Data-Driven Multi-Objective Controller Optimization for a Magnetically-Levitated Nanopositioning System

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Abstract—The performance achieved with traditional model-based control system design approaches typically relies heavily upon accurate modeling of the motion dynamics. However, modeling the true dynamics of present-day increasingly complex systems can be an extremely challenging task; and the usually necessary practical approximations often renders the automation system to operate in a non-optimal condition. This problem can be greatly aggravated in the case of a multi-axis magnetically-levitated (maglev) nanopositioning system where the fully floating behavior and multi-axis coupling make extremely accurate identification of the motion dynamics largely impossible. On the other hand, in many related industrial automation applications, e.g., the scanning process with the maglev system, repetitive motions are involved which could generate a large amount of motion data under non-optimal conditions. These motion data essentially contain rich information; therefore, the possibility exists to develop an intelligent automation system to learn from these motion data, and to drive the system to operate towards optimality in a data-driven manner. Along this line then, this paper proposes a data-driven model-free controller optimization approach that learns from the past non-optimal motion data to iteratively improve the motion control performance. Specifically, a novel data-driven multi-objective optimization approach is proposed that is able to automatically estimate the gradient and Hessian purely based on the measured motion data; the multi-objective cost function is suitably designed to take into account both smooth and accurate trajectory tracking. In the work here, experiments are then conducted on the maglev nanopositioning system to demonstrate the effectiveness of the proposed method, and the results show rather clearly the practical appeal of our methodology for related complex robotic systems with no accurate model available.

Index Terms—Learning-based control, robot learning, data-driven optimization, iterative feedback tuning, magnetic levitation, robot control, precision motion control, nanopositioning.

I. INTRODUCTION

The magnetically-levitated nanopositioning technique [1] is a promising solution for ultra-clean or vacuum precision motion applications due to its excellent characteristics such as multi-axis mobility, ultra-precision, large motion stroke, contact- and dust-free usage, etc. However, due to its fully floating feature, the maglev nanopositioning system requires sophisticated motion control in all its six Degree-of-Freedom (DOF) to even simply stabilize at a constant position. The advanced multi-axis positioning and trajectory tracking further require high-performance precision motion control techniques [3]–[7] to reject the internal/external disturbances and eliminate the coupling effects between axes. Traditionally, such precision motion control systems are designed and optimized based on the model (when available) obtained from the first principle or system identification, i.e., model-based approach [9]–[11]. However, obtaining an accurate model for the multi-axis maglev nanopositioning system is challenging and time-consuming; and the model obtained is typically often not adequately representative of the true dynamics, e.g., the coupling between axes is often not taken into account. To address this often-occurring general issue, it is a notable trend where learning-based methods are increasingly being explored in literature, wherein model parameters are not precisely known, and yet the appropriately optimal control performance can be obtained [12]–[14]. This data-driven methodology enables learning from available signals in the past, and also prevailing, non-optimal control settings to achieve a significant performance improvement for various cases of real-world mechatronic systems [15]–[18].

Data-driven controls are essentially developed based on the concept that machines can improve their performance by learning from previous executions of the same or similar tasks, in a way that closely resembles how humans learn. A promising trend in data-driven controls is deep reinforcement learning [19], wherein a neural network policy is trained based on real-world motion data as well as appropriate simulations. In addition to this end-to-end approach, deep neural networks can also be used for trajectory tracking in many robotic applications [20]. However, the limitation of these neural network based approaches is the requirement for a massive amount of training data. Also, the uncertainty in the important system stability issue due to the black-box nature of neural networks often becomes a concern, especially for safety-critical applications. Apart from the neural network based approaches, [21] proposed a novel model-less feedback control design for soft robotics, and it was further extended to the hybrid position/force control problem in [22]. The proposed approaches in these works allow the manipulators to interact with several constrained environments safely and stably, and then generate a model-less feedback control policy from these interactions. It is worthwhile to note that these works are mainly focused on kinematic-model-free control instead of
dynamic-model-free control, i.e., the Jacobian is unknown and empirically estimated; therefore, challenges in dynamic control remain.

