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Novel hybrid AI-PID controller

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Abstract
In this study, we aim to explore the potential of artificial intelligence (AI) for servo control applications. The prevalent control scheme for such applications is the proportional integral differential (PID) controller. Although PID control is well-established and provides reliable operation, it does not achieve optimal performance, particularly under challenging conditions requiring rapid response. As a solution we realised an AI-based controller using Deep-Q reinforcement learning for a simulated Atomic Force Microscopy (AFM) application, where a servo control is needed to keep the tip-sample interaction constant. Our results showed that the AI-based control may exhibit four times better RMS control deviations than a PID rival. However, further investigations revealed a problem of the AI-based technique: lack of consistency and reliability. The AI may occasionally lose control, although being extensively trained. To solve this problem we propose the application of two hybrid AI-PID controllers and compare them on a real AFM system. Although this study is performed using an AFM as an experimental platform, we believe that the novel concept is of great value for many applications in the field of precision engineering as well.

Keywords: artificial intelligence (AI), servo control, proportional integral differential (PID) control, atomic force microscopy, reliability, hybrid control

1. Introduction

Atomic force microscopy (AFM) employs control systems to maintain constant tip-sample interactions, which is critical for image quality, reducing tip wear and for avoiding potential damage. The proportional-integral-derivative (PID) controller is the standard for this task. While PID control provides reliable operation, it does not achieve optimal performance.

In recent work we proposed artificial intelligence (AI)-based controllers for AFM [1]. In simulated measurements of a low noise AFM, such an AI controller was able to outperform the classical PID by enabling advanced control behaviours, reducing root-mean-square control deviations by a factor of four. Additionally, the AI showed an asymmetric response in critical situations where potential damage could occur, prioritizing safety over achieving minimal control deviations.

While the results underscored the AI's potential to significantly enhance AFM performance and safety, reliability concerns of the AI remain a barrier. The "black-box" and approximative nature of AI makes it susceptible to occasional control failures and difficult to verify for reliability. To address the issue of the AI's missing intrinsic reliability, we test two AI-PID hybrid control (HC) schemes, combining the performance of AI with the reliability of PID, which to our knowledge has not been investigated previously in real world.

2. Hybrid Control Concept

This paper tests two concepts of a hybrid AI-PID control, the Backup and Cooperative Hybrid Control, depicted in Figure 1.

1. **Backup Hybrid Control (BHC)**: In this approach, primarily only the AI controls the system, with PID acting as a fail-safe to take over in case of an AI failure, e.g. if the control deviation reaches predefined limits. This method allows the AI to operate at its full potential while maintaining reliability through an PID intervention.
2. **Cooperative Hybrid Control (CHC)**: In this approach, both AI and PID permanently contribute to the control signal by adding up their individual control outputs. This collaboration results in improved stability as the PID compensates for possible AI failures early. However, as there are always contributions from the non optimal PID, even if they are not required, overall performance is expected slightly decreased.

These HC strategies have been previously explored using simulated measurements of the low-noise AFM [2]. While the BHC achieved on average and in the best cases higher performance, the CHC appeared to be preferable for practical applications due to more stable performance. Building on these results, both HCs are tested here on a real-world AFM.

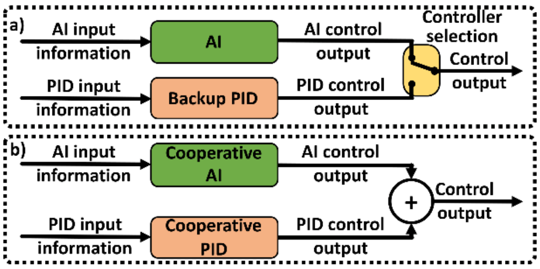

Figure 1. Schematics of (a) the BHC and (b) the CHC concept.

3. Experimental Setup and Implementation

To evaluate the HC schemes in a practical context, we implemented both approaches on a novel interference measuring principle based AFM system (IM-AFM) [3]. This system, rather than the initially planned low-noise AFM, was chosen for implementation because its data processing is handled by a CPU (AMD Ryzen 7 1700X), which could also be utilized directly for training and inference of the AI, without any further hardware requirements. The experimental setup for realizing the HC concepts includes the IM-AFM, the HC and AI software and a sample topography for training and testing the AI/HC.

