Advanced Motion Control for Next-Generation Precision Mechatronics: Challenges for Control, Identification, and Learning

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Manufacturing equipment and scientific instruments, including wafer scanners, printers, microscopes, and medical imaging scanners, require accurate and fast motions. Increasing requirements necessitate enhanced control performance. The aim of this paper is to identify several challenges for advanced motion control originating from these increasing accuracy, speed, and cost requirements. For instance, flexible mechanics must be explicitly addressed through overactuation, oversensing, inferential control, and position-dependent control. This in turn requires suitable models of appropriate complexity, which are identified and learned from inexpensive experimental data. Several ongoing developments are outlined that constitute a part of an overall framework for control, identification, and learning of complex motion systems. In turn, this may pave the way for new mechatronic design principles, leading to fast lightweight machines where the spatio-temporal flexible mechanics are explicitly compensated through advanced motion control.

Keywords: Mechatronics, motion control, robust control, multivariable control, system identification, iterative learning control.

1. Introduction

Positioning systems are a key enabling technology in manufacturing machines and scientific instruments. A state-of-the-art example of such a mechatronic system is a wafer scanner, which is used in the lithographic production of integrated circuits (ICs), see Fig. 1(a)-1(b), and achieves sub-nanometer positioning accuracy with extreme speed and acceleration. Also, in semiconductor assembly processes, including wire-binders and die-binders, products have to be positioned with varying trajectories, up to 72000 products per hour. Furthermore, for printing systems, ranging from desktop printers to industrial printers and 3D printing, see Fig. 1, printing accuracy and speed are essential. In scientific instruments, such as atomic force microscopes (AFMs) and scanning electron microscopes (SEM), the sample needs to be accurately positioned, whereas in CT scanners the detector is positioned for medical imaging, see also Fig. 1. The accuracy and speed of these positioning systems hinges on the motion control design and determines the capabilities and market position of the manufacturing machines and scientific instruments.

Control of these positioning systems is traditionally simplified by an excellent mechanical design. In particular, the mechanical design is such that the system is stiff and highly reproducible. In conjunction with moderate performance requirements, the bandwidth is well-below the resonance frequencies of the flexible mechanics. As a result, the system can often be completely decoupled in the frequency range relevant for control. Consequently, the control design is divided into well-manageable SISO control loops, for which standard guidelines exist for their manual tuning by control engineers for both feedback and feedforward, see and Sec. 2.2. In addition, SISO learning control approaches that are suitable for motion control are well-developed, see. Although motion control design is well-developed, presently available techniques mainly apply to positioning systems that behave as a rigid body in the relevant frequency range. On the one hand, increasing performance requirements hamper the validity of this assumption, since the bandwidth, i.e., the frequency range over which control is effective, has to increase, leading to flexible dynamics in the cross-over region. On the other hand, the requirement for rigid-body behavior puts high requirements on the mechatronic system design, e.g., in terms of exotic and stiff materials and hence cost. The aim of this paper is to sketch the present state of the practice (Sec. 2) and to identify challenges arising in precision motion control (Sec. 3). Recent results that address these challenges in motion feedback control are then outlined (Sec. 4), revealing the need for system identification techniques. Next, feedforward and learning control are addressed (Sec. 5).

Fig. 1. Example state-of-the-art positioning systems.

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2. Traditional motion control

2.1 Motion systems Mechatronic positioning systems consist of mechanics, actuators, and sensors \((i)\). In the frequency range that is relevant for control, mainly the mechanics have a relevant dynamical behavior. In particular, the mechanics can typically be described as \((i)\):

\[
G_m = \sum_{i=1}^{n_{RB}} \frac{c_i b_i^T}{s^2} + \sum_{i=n_{RB}+1}^{n_s} \frac{c_i b_i^T}{s^2 + 2 \zeta_i \omega_i s + \omega_i^2}, \quad \cdots \quad (1)
\]

where \(n_{RB}\) is the number of rigid-body modes, the vectors \(c_i, b_i \in \mathbb{R}^n\), \(n_s \in \mathbb{N}\), and \(\zeta_i, \omega_i \in \mathbb{R}_+\). Here, \(n_s \in \mathbb{N}\) may be very large and even infinite \((i)\). Note that in (1), it is assumed that the rigid-body modes are not suspended, i.e., the term \(\frac{1}{s^2}\) relates to Newton’s law. In the case of suspended rigid-body modes, e.g., in case of flexures as in \((i)\), (1) can directly be extended.