It is worthwhile to note that many industrial processes such as scanning, pick-and-place, welding, and assembly, involve repetitive motions; therefore, less computationally expensive learning approaches can be pursued. For instance, the Iterative Learning Control (ILC) is a data-driven method that is used widely in precision machines [23], [24] and robotics [25]–[28]. It makes use of the repetitive tracking error data gathered in previous cycles to improve the performance of the system in subsequent cycles in a feedforward manner. Thus, it is essentially a feedforward learning approach rather than feedback learning; nevertheless it can serve as a very useful complement to an existing feedback controller. In [29], the authors proposed a novel Gaussian process based feedback controller optimization algorithm with applications to quadrotors. This approach models the cost function as a Gaussian process and explores the new controller parameters with a safe performance guarantee. This enables automatic and safe optimization in repetitive robotic tasks without human intervention. However, while greatly effective especially in guaranteeing safety, the convergence is relatively slow as it takes about 30 iterations to converge.

The Iterative Feedback Tuning (IFT) methodology is one of the approaches in the class of fast-converging data-driven controller optimization algorithms [30]. Conceptually similar to the other approaches, it makes use of the actual motion data to estimate the cost function gradient without relying on the system model. In addition, the Hessian of the cost function can be estimated to speed up the convergence. The estimated gradient and Hessian are subsequently used in the Gauss-Newton optimization procedure to iteratively obtain the optimal controller parameters. This IFT approach has been widely used in many applications such as path-tracking control of industrial robots [17], [31], ultra-precision wafer stage [32], [33], flow control over a circular cylinder [34] and compliant rehabilitation robots [35], etc. Extensions of the IFT idea to other types of controller includes iterative dynamic decoupling control [36], disturbance observer sensitivity shaping [37], iterative feedforward tuning [38], and 3-DOF controller tuning [39], [40] etc. However, most of the existing work focused mainly on accurate tracking and did not take smooth tracking into account. In fact, in semiconductor manufacturing and many other robotic applications, both accurate and smooth trajectory tracking are required [41], [42], and this challenge remains unsolved. Hence, the contribution of this paper is to propose a learning-based controller optimization algorithm to enable smooth and accurate tracking in repetitive tasks as illustrated schematically and conceptually in Fig. 1. To the best of our knowledge, this work is the first feedback controller optimization method to take into account both accurate and smooth tracking in a data-driven manner. Furthermore, it is worthwhile to note that the optimization process is both data-efficient and fast-converging.

This paper is organized as follows. In Section II, a brief description of the magnetically-levitated nanopositioning system is provided. Then, in Section III, the proposed multi-objective controller optimization algorithm is described and analyzed in detail. In Section IV, experimental work is conducted based on the magnetically-levitated nanopositioning system to show the effectiveness of the proposed algorithm. Finally, conclusions are drawn in Section V.

II. MAGNETICALLY-LEVITATED NANOPositionING SYSTEM

In this section, the magnetically-levitated planar nanopositioning system (which is the typical prototype application of our data-driven controller optimization approach) is first illustrated, including its working principles and associated overall control scheme. The design objective of our magnetically-levitated planar nanopositioning system is to enable 6-DOF motion with low system complexity and high energy efficiency. For large-stroke applications, the stroke expandability is also important as well as the affordability to simultaneously operate multiple motion translators. The schematic design of the implemented magnetically-levitated planar nanopositioning system for this work is illustrated in Fig. 2. Although the square coil array in Fig. 2 is covered here in a small area for evaluation, such a square coil based design allows suitably unlimited planar motion stroke as long as the coils spread...
over. Notably, this system adopts the tiled square coil array for actuation, which shows the comparative advantages in control complexity and energy efficiency as it only requires 8-phase for 6-DOF motion control and coils far away can be actively switched off to save energy [43]. Furthermore, the interference between coils is minimized at the maximum extent by using the square coil arrangement, so that multiple translators are feasible by individually controlling each or set of coils. From Fig. 2 it can be seen that the 6-DOF motion is achieved by the combined force from Forcer 1 to 4, where each forcer can provide a vertical levitation force and horizontal thrust force. As illustrated in Fig. 3 the moving part of one forcer is a Halbach permanent magnet array and the stationary part is a square coil array grouped into two phases. Due to the periodic arrangement of magnetization directions indicated in Fig. 3 the Halbach array generates an almost ideal sinusoidal periodic arrangement of magnetization directions indicated in Fig. 3, each square coil is divided into three segments, and thus be closed-loop controlled as Single-Input Single-Output (SISO) systems and ready for the deployment of the algorithm in Section III.

III. DATA-DRIVEN MULTI-OBJECTIVE OPTIMIZATION

As noted earlier, certain important precision motion systems such as the maglev nanopositioning system emphasize the requirement for smooth and accurate tracking in terms of control performance. To achieve these objectives, both the
tracking accuracy and control signal variation needs to be taken into account concurrently in the optimization. Hence, the overall cost function in this paper is defined as

$$J(i, \rho) = \frac{w_1 e(i, \rho) + w_2 \dot{u}(i, \rho)}{J_s}$$

where $^i\rho$ is the controller parameter vector in the $i^{th}$ iteration, and $J(i, \rho)$ is the total cost function consisting of the tracking related cost function $J_s$ and control variation related cost function $J_c$. Here, $w_1$ is the weighting for the tracking performance wherein $e(i, \rho)$ is the tracking error measured in the $i^{th}$ iteration; $w_2$ is the weighting for the control variation wherein $u(i, \rho)$ is the control input and $\dot{u}(i, \rho)$ is the variation of control input. Thus consider the typical feedback control system for the magnetically-levitated system as in Fig. 1 where a fixed structure controller $C(s)$ is used for motion control and can be expressed as

$$C(s, \rho) = \rho^T \bar{C}(s).$$

Here, $\rho$ is a vector of the controller parameters to be optimized and $\bar{C}(s)$ is a vector of parameter independent transfer functions. We can now formulate the data-driven multi-objective optimization problem as:

**Problem 1.** Assume the motion system is unknown and controlled by a fixed structure controller $C(s, \rho)$ in (7); use only the closed-loop experimental data to determine the parameter vector $\rho$ that minimizes the multi-objective cost function $J(\rho)$ (6), i.e., to find

$$\rho^* = \arg \min \rho J(\rho).$$

**A. Gradient Calculation and Estimation**

With equation (6), the gradient of the cost function $J(i, \rho)$ with respect to the parameter in the $i^{th}$ iteration $^i\rho$ can be derived as

$$\nabla J(i, \rho) = 2w_1 [\nabla e(i, \rho)]^T \cdot e(i, \rho) + 2w_2 [\nabla \dot{u}(i, \rho)]^T \cdot \dot{u}(i, \rho),$$

and the Hessian of the cost function can be approximated as

$$\nabla^2 J(i, \rho) = 2w_1 [\nabla e(i, \rho)]^T \cdot \nabla e(i, \rho) + 2w_2 [\nabla \dot{u}(i, \rho)]^T \cdot \nabla \dot{u}(i, \rho).$$

The purpose of obtaining the gradient and the Hessian of the cost function is to apply the Newton’s optimization algorithm (14):

$$^i+1\rho = ^i\rho - \gamma (\nabla^2 J(i, \rho))^{-1} \nabla J(i, \rho).$$

where $^i+1\rho$ is the updated parameter value for iteration $i+1$ and $\gamma$ is the step size at iteration $i$. From (9) and (10) the Newton’s optimization algorithm requires $\nabla e(i, \rho)$, $\nabla \dot{u}(i, \rho)$, $^i e(i, \rho)$ and $^i \dot{u}(i, \rho)$ can be obtained directly from the sensor measurement and the control software. However, $\nabla \dot{u}(i, \rho)$ cannot be obtained directly and have to be estimated with the input-output data collected from the closed-loop experiments. The gradient of the tracking error can be derived as:

$$\nabla e(i, \rho) = -P \frac{\partial C(i, \rho)}{\partial \rho} \cdot \frac{1}{1 + PC(i, \rho)} \cdot e(i, \rho).$$

Inspired by the IFT approach [30], $\nabla^2 e(i, \rho)$ can then be obtained by setting $^i e(i, \rho)$ as the new reference $r$ in the “special” experiment, and we have

$$\nabla^2 e(i, \rho) = \frac{\partial^2 C(i, \rho)}{\partial \rho^2} \cdot \frac{1}{1 + PC(i, \rho)} \cdot y_s,$$

where $y_s$ denotes the position measurement for this experiment. Apart from $\nabla e(i, \rho)$, the gradient of $^i \dot{u}(i, \rho)$ can also be derived as

$$\nabla \dot{u}(i, \rho) = \frac{\partial C(i, \rho)}{\partial \rho} \cdot \frac{1}{1 + PC(i, \rho)} \cdot \dot{r} = \frac{\partial^2 C(i, \rho)}{\partial \rho^2} \cdot \frac{1}{1 + PC(i, \rho)} \cdot \dot{r} \cdot \dot{e}$$

