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Accurate and agile control of a pneumatic robotic actuator by GP-based feedforward learning

A. Pawluchin[1*], M. Meindl[2,3], T. Seel[2], and I. Boblan[1]

[1] *Humanoid Robotics, Berliner Hochschule für Technik, Berlin, Germany*
[2] *Intelligent Sensorimotor Systems Lab, Department AIBE, FAU Erlangen-Nürnberg, Erlangen, Germany*
[3] *Embedded Mechatronics Laboratory, Hochschule Karlsruhe, Karlsruhe, Germany*
[*] *Corresponding author, email: apawluchin@bht-berlin.de*

Abstract: This paper proposes the combination of PD-feedback and learning-based feedforward control to solve reference tracking tasks in pneumatic actuators and soft robotics (SR) with unknown nonlinear dynamics and complex hysteresis characteristics. The feedforward control consists of a static gain and a hysteresis compensation, which are predicted by Gaussian Process models. The proposed method is validated on a pneumatic actuator, and the experimental results demonstrate the method's capability to solve the reference tracking tasks, despite requiring only 22 seconds of training data. The results further demonstrate the potential of learning-based control for pneumatic actuators and SR, by superseding the need for laborious manual tuning and controller design.

I. Introduction

Soft actuators can be employed in a variety of medical applications such as, e.g., rehabilitation because the inherent compliance of soft robotics enables safe interaction and support of patients [1, 2].

However, these remarkable properties come at the price of highly nonlinear dynamics, and the inherent uncertainties typically lead to a slow and inaccurate actuator. First-principles modeling and controller synthesis require laborious system identification, including sophisticated measurement setups, manual parameter adjustment, and often tedious controller tuning to achieve decent trajectory tracking performance [3]. Data-driven methods have the potential to mitigate these drawbacks by autonomously learning controllers for SR. However, many of them typically require either hours of training data, see e.g. [4], or disregard data-hungry hysteresis completely.

In this work, a data-driven control scheme is proposed that achieves precise reference tracking by learning Gaussian Process (GP) models of the soft actuator's static non-linearities while only requiring as little as 22 seconds of training data.

I.I. Problem statement

We consider a bellows-actuated 1-DOF actuator that consists of two antagonistic chambers and an aluminum skeleton (see Figure 1, highlighted in blue). The system suffers from a strong hysteresis and an unknown force-to-position mapping. Because the actuator has redundant kinematics and is already assembled, the force cannot be measured. We consider the task of achieving precise tracking performance (error $< 5°$), while requiring minimal manual tuning effort.

II. Material and methods

A common control approach in pneumatics and SR consist in combining feedback u_{fb} and feedforward u_{ff} control [5]. A linear PD feedback controller is tuned to assure robust attenuation of oscillations. However, feedback alone yields unsatisfactory tracking performance, because it cannot deal with the nonlinear force dynamics and the actuator's extensive hysteresis. Therefore, we extend the PD feedback with a feedforward component, which consists of a static gain (SG) u_{SG} and a hysteresis compensation (HC) u_{HC}.

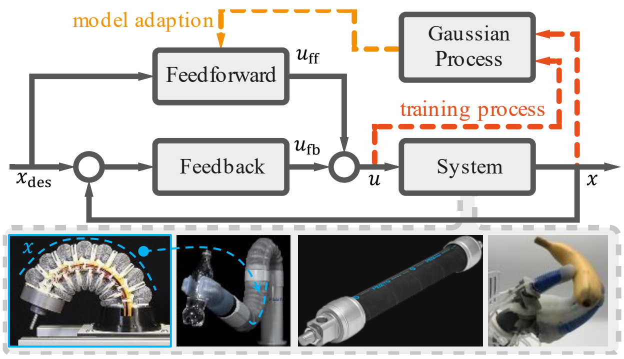

Figure 1: 2 DOF controller design consists of feedback and feedforward which is powered by Gaussian Processes.

A difference pressure approach, in which the pressure in both chambers is distributed as $p_{\text{des}}^{(1)} = p_{\text{m}} + 0.5u$ and $p_{\text{des}}^{(2)} = p_{\text{m}} - 0.5u$, where the superscript denotes the chambers 1 and 2, is employed. The preload p_{m} is a constant value that determines the stiffness of the system.