In traditional positioning systems, the number of actuators \(n_a\) and sensors \(n_s\) equals \(n_{RB}\), and are associated such that the matrix \(\sum_{i=1}^{n_{RB}} c_i b_i^T\) is invertible. In this case, matrices \(T_u\) and \(T_y\) can be selected such that

\[
G = T_g G_m T_u = \frac{1}{s^2} I_{n_s} + G_{\text{flex}}, \quad \cdots \cdots \quad (2)
\]

where \(T_y\) is typically selected such that the transformed output \(y\) equals the performance variable \(z\), as is defined in Sec. 3.3. Importantly, the selection of these matrices \(T_u\) and \(T_y\) can be done directly on the basis of frequency response function (FRF) data, e.g., \((i)\). Such frequency response data is inexpensive, fast, and accurate to obtain and its importance is further clarified in Sec. 4.8.

2.2 Traditional control architecture The motion control architecture in Fig. 2 is standard, where

\[
e = S (r - G f) - S v, \quad \cdots \cdots \quad (3)
\]

with \(S = (I + G K)^{-1}\). Typically, \(r\) is a prespecified reference trajectory for the output \(y\), \(e\) is the error vector to be minimized, \(f\) is a feedforward signal, \(K\) is the feedback controller, and \(v\) represents disturbances. It is remarked that these are tacitly used for both continuous and discrete time systems. Indeed, for manual tuning often the continuous time domain is used as in (1) - (2). For automated algorithms, as developed in Sec. 4 and Sec. 5, the discrete time domain is more natural. These domains can be directly linked, see \((i)\) for details.

In view of (2), \(G\) is decoupled in the relevant frequency ranges, in which case the elements \(e\) may be minimized step by step. This is investigated in the following subsections.

2.2.1 Traditional feedforward design Feedforward can effectively compensate for reference-induced error signals. In particular, \(f\) should be selected such that \(r - G f\) is minimized. In the low-frequency range, the system is decoupled and \(G_{\text{flex}}\) can be ignored in (2), in which case \(f = G^{-1} r = \tilde{r}\), which is the Laplace transformation of the acceleration profile. Note that in (2), the mass of the rigid-body mode is normalized to unity. In practice, the feedforward signal is selected as \(f = m \tilde{r}\), which is tuned in the time domain by decorrelating the measured error signal in (3) and the acceleration profile, details of which can be found in \((i)\). Furthermore, the compliance of the higher-order modes \(G_{\text{flex}}\) can be addressed in a snap term, as well as friction terms, all of which can be directly tuned manually in a straightforward manner \((i)\).

2.2.2 Traditional feedback design For an appropriately designed feedforward signal, \(\delta = r - G f\) is small. In this case, the feedback controller has to minimize \(S (\delta - v)\), where \(S\) is subject to a number of constraints and limitations \((i)\), and hence cannot be made zero in general. Due to rigid-body decoupling, \(S\) is diagonal at low frequencies for a decentralized controller \(C\). As a result, each diagonal element of \(C\) may be tuned independently. Typically, due to the low-frequency rigid-body behavior, a PID controller is tuned through manual loopshaping, followed by notch filters to account for those flexible modes in \(G_{\text{flex}}\) that hamper stability and/or performance.

2.2.3 Traditional learning control In the case where the setpoint \(r\) does not vary, the feedforward \(f\) may be obtained or improved using learning techniques. For SISO systems, these are fairly well-developed, see, e.g., \((i)\) for an approach that relates to the design approach in Sec. 2.2.2.

2.2.4 Traditional design procedure Traditional motion control design divides the multivariable control design problems into subproblems that are manageable by manual control design. The traditional procedure consists of the following steps:

- identify an FRF of \(G_m\), i.e., \(G_m(\omega)\), for frequencies \(\omega\);
- decouple the plant to obtain an FRF of \(G\);
- design \(C\) using manual loopshaping on the basis of the FRF, consisting of a PID with notchies; and
- tune a feedforward controller, e.g., \(f = m \tilde{r}\), using correlation techniques, optionally followed by learning control.

3. Precision motion control developments

3.1 Future mechatronic control A radically new lightweight mechatronic system design is envisaged to meet the requirements imposed by innovations in manufacturing machines and scientific instruments in terms of throughput, accuracy, and cost for the following reasons.

\(1\) Increased throughput is directly related to faster movements. The acceleration is directly determined by Newton’s law \(F = ma\). Here, the forces \(F\) that the actuators can deliver are bounded due to size and thermal aspects. Hence, throughput is increased by reducing the moving mass \(m\).
(2) Increased accuracy is enabled by contactless motion, e.g., through magnetic levitation\(^{(84)}\), since this avoids friction and enhances reproducibility. In addition, in certain applications, including EUV lithography, motion has to be performed in a vacuum environment. Contactless motion is then essential to avoid pollution caused by mechanical wear and lubricants.

(3) Reduced cost can be enabled by reducing the requirements on material properties. In particular, present state-of-the-art systems involve exotic materials that provide high stiffness in conjunction with good thermal behavior. Combining these aspects reveals that a lightweight system design is highly promising for next-generation motion systems. Such lightweight systems exhibit predominant flexible dynamical behavior, as is schematically illustrated in Fig. 3, as well as an increased susceptibility to disturbances\(^{(63, Sec. 9.5.2)}\). The prime reason why such systems are not yet feasible is the lack of control methodologies that handle the increased complexity, since the overall control design problem cannot be divided into subproblems as in Sec. 2, which are manageable by manual tuning techniques.

In particular, the envisaged future designs of next-generation systems lead to several challenges for motion control design, as are outlined next.

3.2 Advanced motion control challenges for future mechatronic systems

The envisaged mechatronic designs in Sec. 3.1 lead to several challenges for motion control design, including the following.

(1) Unmeasured performance variables are introduced by spatio-temporal deformations. In particular, the location where the performance is desired may not be directly measured. For example, performance in lithographic wafer stages is required at the spot of exposure, whereas sensors typically measure the edge of the stage, see Fig. 3. A key challenge lies in inferring the unmeasured performance variables.

(2) Many additional inputs and outputs can be exploited to actively control the flexible dynamical behavior. In particular, the presence of spatio-temporal deformations and spatially distributed disturbances lead to highly complex deformations. A large number of sensors, which is enabled by the availability of inexpensive sensors and ubiquitous computing power, enable a high quality estimation of the dynamical behavior. Subsequently, spatially distributed actuators, including inexpensive smart materials such as piezos, will actively provide stiffness and damping to the mechanical deformations. Such an oversensed and overactuated situation is in sharp contrast to the present rigid-body situation, as is outlined in Sec. 2, and a key challenge lies in dealing with a large number of measured variables and manipulated variables.

(3) Position-dependent behavior is almost unavoidable in the case of spatio-temporal deformations, since motion systems perform motion by definition. For instance, for the single-mass system in Fig. 3, the spatio-temporal deformations are observed differently if the sensor is not moving. In addition, in certain systems, including H-drive designs, mass distributions change due to motion, leading to additional position-dependent behavior. A key challenge lies in handling the position dependence of future systems.

(4) A systems-of-systems perspective on motion control design provides a strong potential for performance enhancement of the overall system. In particular, typical manufac-

![Fig. 3. Example of flexible tasks in 2D and 3D printing.](image)

Fig. 4. Example of flexible tasks in 2D and 3D printing.

![Fig. 5. Standard plant setup, where P(G). Note that K can be equal as in Fig. 2, but can also be extended to generate the signal f in Fig. 2.](image)

Fig. 5. Standard plant setup, where \( P(G) \). Note that \( K \) can be equal as in Fig. 2, but can also be extended to generate the signal \( f \) in Fig. 2.
drastically increase in view of Challenge 2. The variable \( w \) contains the exogenous inputs, typically including both reference signals and disturbances (Challenge 6), i.e., \( r \) and \( d \) in Fig. 2. Now, these variables may all be position-dependent (Challenge 3), an in addition, the variable \( r \) may vary for each task (Challenge 7). Furthermore, if multiple systems are addressed simultaneously, either due to their interaction, or their interaction due to a shared, overall machine control goal (Challenge 4), then this substantially increases the signal dimensions. Similarly, a joint thermal-mechanical control design (Challenge 5) involves signals and systems in both the thermal domain and the positioning domain.

The standard plant approach in Fig. 5 directly reveals the additional complexity arising from the challenges outlined in Sec. 3.2. Here \( P(G) \) denotes the standard plant, which contains the input-output plant \( G \) as well as the interconnection structure, e.g., Fig. 2. These increased complexity and accuracy requirements necessitate new developments in control algorithms, since these undermine the basic assumptions on which the approach in Sec. 2 relies on. Indeed, the standard plant is a conceptual framework to pose the overall problem, where the goal is to compute an interconnection structure \( G \) and its dimensions. Similarly, a joint thermal-mechanical control design (Challenge 5) involves signals and systems in both the thermal domain and the positioning domain.

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Here, \( K \) is posed, where the goal is to compute

\[
J(G, K) = \|[\mathcal{F}_i(P(G), K)]\| \tag{4}
\]

is posed, where the goal is to compute

\[
K^{\text{opt}} = \arg \min_K J(G_o, K). \tag{5}
\]

Here, \( \| \cdot \| \) denotes a suitable norm, e.g., \( \mathcal{H}_\infty \) or \( \mathcal{H}_2 \). Also, \( \mathcal{F}_i \) denotes a lower linear fractional transformation (LFT), i.e.,

\[
\mathcal{F}_i(G, K) = P_{11} + P_{12}K(I - P_{22}K)^{-1}P_{21}. \tag{6}
\]

where \( P(G) \) is the interconnection structure and contains \( G \). In particular, \( \mathcal{F}_i(G, K) \) is typically a closed-loop transfer function, e.g., the general four-block problem

\[
\mathcal{F}_i(G, K) = W \begin{bmatrix} G & 0 \\ I & I \end{bmatrix} \begin{bmatrix} I + KG)^{-1} & K \\ 1 & 1 \end{bmatrix} V, \cdots \cdots \cdots \cdots \tag{7}
\]

where \( W \) and \( V \) are user-chosen weighting filters of suitable dimensions. For instance, these can be chosen such that (7) reduces to

\[
G(I + KG)^{-1}. \cdots \cdots \cdots \cdots \cdots \tag{8}
\]

Finally, and very importantly, \( G_o \) in (5) denotes the true system, e.g., one of the systems depicted in Fig. 1.