3.1. Interference Microscopy AFM

The IM-AFM integrates a contact AFM mode into an conventional surface measuring interference microscope (IM). In its AFM mode, an AFM cantilever is positioned in the IM's optical path at the objective's focus plane. The AFM tip movement is evaluated through the phase of the interference fringe on the AFM cantilever. The interference fringes are captured with a CMOS camera, with 3000 Hz frame rate. They are evaluated in a LabVIEW-based software on a PC, providing the current bending of the cantilever. To maintain a constant cantilever bending during AFM scans, control/motion signals are calculated for a 3-axis piezo stage (PI P-545), which operates in closed-loop with 800Hz communication frequency.

3.2. AI/Hybrid Control Setup

The hybrid control software and AI code is executed in TensorFlow Lite. It receives the current AFM control state via an UDP loopback link from the IM-AFM LabVIEW software and replies with calculated control commands.

For realisation of the AI Double Deep Q-Learning is used, where an artificial neural network (ANN) is trained to predict the best possible action for a given (control-) state. The ANN used for both HC approaches consists of an input layer with 40 neurons receiving the latest 20 measured control deviations and the last 20 motion commands sent to the piezo stage, two hidden layers with 60 neurons each and tanh activation function, followed by an output layer with 61 neurons, representing equally distributed motion commands for the piezo stage z-axis in the range of ±6 nm for the CHC and ±7.5 nm for the BHC.

The PID controller used for both approaches is by manual testing parametrised as P=0.3, I=0 and D=0.8. For the CHC the output motion command from the PID and the AI are permanently added and sent to the IM-AFM software, whereby the PID becomes dominant when the control deviation reaches ±20 nm. For the BHC the AI soley calculates the motion command for the piezo stage as long as the control deviation is in the range of ±25 nm, otherwise the PID is used.

3.3. AI Training

For the training of the two AIs 10 µm profiles of a training topography are scanned with a speed of 5 µm/s. During each scan the AI choses the expectedly best available motion command for a given control state and sends this to the AFM. Afterwards a reward is calculated, which is larger the smaller the following observed control deviations are. This reward is stored in a buffer and used to train the ANN's prediction capability. This process is repeated 500 times before the training is stopped.

3.4. Training and Testing Topography

The training and testing of the HCs is performed on a manufacturing prototype of a chirp standard sample. In Figure 2

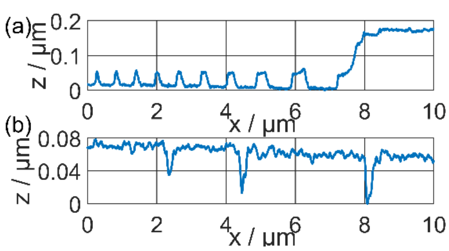

Figure 2. Topographies used for training (a) and testing (b) of the HCs.

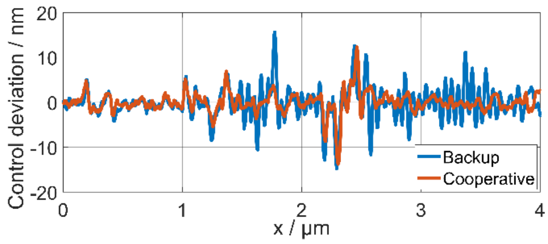

Figure 3. Instability/oscillation of the BHC compared to the more stable CHC during the scan of the test topography profile.

(a) one of the training topography profiles can be seen. For testing this profile and the profile in Figure 2 (b) are scanned and the control deviations are recorded.

4. Testing Results

In Table 1 the root mean square (RMS) control deviations of three test scans of the PID control and the two HCs are given. As can be seen, the HCs outperform the PID noticeably, even if the outperformance is not as large as in previous simulations due to different dynamic behavior of the IM-AFM and a relatively large dead time of the piezo stage. Overall the BHC shows the best performance, except for the scan on the topography in Figure 1 (b), where the CHC has smaller control deviation. On this profile the BHC was slightly unstable, which resulted in an oscillation of the piezo stage movement and control deviations. This can be seen in Figure 3, where the control deviations of the two HCs are compared for a subsection of topography 2.

Table 1. RMS control deviations in nanometer for different HC setups on the training topography (1) and test topography (2)

Topography:	PID / nm	Cooperative control / nm	Backup control / nm
Topography 1 5 µm/s	5.51	4.65	4.41
Topography 1 8 µm/s	9.69	7.64	7.34
Topography 2 5 µm/s	3.73	3.10	3.92

5. Conclusion and Outlook

The results of this study demonstrate that the fundamental findings from previous simulations can be reproduced on a real AFM. The CHC approach is particularly suited for practical applications, as it better combines the advantages of AI with the reliability of a PID. While this study represents only a preliminary test of the AI-PID HC concept for real-world measurement instruments, the results indicate that the concept could be of interest in other fields requiring precision control, opening avenues for broader implementation.

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