We propose the use of three GP [6] models to learn a generic model of the static nonlinearities of the system. The learning data consists of a short back and forth motion. The trained GPs are used to predict a feedforward control u_{ff} that depends on the coordinate x and the hysteresis. Because hysteresis leads to data ambiguity in the configuration space, the HC is predicted by two separate GPs [7], one predicting the HC in case of an ascending motion ($\dot{x} > 0$) and one GP predicting the HC in case of an descending motion ($\dot{x} < 0$). To avoid discontinuities in the prediction of u_{ff}, the GPs predict the gradient of u, which is denoted by f_{H} and multiplied with the absolute value of the reference's gradient Δx_{des}. Subsequently the integration step for the timestamp $k+1$

$$u_{\mathrm{HC}}(k+1) = u_{\mathrm{HC}}(k) + f_{\mathrm{H}} \cdot |\Delta x_{\mathrm{des}}(k)|$$

is necessary to calculate the feedforward control input. Here f_{H} is either the GP ascent or GP descent prediction dependent on the motion direction. Finally, we incorporate the control law as follows: $u_{\mathrm{ff}} = u_{\mathrm{HC}} + u_{\mathrm{SG}}$.

According to this controller implementation the prediction of the hysteresis depends only on the current and previous time step. This makes the controller causal and therefore real-time capable. Thus, it is not necessary to provide the reference trajectories batch-wise ahead of time.

III. Results and discussion

To train the GP models, 22 seconds of system interaction time were recorded, in which the pneumatic actuator performs a predefined back-and-forth motion. The training data depicted in the configuration space, see Figure 2, illustrates the complex hysteresis and the nonlinearity of the static gain.

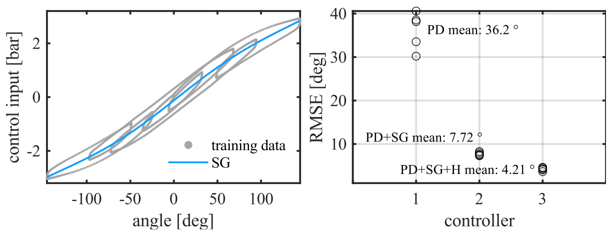

Figure 2: The training data depicted in the configuration space (left) demonstrates the actuator's complex hysteresis characteristics and the nonlinearity of the static gain. Adding learning-based feedforward control drastically reduces the tracking errors (right).

The benchmark task consists in tracking five randomly generated, smooth trajectories that are depicted in Figure 3. To solve the tracking problem, the feedback-only approach, the feedback plus static feedforward gain approach, and the feedback plus static feedforward gain plus hysteresis feedforward compensation approach are applied. Results depicted in Figure 3. show that the feedback-only approach fails to track the references and large average errors of roughly 36 ° occur. However, by adding the static feedforward gain, the error is drastically reduced to an average of roughly 8 ° and decent tracking performance is achieved. If the hysteresis compensation is added on top of the static feedforward gain, the tracking error decreases even further to an average value of only 4 °, and almost perfect tracking is achieved.

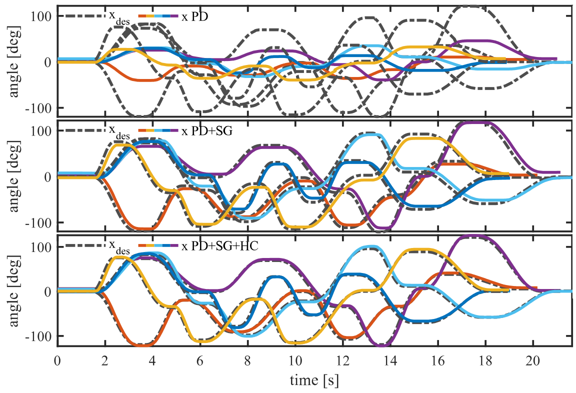

Figure 3: The benchmark consists in tracking 5 references. The feedback-only approach (top) fails to solve the task. However, adding the static feedforward gain predicted by a GP model (middle), as well as further adding a GP-based hysteresis compensation (bottom) leads to much smaller tracking errors.

IV. Conclusions

In this work, the problem of reference tracking for pneumatic actuators with complex nonlinear dynamics was considered, and a control approach was proposed that consists in combining simple PD-feedback with learning-based feedforward control. The latter consists of two components. Namely, a static gain and a hysteresis compensation, which are predicted by GP models. The experimental results demonstrate that the proposed approach achieves remarkable tracking performance with average errors of just 4 °, despite the GP models only requiring training data of as little as 22 seconds of system interaction time.

In the context of pneumatic actuators and SR, these results demonstrate the potential of learning-based control approaches, because they do not only solve the control problem, but also eliminate the major drawback of conventional, model-based control approaches, which require enormous, manual design efforts.

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