4.2 Nominal modeling for control: motivation

To arrive at a mathematically tractable optimization problem in (5), knowledge of the true system is represented through a model \( \hat{G} \). The central question is how to obtain such a model that is suitable for controller design. System identification, or experimental modeling as opposed to first principles modeling, is an inexpensive, fast, and accurate approach to obtain such a model, see \( \text{(48)} \), \( \text{(49)} \) and \( \text{(50)} \) for a general overview of such approaches. Indeed, the positioning system often is already built, enabling direct experimentation.

The model \( \hat{G} \) that results from system identification is an approximation of the true system \( G_o \) for several reasons: i) motion systems, typically of the form (2), often contain an infinite number of modes \( n_i \). While a model of limited complexity may be desirable from a control perspective; ii) parasitic nonlinearities are present, including nonlinear damping \( \sim \cos \theta \); and iii) identification experiments are based on finite time disturbed observations, leading to variance errors on estimated parameters, e.g., \( \zeta \) and \( \omega_i \) in (2).

Although a large variety of system identification approaches and algorithms have been developed, many of these do not directly deliver a model that is suitable for designing a high-performance controller when implemented on the true system in view of (5). The main reason is that most identification techniques deliver a model that predicts the open-loop response as well as possible, instead of the desired closed-loop response, which is unknown before the controller is actually synthesized. This is illustrated in the following example.

Example 1 Consider the true system

\[
G_o = \frac{1}{s^2 + 2 \cdot 0.1 \cdot (2\pi 100)s + (2\pi 100)^2} \tag{9}
\]

and the models

\[
\hat{G}_1 = \frac{1}{s^2 + 2 \cdot 0.1 \cdot (2\pi 100)s + (2\pi 100)^2} \tag{10}
\]

\[
\hat{G}_2 = \frac{1}{s^2 + 2 \cdot 0.1 \cdot (2\pi 100)s + (2\pi 100)^2} \tag{11}
\]

see Fig. 6 for a Bode plot.

Next, an input

\[
f(t) = \begin{cases} 
1 & 0.1 \leq t \leq 0.2 \\
0 & \text{elsewhere}
\end{cases} \tag{12}
\]

is applied to the true system \( G_o \) as well as to both models \( \hat{G}_1 \) and \( \hat{G}_2 \), all of which are in open-loop, i.e., \( K = 0 \) in Fig. 2. In addition, \( r \) and \( v \) are zero in Fig. 2. The responses are depicted in Fig. 6. It is observed that \( \hat{G}_1 \) matches the true response accurately, while \( \hat{G}_2 \) shows a very different response. In particular, \( G_o \) and \( \hat{G}_1 \) show an unbounded response due to the rigid-body behavior, while \( \hat{G}_2 \) shows a bounded response. The Bode plots in Fig. 6 support this, since the model \( \hat{G}_2 \) does
which is then implemented on the true system. Since the order of the controller is directly related to the complexity of the model has to be justified by the control requirements.

A strategy to obtain such control-relevant models is to note that $J(G_o, K)$ involves a norm. Hence, by rewriting and applying the triangle inequality for a certain $K$,

$$J(G_o, K) = J(\hat{G}, K) + J(G_o, K) - J(\hat{G}, K) \leq J(\hat{G}, K) + ||F(P(G_o), K) - F(P(\hat{G}), K)||$$

Here, the first term $J(\hat{G}, K)$ can be minimized, which in fact equals the model-based design (13). The second term is a function of $G_o$, $\hat{G}$, and $K$. To arrive at a well-posed identification problem, assume that a reasonable feedback controller $K^{\text{exp}}$ is already designed and implemented, e.g., following the procedure in Sec. 2.2.2. In fact, such a controller is typically required for identification experiments, since the open-loop system is often unstable, see (1). Then, $F(P(G_o), K^{\text{exp}})$ is simply the closed-loop system with $K^{\text{exp}}$ implemented.

