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Advanced Feedforward and Learning Control for Mechatronic Systems

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1. THE POTENTIAL OF LEARNING FEEDFORWARD IN MECHATRONICS

Feedback and feedforward control are key components in mechatronic systems. Regarding feedback control, PID controllers are often used due to their intuitive tuning, disturbance suppression capabilities and robustness for variations in the system dynamics. By including a feedforward controller, a significant performance increase can be obtained, often at least a factor ten for motion control applications. This increase is achieved due to the fact that feedforward can essentially compensate for known ‘disturbances’ before these affect the system. For instance, the reference signal is known beforehand and its scaled velocity, acceleration, jerk, and snap profiles enable a straightforward feedforward tuning [1].

Iterative learning control [2] enables a possible further significant performance increase over common feedback and feedforward approaches. The main idea is to combine the advantages of feedback and feedforward: by learning from feeding back the error of a previous experiment, a new feedforward signal is generated that potentially compensates all repeating components of the error signal. Thus, in addition to known disturbances such as reference signals, it can also compensate for repeating disturbances such as friction and parasitic actuator forces.

Although the theory underlying ILC is reasonably mature and several design frameworks have been developed, its full potential for mechatronic applications is still largely unexploited. The aim of this paper is to identify some of the shortcomings of traditional ILC and related approaches, and to provide an overview of recent developments that are particularly tailored towards successful implementation in an industrial mechatronic environment. Several relevant industrial applications that are being addressed are depicted in Fig. 1.

Figure 1. Top left: Océ Arizona flatbed printer; top right: Océ Varioprint sheetfed inkjet press; bottom left: A7 experimental wafer stage; bottom center: ASML lithography system; bottom right: NXP ITEC diebonder.
2. TOWARDS A UNIFIED ADVANCED FEEDFORWARD AND LEARNING CONTROL FRAMEWORK

The goal of present research, which is outlined in the subsequent sections, is to develop a unified framework that is applicable to a wide range of systems, ranging from printing systems to wafer stages, and from additive manufacturing machines to pick and place machines, see also Fig. 1. Each of these systems involve application-specific aspects that are not fully addressed in pre-existing learning approaches. The proposed extensions include, but are not limited to: advanced feedforward to provide flexibility to varying tasks, multivariable (MIMO) learning control, linear time-varying (LTV) approaches to deal with time-varying dynamics, and position-dependent dynamics. In addition, implementation aspects are explicitly considered to fully exploit non-causality in feedforward signals and resource-efficient computations.

2.1. Breaking the Trade-Off: High Performance and Flexibility for Varying Tasks

Learning control can potentially compensate for all repeating components in the error signals through learning. This is potentially very strong if the error is exactly repeating. However, this advantage comes at the price of a high sensitivity to non-repeating errors. For instance, in case of small variations of the reference signal, e.g., required due to small corrections on the desired location in pick-and-place machines [3], ILC can significantly deteriorate the error signal, see Fig. 2. In contrast, traditional feedforward and feedback controllers provide high flexibility with respect to varying tasks while retaining a reasonable level of performance. As a result, there seems to be a fundamental trade-off in performance and flexibility with respect to varying tasks, see also Fig. 2. This trade-off is visualized using an Océ Arizona flatbed printer, see Fig. 1, equipped with markers in order to draw conclusions on the apparent trade-off.

Figure 2: Top left: the aim of learning feedforward is to combine the advantages of ILC and model-based feedforward, i.e., high performance and flexibility to varying tasks, which seem to suffer from a trade-off. Top right and bottom row: visualization of the performance-flexibility trade-off. ILC can significantly enhance performance through learning, i.e., learning to draw the square (top right: green line at iteration 4 is much lower than traditional (model-based) feedforward). This comes at the price of high sensitivity to non-repeating tasks: when the task is changed to a triangle, the performance degrades and ILC has to relearn. The consecutive iterations are drawn in different colors. See also http://arizona.toomen.eu.
To enhance flexibility to varying tasks while achieving high performance, we have recently developed new approaches that combine the performance associated with ILC with the advantages of common feedforward control. In particular, the idea is to parameterize the feedforward signal as a rational filter, i.e., with poles and zeros, where the parameters are learned from previous tasks. This concept is visualized in Fig. 3.