$\nabla \dot{u}(i, \rho)$ can be estimated with the same special experiment by feeding in $^i e(i, \rho)$ as the reference $r$

$$\nabla \dot{u}(i, \rho) = \frac{\partial C(i, \rho)}{\partial \rho} \cdot \frac{1}{C(i, \rho)} \cdot \dot{u}_s,$$

where $u_s$ denotes the control input of this special experiment. Notice that $\nabla e(i, \rho)$ and $\nabla \dot{u}(i, \rho)$ can be estimated solely based on the experimental data. In addition, $^i e(i, \rho)$ and $^i \dot{u}(i, \rho)$ can be directly obtained or calculated based on the sensor measurement and control software. Hence, the gradient $\nabla J(i, \rho)$ and Hessian $\nabla^2 J(i, \rho)$ of the cost function can also be estimated according to (9) and (10). It should be noted, as will be discussed in Section III-B and III-C, that an additional normal experiment needs to be conducted in order to obtain an unbiased estimate of the gradient when the measurement noise is taken into consideration.

**B. Data Collection**

To make the data-driven optimization procedure clearer, all the experiments needed and data to be collected within a single iteration are listed below.

- **Experiment I:** Normal experiment.
  
  $$r^1 = r,$$
  
  $$y^1 = \frac{PC(i, \rho)}{1 + PC(i, \rho)} \cdot r^1 - \frac{1}{1 + PC(i, \rho)} \cdot n^1,$$
  
  $$e^1 = \frac{1}{1 + PC(i, \rho)} \cdot r^1 + \frac{1}{1 + PC(i, \rho)} \cdot n^1.$$

- **Experiment II:** Special experiment.

  $$r^2 = e^1,$$

  $$y_s = y^2 = \frac{PC(i, \rho)}{1 + PC(i, \rho)} \cdot e^1 - \frac{1}{1 + PC(i, \rho)} \cdot n^2,$$

  $$u_s = u^2 = \frac{C(i, \rho)}{1 + PC(i, \rho)} \cdot e^1 + \frac{C(i, \rho)}{1 + PC(i, \rho)} \cdot n^2.$$

- **Experiment III:** Normal experiment.

  $$r^3 = r,$$

  $$e^3 = \frac{1}{1 + PC(i, \rho)} \cdot r^3 + \frac{1}{1 + PC(i, \rho)} \cdot n^3,$$

  $$u^3 = \frac{C(i, \rho)}{1 + PC(i, \rho)} \cdot r^3 + \frac{C(i, \rho)}{1 + PC(i, \rho)} \cdot n^3.$$
The bold right superscript refers to the experiment index within a single iteration. In Experiment I, the normal operation with, e.g., a S-curve trajectory, is conducted while $y^1$ is measured and used to generate $e^1$ as the reference of Experiment II. In Experiment II, measurement of $y_s$ and $u_s$ is taken and it is then used to obtain $\nabla^1 e(i\rho)$ and $\nabla^1 \dot{u}(i\rho)$ according to (12) and (14). In Experiment III, measurement of $e^3$ and $u^3$ is taken and used to calculate the cost function gradient $\nabla J(i\rho)$. The complete data-driven multi-objective optimization algorithm can be summarized in Algorithm 1. It is worth noting that, similar to the IFT and many other algorithms inspired by the IFT, there is no strong guarantee (proofs) for robust stability throughout the iterations, due to the lack of the system model. Hence, as also suggested in [35], we shall use cautious updates, i.e., use small step-sizes, especially during the first iterations.

**Algorithm 1 Data-Driven Multi-Objective Controller Optimization Algorithm**

1. Set the iteration number $i = 0$ and select the initial controller parameter $\rho_0$.
2. Conduct Experiment I and measure the output $y^1$ and tracking error $e^1$.
3. Evaluate the cost function $J(i\rho)$. Stop if the cost function value is satisfactory. Otherwise, proceed to Step 4.
4. Conduct Experiment II and measure the output $y^2$ from this special experiment.
5. Obtain $\nabla^1 e(i\rho)$ and $\nabla^1 \dot{u}(i\rho)$ according to (12) and (14) respectively.
6. Conduct Experiment III and measure $e^3$ and $u^3$.
7. Compute $\nabla J(i\rho)$ as well as $\nabla^2 J(i\rho)$ according to (9) and (10), where $e^1(i\rho)$, $\dot{u}(i\rho)$ are obtained from Experiment III and $\nabla^1 e(i\rho), \nabla^1 \dot{u}(i\rho)$ are obtained from Step 5.
8. Execute the Gauss-Newton algorithm (11), and update the controller parameters.
9. Set the iteration number $i ← i + 1$ and proceed to Step 2.