In this case, a suitable identification criterion is to substitute $K^{\text{exp}}$ into the term in (16), leading to

$$\hat{G}_{CR} = \arg \min_{\hat{G}} ||F(P(G_o), K^{\text{exp}}) - F(P(\hat{G}), K^{\text{exp}})||$$

Essentially, in (17) a model is identified that aims at representing closed-loop behavior. Note that (17) depends on the controller. If $K$ is chosen equal to $K^{\text{exp}}$, then typically the best result is obtained. Since $K^{\text{exp}}$ is unknown, the result will depend on the quality of $K^{\text{exp}}$. To mitigate this dependence, the controller synthesis (13) and control-relevant identification (17) can be solved alternately, aiming to minimize the upper bound (16). Such an iterative procedure is at the basis of many approaches, including (82) - (91). Unfortunately, such an approach does not work, since the triangle inequality in (16) only holds valid for a fixed $K$, and does not allow for iterative updating of the controller. Still, (17) is a very valuable criterion for model identification, as will be shown in Sec. 4.5.

4.4 Toward robust motion control

The key reason why alternating between control-relevant identification (17) and model-based control design (13) does not work is the lack of robustness. Indeed, if $K(\hat{G})$ is designed solely based on $\hat{G}$, there is no reason to assume that it achieves a suitable level of performance on $G_o$. In fact, there are no guarantees that it actually stabilizes $G_o$ in closed-loop. This motivates a robust control design, where the model quality is explicitly addressed during controller synthesis, as is outlined next.

In a robust control design \footnote{Here, the true system behavior is represented by a model set $\hat{G}$ such that $G_o \in \hat{G}$}, the key idea is to use information about the uncertainty set $\Delta$ to enforce a minimum model quality. In particular, the robust design is obtained as

$$\hat{G}_{CR} = \arg \min_{\hat{G}} \{ F(P(G_o), K^{\text{exp}}) - F(P(\hat{G}), K^{\text{exp}}) \}$$

with the upper linear fractional transformation (LFT)

$$F_p(\hat{H}, \Delta_o) = \hat{H}_{22} + \hat{H}_{21} \Delta_o (I - \hat{H}_{11} \Delta_o)^{-1} \hat{H}_{12} \cdots \cdots (20)$$

and $\hat{H}$ contains the nominal model $\hat{G}$ and the model uncertainty structure. Note that $\hat{G}$ is recovered if the uncertainty is
zero, so that $\dot{G} = T_c (\dot{H},0)$.

It remains to specify $\Delta_o$ in more detail. In view of the considered motion control objectives, an $\mathcal{H}_\infty$ norm, i.e.,

$$||H||_\infty = \sup_{\omega} \tilde{\sigma} (H(j\omega)), \quad \text{-------------------------(21)}$$

with $\tilde{\sigma}$ denoting maximum singular value, is selected for the following reasons.

1. $\mathcal{H}_\infty$-norm-bounded uncertainty enables a frequency-dependent characterization of dynamic uncertainty, which is very well suited for representing lightly damped modes in systems of the form (1). This is in sharp contrast to parameter uncertainty as is used in, e.g., \cite{166}.

2. The $\mathcal{H}_\infty$ norm provides a suitable means to quantify performance objectives for motion systems in (4). In particular, the $\mathcal{H}_\infty$ norm allows a loopshaping-based design, see \cite{166} for a general perspective and \cite{167, 168, 168, 168, 168} (13). In addition, controller synthesis is typically most straightforward if a single norm is used for representing uncertainty and specifying the performance objectives.

Hence,

$$\Delta_o = \left\{ \Delta_o \in \mathcal{H}_\infty \big| ||\Delta_o||_\infty \leq \gamma \right\}, \quad \text{-------------------------(22)}$$

$\gamma \in \mathbb{R}_+$. Associated with $G$ is the worst-case criterion

$$J_{WC} = \sup_{G \in \Delta_o} J(G,K), \quad \text{-------------------------(23)}$$

Hence, by minimizing the worst-case performance

$$K_{RP} = \arg \min_J J_{WC}(G,K), \quad \text{-------------------------(24)}$$

this leads by using (18) to the guaranteed upper bound

$$J(G_o,K_{RP}) \leq J_{WC}(G,K_{RP}), \quad \text{-------------------------(25)}$$

Hence, this leads to a performance guarantee when $K_{RP}$ is implemented on the true system $G_o$. This is in sharp contrast to (14), which may actually be unbounded.

4.5 Modeling for robust motion control

Robust control provides a performance guarantee when implementing the controller $K_{RP}$ on the true system $G_o$. The question on how to minimize the upper bound (25) hinges on the model set $\mathcal{G}$. Essentially, this involves the robust-control-relevant identification of a model set, which is the counterpart of the nominal control-relevant identification problem in Sec. 4.3.

The main idea is to follow a very similar approach as in Sec. 4.3. In particular, assume again that a controller $K^{exp}$ is already implemented. Then, instead of minimizing (4) over $K$ as in (24), it is minimized for the entire set $\mathcal{G}$, i.e.,

$$\min_{\mathcal{G}} J_{WC}(G,K^{exp}), \quad \text{-------------------------(26)}$$

subject to (18).

