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Performance-oriented data-driven controller tuning for smooth and precise tray indexing

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Abstract
The feedback controller design and tuning play an important role in mechatronics and robotic systems for robust and high precision motion control. For instance, in a typical tray indexing application, when the controller is not appropriately tuned, large tracking error, dislodged chips and humming sound could occur. Traditional feedback controller design and tuning is based on system modelling, but it faces challenges when modelling is difficult or less accurate. Hence, in recent years, more and more data-driven approaches are developed, which utilize the actual motion data to optimize the controller parameters iteratively, without relying upon a detailed system model. Such control design is also performance-oriented as the design objective is directly taken into account during the optimization as the cost function.

In our work, a data-driven tuning procedure for tray indexing applications is proposed. Different with existing data-driven approaches, the cost function of the proposed method takes into account both the tracking error and jerk minimization as it is particularly suitable for the tray indexing application. Subsequently, the gradient and Hessian matrix of the cost function is estimated solely based on the motion data collect from the encoder without any attempt to build a system model. At last, Gauss-Newton optimization algorithm is executed based on the estimated gradient and Hessian matrix in order to provide the next set of controller parameters to reduce the pre-defined cost function. The effectiveness of the proposed method is shown on an industrial tray indexing setup with significantly improved performance in terms of tracking and jerk reduction.

Data-Driven control, Intelligent controller tuning, Learning Control, Gradient-based optimization

1. Introduction

Timing-belt based tray indexing is widely used in semiconductor back-end applications such as fabrication, packaging and inspection. Smooth and precise tray indexing motion control is essential to guarantee good production quality and reduce production risk in such applications.

Classical model-based control requires modelling of the system under control using first principle or identification. However, in some complex and nonlinear motion systems, the exact system model can be extremely intricate and difficult to obtain. In these cases, data-driven control methods which take full advantages of the measurement data without relying on the system models may provide a better solution. The Iterative feedback tuning (IFT) [1] is one of the data-based approaches as it is able to tune the parameters of the feedforward controller as well as the feedback controllers solely based on the measurement data. However, the classical IFT is not able to achieve a good performance in terms of jerk reduction in applications similar to tray indexing.

This paper is organized as follows. In Section 2, we introduce the classical IFT algorithm. The proposed data-driven controller tuning algorithm with jerk reduction will be introduced in Section 3. The experiment results are shown in Section 4. Finally, conclusions are drawn in Section 5.

2. Overview of the classical IFT

The classical IFT structure is shown in Figure. 1, where $C_r(s)$, $C_y(s)$, $G_0(s)$ are the feedforward controller, the feedback controller, and the system under control respectively. *r, u, v,* and *y* denote reference signal, control effort, disturbance, and system output, respectively.

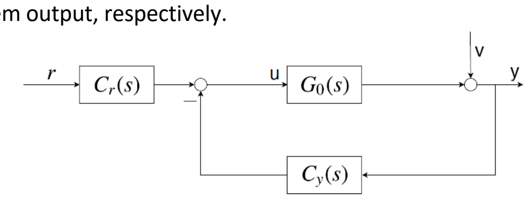

Figure 1. Iterative feedback tuning controller structure

The cost function of classical IFT is given by

$$F(\rho_i) = \frac{1}{2N} E\left[\sum_{t=1}^{N} \tilde{y}_t^2(\rho_i) + \lambda \sum_{t=1}^{N} u_t^2(\rho_i)\right] \qquad (1)$$

where $\tilde{y}$ and u_t denote tracking error and control effort respectively. N is the number of samples. E denotes expectation and ρ_i denotes the controller parameter in the ith iteration. The key idea of IFT is to provide a way to estimate the gradient of the cost function solely based on the actual motion data, which is subsequently used in a Gauss-Newton optimization algorithm. For further details, we refer the readers to [1][2].

3. Data-Driven Controller Tuning Procedure

The data-driven controller tuning is essentially a gradient based optimization procedure, whereby the gradient is estimated by conducting three closed-loop experiments in each iteration. Here, the cost function is defined as

$$F(\rho_i) = \frac{1}{2N} E\left[\sum_{t=1}^{N} \tilde{y}_t^2(\rho_i) + \lambda \sum_{t=1}^{N} \left(\frac{\partial u_t(\rho_i)}{\partial t}\right)^2\right] \quad (2)$$

and the gradient can be calculated as

$$J(\rho_i) = \frac{\partial F(\rho_i)}{\partial \rho_i} = \frac{1}{N} E\left[\sum_{t=1}^{N} \tilde{y}_t(\rho_i) \frac{\partial \tilde{y}_t(\rho_i)}{\partial \rho_i} + \lambda \sum_{t=1}^{N} \frac{\partial u_t(\rho_i)}{\partial t} \frac{\partial u_t(\rho_i)}{\partial t \partial \rho_i}\right] \quad (3)$$

In order to estimate $\frac{\partial \tilde{y}_t(\rho_i)}{\partial \rho_i}$ and $\frac{\partial u_t(\rho_i)}{\partial t \partial \rho_i}$ based on the real motion data, three experiments are required in each iteration. The first and the third experiment are simply the normal S curve motion profile, whereas the second experiment is conducted with the tracking error from the first experiment as the reference profile. Then the estimation of $\frac{\partial \tilde{y}_t(\rho_i)}{\partial \rho_i}$ and $\frac{\partial u_t(\rho_i)}{\partial t \partial \rho_i}$ is given by

$$est\left[\frac{\partial y_t(\rho_i)}{\partial \rho_i}\right] := = \frac{1}{C_r(\rho_i)}\left[\left(\frac{\partial C_r(\rho_i)}{\partial \rho_i} - \frac{\partial C_y(\rho_i)}{\partial \rho_i}\right) y_{3,i} + \frac{\partial C_y(\rho_i)}{\partial \rho_i} y_{2,i}\right] \quad (4)$$

$$est\left[\frac{\partial u_t(\rho_i)}{\partial t \partial \rho_i}\right] := = \frac{1}{C_r(\rho_i)}\left[\left(\frac{\partial C_r(\rho_i)}{\partial \rho_i} - \frac{\partial C_y(\rho_i)}{\partial \rho_i}\right)\left(\frac{\partial u_t}{\partial t}\right)_{3,i} + \frac{\partial C_y(\rho_i)}{\partial \rho_i}\left(\frac{\partial u_t}{\partial t}\right)_{2,i}\right] \quad (5)$$

where the first number in the subscript of y and $\frac{\partial u_t}{\partial t}$ denotes the number of experiment and the second number denotes the ith iteration. Now the gradient can be solely obtained from closed-loop experiment data, and the gradient-based algorithm can be executed to iteratively improve the tracking performance.

4. Experiment result

In this section, the proposed data-driven tuning is applied to an industrial tray indexing setup. The PID controller implemented in this motion system is optimized iteratively as shown in Figure 2 with 20 iterations. Figure 3 shows the performance improvement in terms of the defined cost function, and significant reduction in both the tracking error and jerk reduction can be observed. The time domain tracking error and jerk reduction comparison is plotted in Figure 4 and Figure 5 respectively to further demonstrate the performance improvement in this tray indexing setup.

5. Conclusion

In this paper, we propose a data-driven feedback controller tuning approach. It takes into account both the tracking error and jerk reduction, and thus is particularly suitable for tray indexing applications. The optimization process is entirely model-free, avoiding the tedious process of system modelling.

This proposed approach is especially useful for the control practitioners as no changes to the existing controller structure are needed and only the parameters need to be tuned.

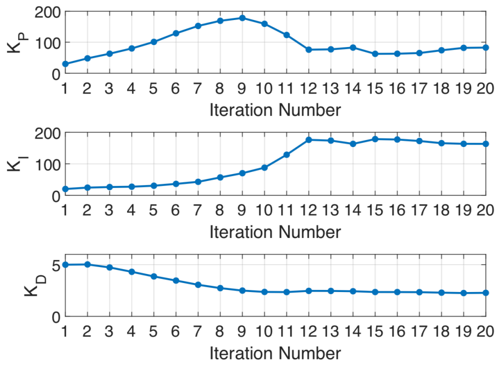

Figure 2. Control parameters convergence diagram.

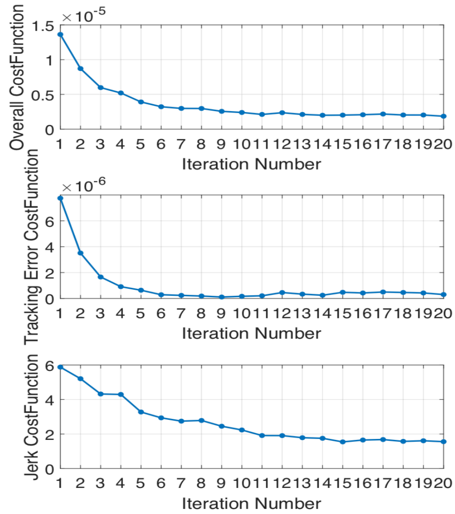

Figure 3. Cost function reduction diagram.

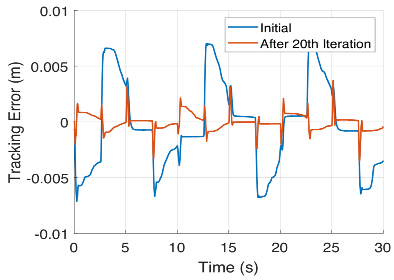

Figure 4. Tracking performance improvement.

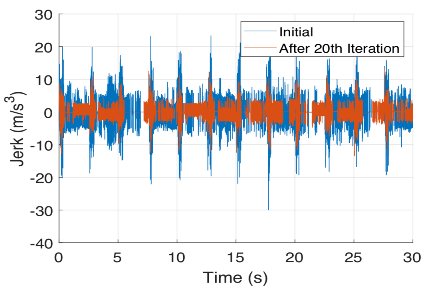

Figure 5. Jerk reduction performance improvement.

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