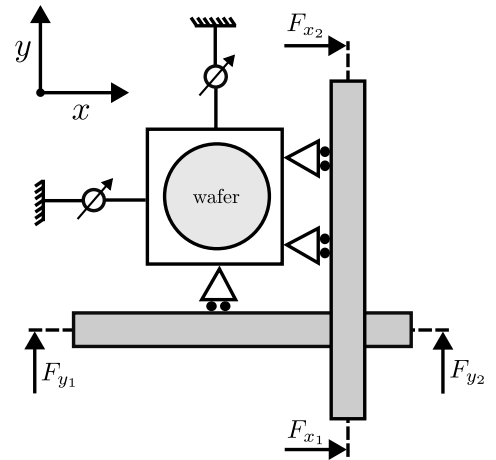


Fig. 3. 2D-representation of the wafer-stage inside the metrology and inspection system with interferometers that measure the x and y position with two beams to which the carrier with the wafer is attached.

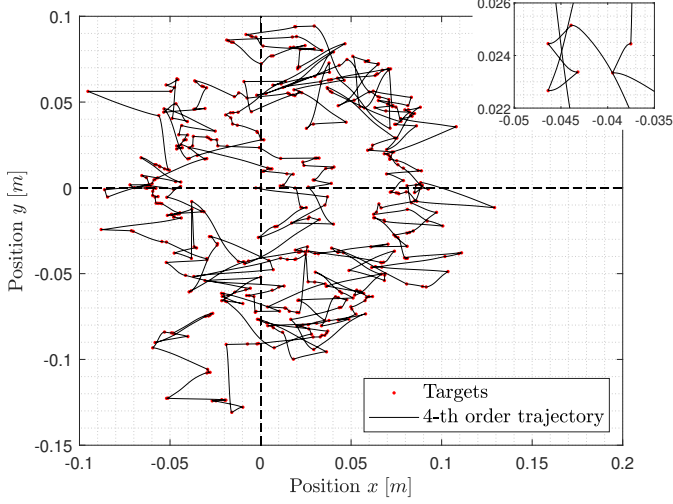


Fig. 4. Reference trajectory in x and y of 500 point-to-point moves with bounded 4-th order time-derivative.

in the learning framework. The individual contributions for the velocity, acceleration and compliance compensation contribute to 92.5%, 6.5%, 1%, respectively, where the contribution of jerk feedforward is negligible for the setting considered. Fig. 5 shows the servo error over time resulting from simulation $\mathcal{D}_s$ for three specific acceleration profiles. The corresponding experimental results $\mathcal{D}_1$ for three specific moves are shown in Fig. 7. Observe that for the simulation $\mathcal{D}_s$, the inclusion of recursive compliance compensation learning yields a significant performance improvement. In the experimental results $\mathcal{D}_1$, the overall performance gain is primarily attributed to velocity feedforward. This can be explained by the fact that the a priori tuned y -position-dependent nominal compliance compensation $\hat{\gamma}_0(y)$ is already close to the true compliance, thereby limiting the additional improvement achievable through online adaptation.

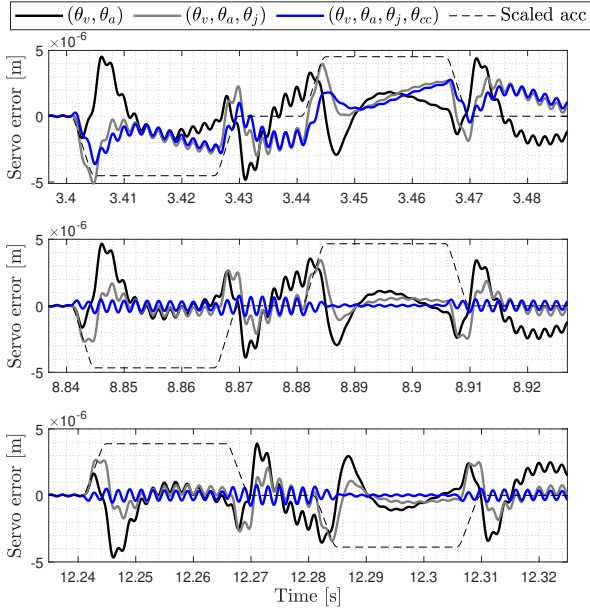


Fig. 5. Simulation results $\mathcal{D}_s$ providing the servo error for different parameter sets.

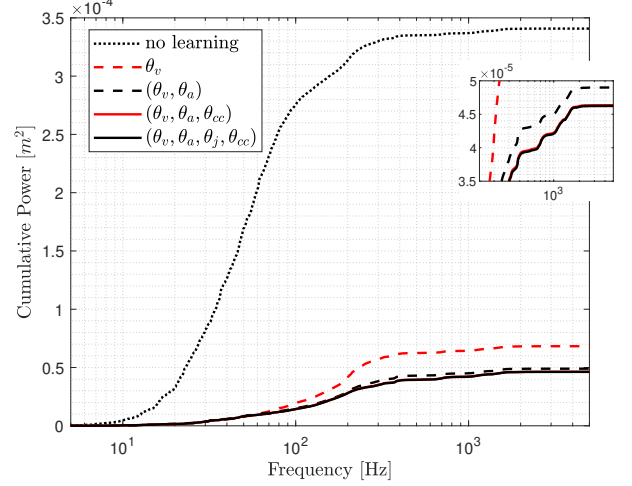


Fig. 6. Experimental results $\mathcal{D}_1$ showing the cumulative power spectral density of the servo error for different parameter sets.

By adopting the univariate regression formulation as presented in (25) while learning all four parameters at once, the coupling between velocity and jerk, as predicted in Sec. 4, and as shown in simulation $\mathcal{D}_s$ in Fig. 8, is now also observed in the experiment $\mathcal{D}_2$ as depicted in Fig. 9. The coupling between acceleration and compliance compensation is also clearly visible in Fig. 8, yet less prominent in Fig. 9, most likely due to relatively high adaptation gains. By adopting multivariate regression as proposed in (20) the coupling between parameters, especially seen in velocity and jerk coupling, has been significantly reduced.

6. CONCLUSION

An algorithm for recursive learning of feedforward parameters in motion control is extended with adaptive com-

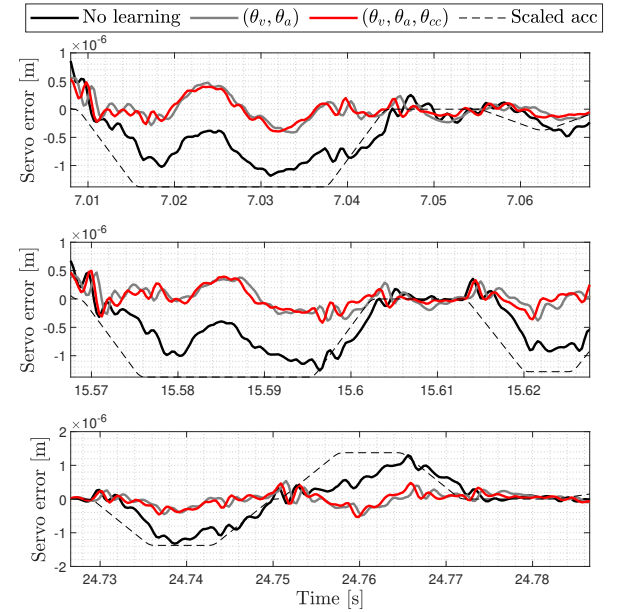


Fig. 7. Experimental results $\mathcal{D}_1$ providing the servo error for different parameter sets.

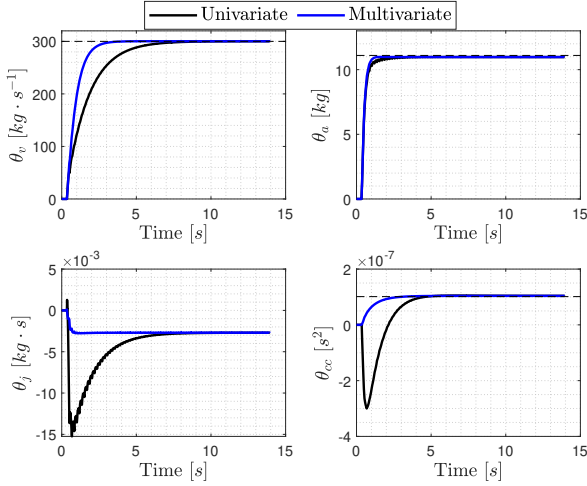


Fig. 8. Simulation results $\mathcal{D}_s$ providing the parameter convergence for θ_v , θ_a , θ_j , and θ_{cc} with respect to univariate and multivariate regression.

pliance compensation. Its effectiveness is demonstrated through simulation and experimental validation on a state-of-the-art industrial metrology inspection machine. Results show that a multivariate regression reduces parameter coupling, predominantly between velocity and jerk feedforward, and between acceleration feedforward and compliance compensation. Future work will focus on learning compliance compensation without nominal tuning to verify convergence properties, potentially reducing manual tuning effort.

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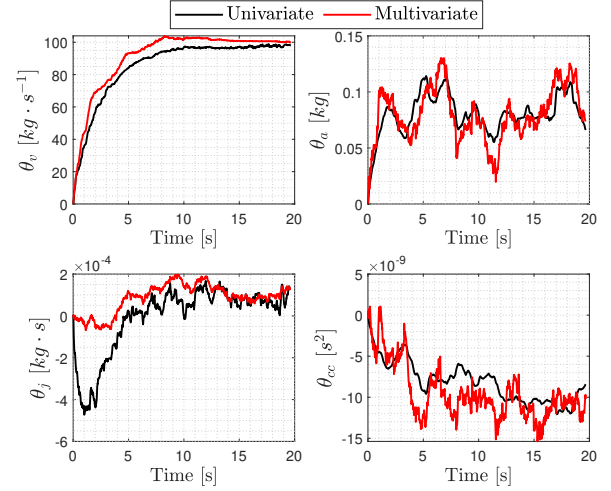


Fig. 9. Experimental results $\mathcal{D}_2$ providing the parameter convergence for θ_v , θ_a , θ_j , and θ_{cc} with respect to univariate and multivariate regression.

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