Combining the arguments implies that

$$J(G_o,K_{RP}) \leq J_{WC}(G,K_{RP}) \leq J_{WC}(G,K^{exp}), \quad \text{-------------------------(27)}$$

hence guaranteed performance enhancement is achieved. Although this also depends on $K^{exp}$, it can be iterated, leading to monotonous performance enhancement \cite{20}, which is in sharp contrast to the suggested iterative procedure in Sec. 4.3.

The key question is how to actually determine the model set (26). The approach pursued here is to continue along the path in Sec. 4.3, i.e., to determine a control-relevant model as in (17). In a second step, it is aimed to extend the model with $\Delta_o$ such that (26) is actually addressed. Very many techniques have been developed for selecting the structure of uncertainty, e.g., \cite{169, Table 8.1}, as well as quantifying its size \cite{26} (27). However, the closed-loop aspect of the identified models, as in Example 1, has important consequences.

1. Constraint (18) has to be satisfied for (25) to hold. Although this may seem trivially satisfied by increasing the size of $\Delta_o$, note that typical uncertainty structures are based on open-loop reasoning. In particular, suppose that in Example 1

$$J(G_o,G_{d,2} + \Delta_o) \leq \gamma \big| \quad \text{-------------------------(28)}$$

Then, since $G_{d,2} \in \mathcal{H}_\infty$, $\mathcal{G} \subset \mathcal{H}_\infty$. However, since $G_o \notin \mathcal{H}_\infty$, (18) cannot be satisfied. The main reason is that $G_o$ contains a rigid-body mode, which is neither included in $G_{d,2}$ nor in an $\mathcal{H}_\infty$-norm-bounded perturbation $\Delta_o$. This is confirmed by Fig. 6, where $G_{d,2}$ and $\Delta_o$ have a bounded magnitude, yet $G_o \rightarrow \infty$ for $\omega \rightarrow 0$.

2. Suppose that (1) is successfully overcome, and a certain bound $\gamma$ guarantees that (18) is satisfied, the next question is how this actually minimizes $J_{WC}(G,K^{exp})$ in (26). Indeed, often $G$ satisfies (18), yet contains an element that is not stabilized by $K^{exp}$, in which case (26) is unbounded, see, e.g., \cite{77, Table 1}.

3. Suppose that Aspects 1 and 2 are addressed, the final question is how $J_{WC}(G,K^{exp})$ in (26) can be actually minimized.

These three aspects are of crucial importance to avoid conservatism in the entire robust control design procedure. Indeed, robust control is often experienced to lead to conservative results or may need a very large user-interaction, e.g., \cite{95, 22}, due to inappropriately dealing with Aspects 1 - 3, above.

The main trick to address aspects 1 and 2 has a very long history in control and is known as the dual form of the Youla parameterization. The Youla parameterization \cite{97} parameterizes all controllers that stabilize a certain system. The dual form, as is considered here, see also \cite{97, 40, 44, 23, 26}, parameterizes all candidate systems that are closed-loop stable with $K^{exp}$ implemented. In particular, the dual-Youla uncertainty structure is generated around the nominal model $G$ obtained from Sec. 4.3.

- $G_o$ is stabilized by $K^{exp}$, hence (18) is satisfied for a sufficiently large $\gamma$.
- All elements in $\mathcal{G}$ are stabilized, hence $J_{WC}(G,K^{exp})$ in (26) remains bounded.

The remaining step to obtain a robust-control-relevant model set in the sense of (26) is to appropriately define the distance metric. Indeed, there is a large amount of freedom left in the dual-Youla parameterization. Recently, in \cite{26}, this freedom is exploited through a new coprime factorization, which directly connects the size of uncertainty $\gamma$ in (22) and the control-relevant identification criterion (17). The underlying theory closely connects to recent developments in, e.g., \cite{24}. A key consequence of this approach is that it provides an automatic scaling of the uncertainty, both in input/output directions and frequency, enabling the nonconservative use of unstructured uncertainty in (22).
Combining the developments in the preceding sections leads to the following design procedure.

1. Specify a control objective $J$ in (4) using the $H_\infty$ norm, e.g., using loop-shaping design as in Sec. 2.2.2.

2. Identify a nominal model $\hat{G}$ by minimizing (17) using data collected while $K^{\text{pr}}$ is implemented.

3. Extend the nominal model with the dual-Youla uncertainty structure as is outlined in Sec. 4.5, and determine the size of $\gamma$ using any model uncertainty quantification procedure that delivers the minimal $\gamma$ such that (18) is satisfied, e.g., (72), (80), (87).

4. Compute and implement the optimal robust controller (24). If the performance is not satisfactory, repeat the procedure from Step 1.

The overall design procedure leads to nonconservative robust motion controllers and applies to highly complex systems. It enables new developments in motion control and addresses the challenges in Sec. 3.2 as is illustrated next.

**4.6 Identification procedure for robust motion control**

Combining the developments in the preceding sections leads to the following design procedure.

1. Specify a control objective $J$ in (4) using the $H_\infty$ norm, e.g., using loop-shaping design as in Sec. 2.2.2.

2. Identify a nominal model $\hat{G}$ by minimizing (17) using data collected while $K^{\text{pr}}$ is implemented.

3. Extend the nominal model with the dual-Youla uncertainty structure as is outlined in Sec. 4.5, and determine the size of $\gamma$ using any model uncertainty quantification procedure that delivers the minimal $\gamma$ such that (18) is satisfied, e.g., (72), (80), (87).

4. Compute and implement the optimal robust controller (24). If the performance is not satisfactory, repeat the procedure from Step 1.

**4.7 Case studies**

The procedure in Sec. 4.6 allows the design of advanced motion controllers that address the challenges in Sec. 3.2. These are elaborated on next.

**4.7.1 Case 1: multivariable modeling for robust control.** To show that the approach in Sec. 4.6 can deal with multivariable dynamics, a robust-control-relevant model set in the sense of (26) of the wafer stage in Fig. 1(a) is identified. The control goal in (4) is set to a bandwidth of $90 \text{ Hz}$ with PID characteristics.

The identification results are depicted in Fig. 7. The model $\hat{G}$ is of order 8, corresponding to $n_{RB} = 2$ and $n_s = 2$ in (1). In addition, the uncertainty is tuned towards the control objective: the uncertainty is small in the bandwidth region and the first two resonances, which typically need notches in the traditional manual design procedure in Sec. 2.2.2. In addition, at low and high frequencies, a very large uncertainty is tolerated. The model set has been shown to lead to a factor two error reduction after a design cycle, see (83) for details. This error can be further reduced by repeating the design cycle in Sec. 4.6, as well as an error-based redesign (83).

**4.7.2 Case 2: overactuation.** The closed-loop bandwidth is often limited by resonance phenomena, even if multivariable loop-shaping techniques are used that address the directionalities of $G_{\text{flex}}$ in (2). In view of the ideas in Sec. 3.2, additional actuators and sensors can be exploited. From a practical perspective, these can be employed to add active damping and stiffness. This technique has been successfully applied to a prototype wafer stage, where in the result of Fig. 8 a single actuator and sensor pair address the torsion mode, leading to a 35% bandwidth increase compared to the traditional input-output situation. These techniques are being extended to the 14 input-14 output prototype reticle stage in Fig. 1(b), which can potentially achieve a significant accuracy and throughput enhancement by lightweight stage design, see Sec. 3.1.

**4.7.3 Case 3: inferential control**

The procedure in Sec. 4.6 can be directly extended towards dealing with unmeasurable performance variables, in which case $z$ contains variables that are not contained in $y$. The main idea is that a model is made that enables prediction of the unmeasurable performance variables, e.g., using temporary sensors. This requires an extension of the controller structure in Fig. 2, details and an experimental example are provided in (80).

**4.7.4 Case 4: position-dependent control.** Motion systems perform motions by definition. Hence, it can be expected that the system in Fig. 3 is position dependent, since the sensor observes the mode-shapes differently for changing positions. Such dependence can be directly seen as linear parameter-varying (LPV) behavior, for which reliable synthesis techniques are available. However, the identification of such systems from data is challenging. Recently, a new approach has been developed to model position-dependent systems for LPV control, which consists of two steps.

1. Identify the system at a large number of frozen positions $n_0$, which are considered as $n_y \cdot n_0$ auxiliary outputs. Identify the high-dimensional $n_0$ input $n_y \cdot n_0$ output system using the procedure in Sec. 4.3 and Sec. 4.5.

2. Interpolate the mode-shapes to obtain a model with a continuous position dependence.

**4.7.5 Case 5: systems of systems.** The overall control of the wafer stage in Fig. 3 involves several subsystems, including the wafer stage and the reticle stage. The overall control problem is the relative positioning of the wafer with respect to the reticle. Instead of dividing the overall control problem in independent subproblems, the overall framework...
of Fig. 5 enables the direct solution of the overall problem through the approach in Sec. 4.6. Interestingly, the technique developed in Sec. 4.4-Sec. 4.5 also allows for a systematic add-on, see [30] for results in this direction.

4.7.6 Case 6: thermomechanical systems. So far, the focus has mainly been on motion control. However, thermal aspects are becoming significant for increasing accuracy. These directly fit in the setup of Fig. 5, and the approach in Sec. 4.6 has recently been applied to a thermal control system with thermal actuators and sensors [42]. This also enables compensating for thermal deformations in motion control.

4.7.7 Case 7: Vibrations. The presence of exogenous disturbances is essential and addressed in various aspects, including the use of active vibration isolation systems (AVIS) [72], compensation through disturbance observers [92], and disturbance-based redesign [77].