**C. Unbiasedness of the Gradient Estimation**

The cost function gradient is estimated using the closed-loop experiment data, so the measurement noises can potentially lead to errors during this estimation. For this stochastic approximation method to work, the gradient estimation has to be unbiased, mathematically

$$E[\text{est} \nabla J(i\rho)] = \nabla J(i\rho).$$

To prove the unbiasedness, we have the following assumptions:

**Assumption 1.** Noises $n$ in different experiments are independent from each other.

**Assumption 2.** Noises $n$ are zero mean, weakly stationary random variables.

**Theorem 1.** For the motion system under the feedback control configuration as shown in Fig. 2 with Assumption 1 and Assumption 2, the estimation of the gradient of the cost function $J$ in (6) is unbiased.

**Proof.** From (12), the estimated gradient of $e$ is given by

$$\text{est}[\nabla^1 e(i\rho)] = -\frac{\partial C^1(i\rho)}{\partial \rho} \cdot \frac{P}{1 + PC^1(i\rho)} \cdot e^1$$

$$= \nabla^1 e(i\rho) + w_e,$$

where

$$w_e = -\frac{\partial C^1(i\rho)}{\partial \rho} \cdot \frac{P}{1 + PC^1(i\rho)^2} \cdot n^1$$

$$+ \frac{\partial C^1(i\rho)}{\partial \rho} \cdot \frac{1}{C^1(i\rho)} \cdot 1 + PC^1(i\rho) \cdot n^2.$$

Notice that $w_e$ contains noises from Experiment I and Experiment II and $e^3$ contains only the noises from Experiment III. With Assumption 1 and Assumption 2, we have

$$E[w_e^T \cdot e^3(i\rho)] = E[w_e^T] \cdot E[e^3(i\rho)],$$

and

$$E[w_e^T] = 0.$$ (28)

Similar results can be obtained for $\dot{u}$ from (14). The expectation of the estimation of the cost function gradient can be derived as follows

$$E[\text{est}[\nabla J(i\rho)]] = 2w_1 E[\text{est} \nabla e^T(i\rho)] e^3(i\rho) + 2w_2 E[\text{est} \nabla \dot{u}^T(i\rho)] u^3(i\rho)$$

$$= 2w_1 E[\nabla e^T(i\rho)] e^3(i\rho) + 2w_1 E[w_e^T \cdot e^3(i\rho)]$$

$$+ 2w_2 E[\nabla \dot{u}^T(i\rho)] u^3(i\rho) + 2w_2 E[w_e^T \cdot \dot{u}^3(i\rho)]$$

$$= \nabla J(i\rho) + 0 \cdot E[e^3(i\rho)] + 0 \cdot E[u^3(i\rho)]$$

$$= \nabla J(i\rho).$$

This completes the proof of the Theorem. □

From the proof, it can be noticed that Experiment III is indeed necessary in order to guarantee the unbiasedness of cost function gradient estimation. If the data from Experiment I were used, i.e., $e^1(i\rho)$ and $\dot{u}^1(i\rho)$ instead of $e^3(i\rho)$ and $\dot{u}^3(i\rho)$, the same noise would exist in both $\text{est} \nabla e^T(i\rho)$ and $e^1(i\rho)$ (as well as in $\text{est} \nabla \dot{u}^T(i\rho)$ and $\dot{u}^1(i\rho)$). This would lead to a biased estimation for the cost function gradient and it is exactly the reason why Experiment III is needed.

**IV. EXPERIMENTAL VALIDATION**

This section documents the experimental results of using the proposed data-driven optimization algorithm for the maglev nanopositioning system as a case study. A National Instruments (NI) PXI-8110 real-time controller is used with two FPGAs (NI PXI-7854R and 7831R) to provide the necessary input/output (I/O) functions. Two Trust TA320 and two TA115 linear current amplifiers are utilized to power up the eight-phase coils. The sampling frequency is 5 kHz, and the current
TABLE I
Overview of the controller parameters for Y and X axis

| Parameters     | Y Axis Before Optimization | Y Axis After Optimization | X Axis Before Optimization | X Axis After Optimization |
|----------------|-----------------------------|---------------------------|-----------------------------|---------------------------|
| $K_p$          | 30                          | 25.1221                   | 30                          | 25.1781                   |
| $T_i$          | 0.002                       | $2.8459 \times 10^{-4}$   | 0.002                       | $3.8538 \times 10^{-4}$   |
| $T_d$          | 0.00012                     | $1.3490 \times 10^{-4}$   | 0.00012                     | $2.3865 \times 10^{-4}$   |

TABLE II
Overview of the cost functions for Y and X axis

| Cost functions | Y Axis Before Optimization | Y Axis After Optimization | X Axis Before Optimization | X Axis After Optimization |
|----------------|-----------------------------|---------------------------|-----------------------------|---------------------------|
| Total cost $J$| $1.3892 \times 10^4$         | $2.4835 \times 10^4$      | $2.8850 \times 10^4$         | $6.1024 \times 10^4$      |
| Tracking cost $J_{tc}$ | $1.0890 \times 10^8$ | $5.6159 \times 10^8$ | $2.3326 \times 10^8$ | $3.9377 \times 10^8$ |
| Control variation cost $J_{cv}$ | $3.0017 \times 10^7$ | $1.9217 \times 10^7$ | $5.5240 \times 10^7$ | $2.2247 \times 10^7$ |

Fig. 4. Magnetically-levitated nanopositioning system used in the experimental validation.

Fig. 5. Fourth-order S-curve motion profile used in the real-time experiment.

Fig. 6. Y axis controller $C(s, \rho)$ comparison before and after the optimization in the frequency domain.

Fig. 7. Y axis and X axis controller parameter convergence diagram.
The motion profile used in the experiment is a fourth-order S-curve which is particularly suitable for precision motion control [46]. In order to meet the requirement of smooth motion, the profile is defined up to the fourth order with limited jerk and snap. The position trajectory as well as its velocity, acceleration, jerk (time derivative of acceleration) and snap (time derivative of jerk) are plotted in Fig. 9. The magnetically-levitated system is controlled by a feedback controller in LabVIEW designed according to the typical proportional-integral-derivative (PID) structure, as the PID control is essentially the most widely adopted control structure in the industry. Nevertheless, it is pertinent at this juncture to also point out that the data-driven multi-objective optimization algorithm proposed here is also applicable to other types of feedback controllers, as long as that it can be expressed in the rather common and standard form of (7). Here specifically, the

limit for each phase of the coil arrays is set as 1.2 A. The Renishaw fiber optic laser interferometers (Model: RLU10) are used for sensing of horizontal positions with a count resolution of 40 nm, and Lion Precision capacitive sensors (Model: CPL290 controller with C18 heads) are used for sensing of vertical positions with a root mean square resolution of 150 nm. The magnetically-levitated system including its actuation and sensor system are shown in Fig. 4, and its designed working range is 30 mm × 30 mm × 3 mm according to the coil array length.

Fig. 8. Y axis and X axis cost function convergence diagram. Top: Overall Cost. Middle: Cost related to tracking error. Bottom: Cost related to control signal variation

Fig. 9. Y axis tracking error and control signal variation comparison before and after the data-driven multi-objective optimization.

Fig. 10. X axis tracking error and control signal variation comparison before and after the data-driven multi-objective optimization.

Fig. 11. X axis disturbance rejection performance comparison under 1 Hz sinusoidal disturbance.
control input $u(t)$ is

$$u(t) = K_p e(t) + \frac{1}{T_i} \int_0^t e(t') dt' + T_d \frac{de(t)}{dt},$$

and the feedback controller can be written in the form of

$$C(s) = \rho^T \hat{C}(s) = \begin{bmatrix} K_p & K_p/T_i & K_p T_d \end{bmatrix} \begin{bmatrix} 1 \\ \rho \\ s \end{bmatrix}.$$  \hspace{1cm} (31)

The goal of the data-driven optimization is to find out the controller parameters that provide a smooth and accurate tracking of the motion profile in Fig. [5] i.e., minimizing the cost function $J(\rho)$ in [6]. Note that during the optimization process, no a priori dynamic model information is needed nor will the algorithm attempt to build a model through system identification. To start with, the initial set of controller parameters $\rho^*$ is designed based on the loop shaping method in [47] with a second order model (neglecting the nonlinearities and higher order dynamics) and further fine-tuned to provide a decent but non-optimized control performance, as in Table [7]. It is worth noting, however, that loop shaping is a model-based method one can choose to use for the controller initialization but it is by no means necessary when there are no models available. In such cases, one shall simply tune the controller manually to achieve a decent performance and then rely on the proposed data-driven algorithm for performance optimization. The weightings are set as $w_1 = 10^7$ and $w_2 = 1$ so that the cost function values for the tracking error and control signal variation are on the same scale (the tracking error has a much smaller numerical value compared with the control signal variation). Nevertheless, we can still adjust the weightings according to the requirement of the motion system, i.e., further improvement on the accuracy or motion smoothness.

Despite the fact that the magnetically-levitated system is capable of conducting 6-DOF motion, we consider here only the X-Y plane motion because it is most commonly used in semiconductor manufacturing [48], [49]. Yet nevertheless, even in this application scenario, it is still the situation where the fully floating behavior and multi-axis coupling make extremely accurate identification of the motion dynamics largely impossible, so that traditional model-based approaches would encounter great difficulties in being properly successfully deployed here. In high precision semiconductor manufacturing applications, it is often required to conduct a series of repetitive motions [50], [51] on one of the axes. Meanwhile, in order to guarantee the accuracy of highly complex semiconductor circuit patterns, the tracking error from both Y and X axes needs to be minimized. Also, smooth motion should be ensured by minimizing the control input variation for both axes and using a higher-order S-curve trajectory. By using the proposed data-driven multi-objective optimization in Algorithm 1, the control parameters in both Y and X axes are iteratively optimized as shown in Table [11] and the control performance in terms of the cost function can be significantly improved as shown in Table [11]. In addition, a comparison of the optimized controller with the initial controller in the frequency domain is plotted in Fig. [6]. One major advantage of this data-driven approach is its fast convergence rate because it takes into account not only the gradient $\nabla J(\rho)$ of the cost function but the Hessian $\nabla^2 J(\rho)$. From Fig. [7] and Fig. [8] we can observe that both the controller parameters and cost function value converge within only four iterations. Note that the tracking cost $J_e$ or control variation cost $J_d$ alone may increase in some iteration, e.g., $J_e$ of the Y axis in the 1st iteration, but the total cost $J$ always decreases iteration by iteration. The time-domain performance improvement for Y axis before and after the data-driven optimization is plotted in Fig. [9] showing a significant reduction in both the tracking error and control signal variation; the root-mean-square (RMS) tracking errors are respectively 0.033 mm and 0.0075 mm. Here, the tracking error peaks, e.g., at 0.2 s of the initial result, could be due to the laser interferometer signal loss or computational delays. Meanwhile, the tracking error and control signal variation of the X axis are also reduced as shown in Fig. [10]. The RMS tracking errors for X axis are respectively $4.8297 \times 10^{-4}$ mm and $2.0365 \times 10^{-4}$ mm. Here, the tracking error is much smaller compared with the Y axis, because the X axis is kept stationary while the Y axis is moving. After 1.5 s, the vibration still exists and this is due to the fact the stage is fully floating with little damping and has to deal with the disturbances from the force coupling. To further demonstrate the disturbance rejection performance, Fig. [11] shows the X axis position measurement comparison under the effect of a 1 Hz sinusoidal disturbance. From all these experimental results, we can see that the proposed approach is certainly effective and able to provide the appropriate optimized trajectory tracking in terms of both accuracy and smoothness, and the convergence rate is also suitably fast enough (only 4 iterations in our experiment) for practical applicability.

V. CONCLUSION

In this paper, we present a data-driven multi-objective optimization algorithm for repetitive motion tasks, where no a priori model information is available. The proposed algorithm is applied to a multi-axis magnetically-levitated system which is difficult to model accurately due to its fully floating behavior and multi-axis coupling. By making use of the rich information contained in the actual motion data under, say, the prevailing non-optimal conditions, the algorithm can provide fast, efficient and effective controller optimization for the system to operate towards optimality in a data-driven and iterative manner. A well-designed cost function is stated and specified, which takes both smooth and accurate tracking into account and the optimization process can be completed within a few iterations. Our experimental results show that the motion performance of the maglev nanopositioning system is enhanced significantly and could certainly meet the stringent requirement of present-day high-performance precision motion applications.

For future work, we believe applications of the proposed algorithm certainly not be limited to such a multi-axis magnetically-levitated system only, and its potential can be further exploited and deployed in other robotic systems (es-
sentially especially those that are challenging to accurately model, e.g., quadrotors, legged robots, and soft robots, etc.

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