![Figure 3: The common goal of learning feedforward approaches is to optimize the feedforward action for performance, through learning the feedforward controller (left) or signal (right) over iterations \( j \).](image)

The application of learning control to rational feedforward filters enables high performance in conjunction with flexibility to varying tasks. Several learning feedforward approaches have been proposed, which are closely related to ILC, see [3], [4], [5], and [6], and system identification techniques, see [7], [8] and [9]. Also, rational feedforward parameterizations in terms of input shapers are presented in [10]. Related results include [11], whereas earlier results [12] are recovered as a special case. The resulting breakthrough of the trade-off between performance and flexibility is visualized in Fig. 2.

### 2.2. Advanced Learning and Feedforward: Beyond SISO

Industrial motion systems (Fig. 1) often include multiple axes of movement, possibly leading to relevant multivariable behavior. ILC is effective over a much larger bandwidth compared to traditional feedback control. Hence, increasing performance demands call for advanced learning techniques which explicitly account for multivariable dynamics. This section presents recent developments on multivariable ILC.

To highlight the potential issues in ILC for MIMO systems, traditional SISO ILC approaches are implemented on the Océ Arizona flatbed printer (Fig. 1). In Fig. 4, the results clearly reveal that these traditional SISO approaches neglect the interaction, which in turn leads to a divergent learning process. This underlines the importance of multivariable ILC design frameworks.

Recently, in [13], a part of the MIMO design framework is described. This framework covers a whole range of multivariable ILC designs, including decentralized and centralized designs, which both explicitly address the interaction during the design of the learning filters. In addition, multivariable algorithms are developed, including ZPETC, stable inversion, and \( \mathcal{H}_\infty \)-optimal preview control. Interestingly, these centralized designs for ILC which explicitly account for the interaction, potentially improve the performance, see Fig. 4.

![Figure 4. Benefits and complications in multivariable ILC design. Left: although the independently designed SISO ILC loops (○, ×) converge when interaction is absent, the full multivariable system may be divergent (□). Right: multivariable centralized ILC designs using \( \mathcal{H}_\infty \)-optimal preview control (○) and ZPETC (○) outperform decentralized designs (×), which may lead to divergent schemes (□) if interaction is ignored.](image)
2.3. Beyond Batch-to-Batch via Repetitive Control

The performance of control systems subject to periodically repeating disturbances can be significantly improved by using repetitive control [14]. Examples of such disturbances include rotating mechanical components such as gears and belts, and repetitive motion tasks as in Fig. 5. As a key difference with ILC, here continuously repeating motion tasks are considered. In Fig. 5, experimental results are shown obtained on an Océ Arizona flatbed printer, see Fig. 1, tracking a repetitive multivariable motion task.

![Figure 5: Left: schematic top view of Océ Arizona flatbed printer, with reference trajectory in red. During printing (solid red), the reference moves synchronously with the constant medium velocity $v_m$. Right: with multivariable repetitive control (--), the servo error during printing (grey areas) is significantly reduced with respect to combined feedback and model-based feedforward (—).](image)

2.4. Towards LTV Feedforward and Learning: Beyond LTI

Traditional ILC mainly involves linear models, whereas typical mechatronic systems in Fig. 1 involve nonlinear dynamics, e.g., due to varying sensor locations, position-dependent commutation in the actuation, or even position-dependent dynamics due to changing mass distributions in H-drive systems, such as with the Océ Arizona flatbed printer. If only an LTI (linear time-invariant) model is assumed for such systems, then large variations either lead to a divergent learning algorithm, or a highly conservative design, see Fig. 6.

![Figure 6: The performance criterion for an LTV system with ILC based on an LTV model (○) converges much faster than for an accurate LTI model (+). For poor LTI models there may not be convergence (☆). Robustness against these model mismatches can be incorporated, but at expense of performance (ₓ).](image)

The nonlinearities in the motion systems can be addressed in ILC and related inverse-model feedforward approaches by linearizing the system around a trajectory, leading to an LTV system model. Even if the time variations are fairly simple, they appear as complex dependencies in the inverse LTV model, as is addressed in [15]. To address this, dedicated stable inversion algorithms for LTV models are developed, as well as optimal LQ based approaches, see [15] for several results in this direction. Instead of using LTV models for the inversion, the position variation can also be explicitly addressed in the feedforward design. This will be discussed in the next section.
2.5. Towards Position-Dependent Learning Feedforward Control

As an alternative to LTV techniques described above, the position variations in system dynamics can be explicitly addressed in the feedforward design.

Consider for example a wafer stage which needs to be accurately positioned with respect to a certain spot of exposure, while the sensor readings also are position-dependent, see Fig. 7. Since these sensor locations change as a wafer is processed, a variable feedforward control strategy can potentially improve the positioning accuracy. In Fig. 7, the potential of linear parameter varying (LPV) learning control is exemplified on a prototype motion system. These approaches enable a systematic design for both approaches in Fig. 3, and a broad range of LPV approaches is developed for advanced feedforward and ILC.

![Figure 7](image)

**Figure 7:** Left: schematic illustration of a flexible wafer stage exhibiting position-dependent behavior caused by motion of the stage relative to sensor positions. Right: the changing sensor locations lead to a significant performance deterioration for LTI feedforward techniques (X), whereas the linear parameter varying feedforward (○) is able to compensate for these dynamics through learning over tasks.

2.6. Towards Inferential Feedforward and Learning

At the extreme performance and accuracy levels enabled by learning feedforward methods, often systems cannot be assumed to be rigid anymore. For instance, in printing systems, the position is measured using an encoder at the motor, while performance is defined at the printing location. Similarly, in wafer stages, the position is typically measured at the edges of the wafer stage using interferometers, while performance is defined at the spot of exposure. This control situation is referred to as inferential motion control [16].

![Figure 8](image)

**Figure 8:** Schematic illustration of inferential motion control applications: wafer stage (left), and printing system (right). When measurements of the performance variables are available off-line, batch-to-batch learning feedforward methods such as ILC enable extreme performance at the point of interest.

Since ILC is a batch-to-batch control approach, it can exploit measurements of the product, e.g., using a scanner that immediately scans the print after each swat [4]. Such approaches have extreme potential for batch-to-batch control approaches such as ILC. However, a recent analysis [17], has revealed that traditional ILC approaches for motion systems are internally unstable in this situation. By using appropriate ILC structures, suitable inferential ILC approaches have recently been developed.
3. IMPLEMENTATION ASPECTS FOR SUCCESSFUL INDUSTRIAL IMPLEMENTATION

The main idea behind feedforward and ILC techniques is to attempt to invert a (possibly non-minimum phase) system, see Fig. 2. In fact, from a system theoretic perspective, ILC simply is a repeating application of feedforward algorithms. In the past, several approximate algorithms have been used, including ZPETC.

To avoid the approximations involved in ZPETC and to facilitate the extension to MIMO and LTV systems, see Sections 2.2 and 2.4, several aspects have been addressed. First, an exact inverse can be computed. Of course, a system may be non-minimum phase, in which case such an inverse may produce an unbounded/unstable feedforward signal, which is highly undesirable. Interestingly, this unbounded nature has its origin in the use of the standard unilateral Laplace or z-transform.

By using the bilateral Laplace transform or z-transform, a bounded yet non-causal inverse can be obtained, which is exact [7] [9]. In an ILC setting, non-causality is not an issue and in fact a desired property since learning is done off-line. Interestingly, this is also not an issue for motion feedforward design, since the motion task is often known beforehand. As a result of these non-causal inverses, the feedforward controller can anticipate on future references through pre-actuation [9]. This can clearly be observed in the experimental results shown in Fig. 8, which are obtained on the A7 experimental wafer stage, see Fig. 1. MIMO applications and LTV extensions are described in, e.g., [13], [15].

![Figure 8: Through stable inversion, rational feedforward controllers (---) can be used to generate pre- and post-actuation. Note that (causal) polynomial feedforward controllers (---) do not enable this. The start and end times of the motion task are indicated by black dashed lines.](image)

Alternatively, LQ optimal feedforward signals have been developed that enable tuning of the approximation using a criterion and, in addition, take into account boundary effects due to finite time tasks. Standard finite-time ILC implementations are based on lifting techniques involving matrices of dimensions $N \times N$, with $N$ the task length. Since matrix multiplication and inversion are involved, computations are slow and limited memory restricts the maximum task length $N$. An alternative resource-efficient implementation based on optimal control and LQ tracking [15] provides the exact same high performance, but at a significantly lower cost, i.e., $O(N)$ instead of $O(N^3)$.

4. SUMMARY

Learning control potentially enables performance of mechatronic systems to the limit of reproducibility. As such, learning control is a key enabler to optimize 1) accuracy, 2) speed/throughput, and 3) cost. In this paper, an overview of several recent developments is presented that will overcome the limitations of conventional ILC and feedforward for mechatronic systems. In the near future, it is expected that the unified framework will be further extended and will have a significant impact on mechatronic system performance in a broad range of applications.

Finally, many of the basic results and extensions are incorporated in a renewed course ‘Advanced Feedforward Control’ of Mechatronics Academy, where participants apply the covered theoretical concepts to practical mechatronic systems. More information can be found at [http://mechatronics-academy.nl](http://mechatronics-academy.nl).
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