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Active Magnetic Bearing Tuning Ability in Reasoning Large Language Models

Mingqu ZHOU* and Dong JIANG*
* School of Electrical and Electronic Engineering, Huazhong University of Science and Technology
Luoyu Road 1037, Wuhan 430074, China
E-mail: jiangd@hust.edu.cn

Abstract

Active Magnetic bearing (AMB) is widely applied to high-speed rotation machines because of its advantages of no contact and no friction. However, the AMB is unstable without a tuned displacements controller and the tuning process greatly depends on the engineering experience or the accurate models, causing the high use-cost. The large language models (LLMs) develop recently and can help solve some practical problems. The applications of LLMs in industry fields are also more common.

In this article, the reasoning LLMs including the Deepseek-r1 and the ChatGPTo3-mini are used to help tune the PID controller parameters of a single axis AMB system. The first test is telling the PD parameters' size relation compared to the suitable PD parameters when the AMB is not stable, which relies on the LLMs' knowledge. The second test is the continuous PD parameters tuning to get a better performance, which relies on the LLMs' reasoning ability. According to the test results, the tested LLMs have little prior knowledge about the AMBs, making them difficult to give the correct tuning advice directly. Nevertheless, in the continuous tuning, the reasoning LLMs can study from the changes in the waveforms of different PD parameters and provide true tuning direction gradually, like human beings. If the additional AMB knowledge is supplied initially, the tested LLMs performance better. The test shows the possibility of the preliminary application in the AMB system and the fine-tuning is necessary for better performance.

Keywords : Active magnetic bearing, PID displacement controller, parameters tuning without human, reasoning large language model, artificial intelligence.

1. Introduction

Active magnetic bearing (AMB) is a kind of novel bearing system, which is widely used in high-speed rotation machines (W. Ma, et al., 2024). However, the AMB system is unstable without an effective closed-loop displacement control (M. Hutterer and M. Schroedl, 2022). The most used displacement controller is still the PID controller because of its easy structure (S. Gupta, et al., 2018), whose designs greatly rely on engineers' experiences. Thus, the design or parameter tuning is still a hot topic.

The frequency domain analysis methods can be applied to get the stability and the performances of a controlled AMB system (G. Lei and Z. Changsheng, 2024). