Learning in Machines: From Data to Models, Control Performance, and Monitoring

Learning in Machines: From Data to Models, Control Performance, and Monitoring

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I. Research Overview: Complexity in Future Data-Intensive High-Tech Systems

Future high-tech systems are subject to increasing performance demands [1], including accuracy, throughput, and versatility. Important examples of such systems in the manufacturing domain include wafer stages for integrated circuit production, see Fig. 1(a), and the generic substrate carrier for industrial production, see Fig. 1(b). Important examples of scientific instruments include large scale telescopes with deformable mirrors, see Fig. 1(c) and the gravitational wave detector in Fig. 1(d).

Radically new (opto-)mechatronic system designs and control approaches are envisaged to meet increasing performance requirements, including the following examples.

1) The use of additional actuators and sensors to increase performance and enable innovative designs [2]. Spatially-distributed actuators control flexible mechanics in new lightweight designs, see Fig. 1(a). Individually controlled segmented rollers are used in carriers for extreme positioning accuracy, see Fig. 1(b). Deformable mirrors are controlled using a large number of actuators, see Fig 1(c). Additional actuators enhance accuracy in gravitational wave detectors, see Fig 1(d).

2) Directly addressing overall system performance goals. In traditional approaches, the control problem is subdivided into manageable subproblems associated with system submodules, leading to suboptimal performance. Directly addressing the overall performance requirements leads to unparalleled performance at the price of an extreme increase in complexity, e.g., the integrated control of the two motion stages in Fig. 1(a), see [3]. Relevant aspects also include unmeasurable performance variables [4], intermittent sampling [5], and sampled-data aspects [6]. Furthermore, multi-physics control problems are addressed, including the thermo-mechanical control system in Fig 1(a), see [7], and the opto-mechatronic systems in Fig. 1(c)-1(d), see [8] and [9], respectively.

The key step to enable the envisaged future data-intensive equipment lies in control design, where the major challenge lies in dealing with the extreme complexity.

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From Data to Models for Control

Models are essential to provide performance and robustness guarantees in future data-intensive machines. To this end, major developments have been made to identify complex mechatronic systems from data, including

- nonparametric models for complex [10], multi-physics [7], operating-condition-dependent [11], slowly-sampled [12], missing-data [13], and Lebesgue-sampled [14] systems; and
- parametric models for complex [2] and operating-condition-dependent [15], [8] systems.

These models are essential for subsequent feedback control design, see [2] for an overview.

From Data to Control Performance via Learning

The availability of ubiquitous data in future data-intensive systems provides major opportunities for performance enhancement through learning. Essentially, all predictable behavior can be fully compensated. First, disturbances are typically present that are accurately modelled as a stochastic process.

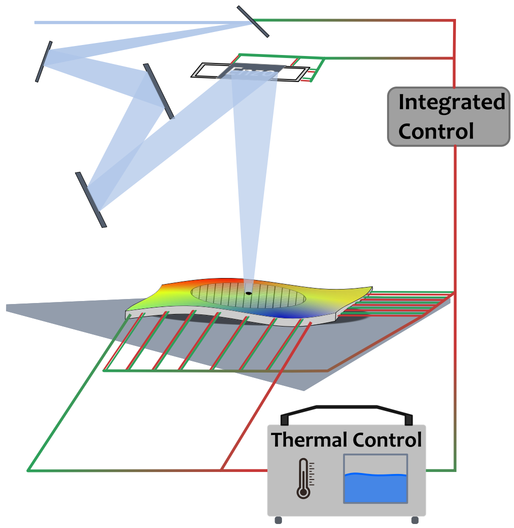
- Feedback control, [2], is essential to suppress these stochastic disturbances. These disturbances cannot be predicted before the task starts, yet typically these have a certain spectrum. Feedback can suppress these disturbances leading to an optimal error that is white noise.

Second, many motion systems have repeating signals that disturb the system, often of a deterministic nature. A large range of approaches are relevant.

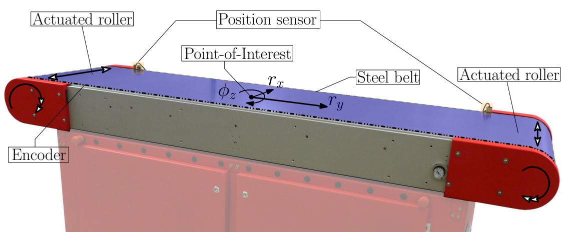
- Iterative learning control and repetitive control [16], [17].
- Batch-to-batch feedforward [18], including recursive [19], [20], data-driven [21], and hysteresis [22] variants.
- Gaussian process models for position-dependent and task-flexible feedforward [23].
- Neural-networks [24] as add-on inverse model completion of the explainable models in the previous subsection.

From Data and Models to Monitoring

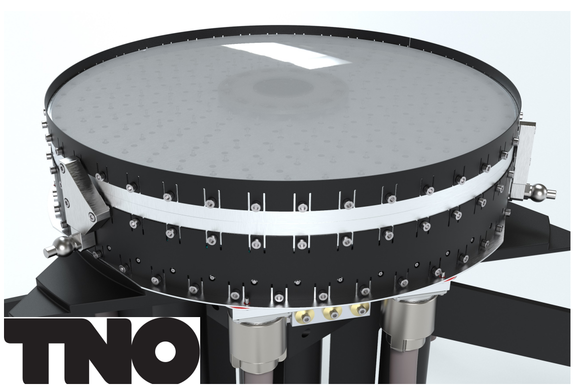
Any physical system degrades due to wear, ageing, etc. Feedback, feedforward, and learning algorithms provide a large amount of data on the state of the system during operation. Besides these data, accurate models are readily available from control design. These models can be re-purposed and integrated with data, enabling fault identification, isolation, and predictive maintenance, leading to drastic downtime minimization and increasing productivity [25], [26].



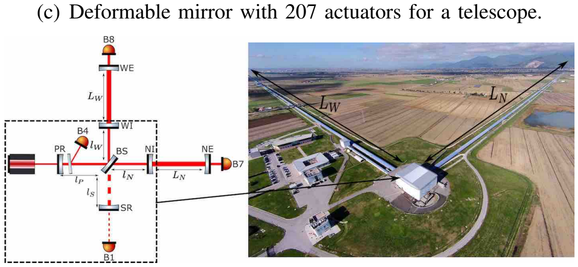
(a) Envisaged wafer stage.



(b) Industrial substrate carrier.



(c) Deformable mirror with 207 actuators for a telescope.



(d) Gravitational wave detector.

Fig. 1. Selection of complex data-intensive (opto-) mechatronic systems.

II. Seminar Topics

A. Gaussian Processes for Advanced Motion Control

Manufacturing equipment and scientific instruments are subject to increasing speed, accuracy, and flexibility requirements. Examples of such systems include wafer scanners, printing systems, pick-and-place machines, and microscopes. Learning from data provides huge opportunities in these future data-intensive mechatronic systems to meet increasing speed, accuracy, and functionality requirements. To this end, learning techniques are presented, including Gaussian Processes (GPs). Successful applications of GPs for feedforward and learning control, including identification and learning for noncausal feedforward, position-dependent snap feedforward, motor force constants (Fig. 2), nonlinear feedforward, and GP-based spatial repetitive control, are outlined. Experimental results on various systems, including a desktop printer, wirebonder, and substrate carrier, confirm that data-based learning can significantly improve the accuracy of mechatronic systems.

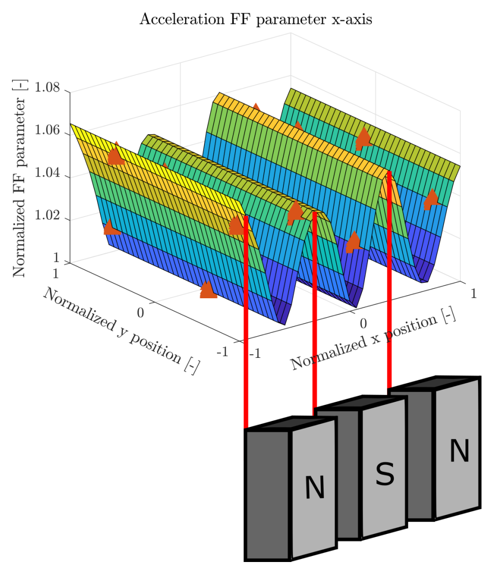


Fig. 2. Data-driven learning of Gaussian-Process based motor force compensation.

B. Learning for Precision Motion Control

Iterative Learning Control (ILC) can achieve perfect tracking performance for mechatronic systems. The aim is to present an ILC design tutorial for industrial mechatronic systems. First, a preliminary analysis reveals the potential performance improvement of ILC prior to its actual implementation. Second, a frequency domain approach is presented, where fast learning is achieved through noncausal model inversion, and safe and robust learning is achieved by employing a contraction mapping theorem in conjunction with nonparametric frequency response functions. The approach is demonstrated on a desktop printer, see Fig. 3. Finally, a detailed analysis of industrial motion systems leads to several shortcomings that obstruct the widespread implementation of ILC algorithms. An overview of recently developed algorithms is given, including extensions using machine learning algorithms. These are aimed to facilitate broad industrial deployment.

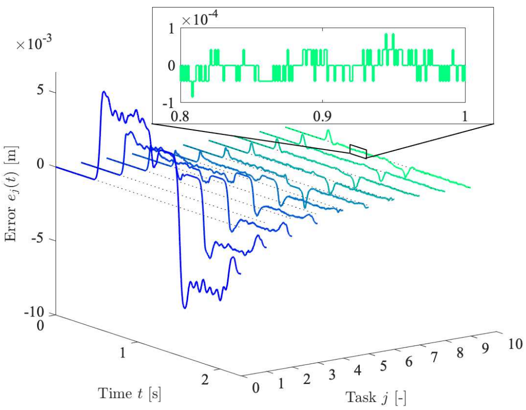


Fig. 3. Performance enhancement on a desktop printer through iterative learning control

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