4.8 Discussion and overall design procedure In Sec. 4.7, several successful case studies of the approach in Sec. 4.6 are presented. This raises the question whether the approach in Sec. 4.6 has disadvantages compared to the traditional approach in Sec. 2.2.2. Although the theory is laid out, the algorithms still require significant user interaction. Also, numerical aspects are highly challenging [30] (49) (47), especially for complex systems as arising from the challenges in Sec. 3.2.

Taking into account the present level of maturity of the tools described in this section and based on significant experience with multivariable motion systems, the general procedure in Fig. 10 has proven to perfectly balance effort vs. control requirements. Indeed, the effort in terms of user intervention and modeling are only increased if necessitated by the control requirements. Interestingly, the first three steps are all based on FRF data, whereas the latter step, i.e., the procedure of Sec. 4.6 involves the use of a parametric model.

Note that all four steps in Fig. 10 are based on FRF data. Indeed, Step 4 in Fig. 10 involves the identification problem Sec. 4.3, which is again based on FRFs. This has led to a renewed interest in identifying FRFs of complex mechatronic systems, where traditionally noise excitation has been used [97] (99). These have been extended towards periodic excitation [77], and more recently substantial advancements have been made using local parametric modeling techniques [81] (87).

5. Feeding and learning

Feedforward and learning control are essential for high performance motion control. In this section, first learning control is investigated, the connection to feedforward is further outlined in Sec. 5.1.5.

5.1 Learning control Iterative learning control (ILC) [10] is particularly promising for positioning systems that perform repeating tasks. Typically, the feedforward signal $f$ in Fig. 2 is updated based on past experiments or trials $j$, e.g.,

$$f_{t+1} = Q(f_j + L_j),$$

with $Q$ and $L$ appropriate learning filters. Essentially, (29) involves a trial domain feedback, hence the resulting system is a 2D system [77]. For SISO systems, a well-developed design framework is available [90], yet in view of the challenges in Sec. 3.2, ILC algorithms of the form (29) are not directly applicable. The challenges in Sec. 3.2 are now briefly investigated in the context of ILC, see [77] for a more detailed overview.

5.1.1 Inferential ILC for unmeasurable feedback signals. Often, the performance variables are not directly accessible to the feedback controller, but they can be measured after a task is completed. For instance, in printing invisible markers can be used [17] Sec. 5.3. However, this requires a major extension to traditional ILC structures [80].

5.1.2 Multivariable ILC with additional inputs and outputs. ILC for multivariable systems is significantly more challenging compared to feedback. Although ILC is fairly robust with respect to modeling errors, it is effective up to the Nyquist frequency, imposing model quality requirements over the entire frequency range, which is in sharp contrast to the results in Fig. 7. In [60], the ILC analogue of the advanced motion feedback control design procedure in Fig. 10 is developed. In addition, in [90], the potential of additional inputs for ILC is established.

5.1.3 ILC for position-dependent systems. Since ILC is effective over a much larger frequency range compared to feedback, the effect of position-dependent dynamics is amplified. These are effectively addressed through an LTV approach in [90] and an LPV approach in [78].

5.1.4 Systems of systems. The design procedure in [30] can directly be applied to such systems, whereas a systematic ILC add-on as in Sec. 4.7.5 is developed in [61].

5.1.5 Flexible tasks One of the largest drawbacks of ILC is that it requires the reference $r$ in Fig. 2 to be constant. This is in sharp contrast to traditional feedforward control as is outlined in Sec. 2.2.1. The main goal of recent research, including [86] (44) (53) (17), has been to combine the performance advantages of learning control with the extrapolation capabilities of the feedforward structures in Sec. 2.2.1. This is further extended towards input shaping [11] and rational feedforward structures in [17] (47), which have as key advantage that these can exactly compensate non-minimum phase dynamics, e.g., [20] (60) (60). These are successfully applied to the printer system of Fig. 1(c) [15] and the wire bonder of Fig. 1(d) in [88].

A related approach that further connects to system identification in Sec. 4.3 is developed in [12] (10), see also [96].
6. Conclusion

Advanced motion control is a highly challenging area. Several issues arising from ongoing developments in applications have been identified, along with several solution strategies that are being developed. Many of these exciting control challenges are still ahead of us, and several open problems have not been addressed in the present paper, including (27) (24) (31) (2). Furthermore, nonlinear control techniques have been investigated in, e.g., (76) (46) (89). Implementation aspects are investigated in (2) (69) (35). Finally, data-driven techniques to avoid modeling altogether are being investigated in, e.g., (88) (34) (45) for feedback control and (14) for ILC.

In the near future, developments in advanced motion control may enable a paradigm shift in mechatronic system design. Indeed, a very lightweight design is foreseen, see Fig. 3, where stiffness is obtained through active control. In addition, thermal behavior will be actively controlled. These future systems may achieve unprecedented accuracy, speed, and cost.

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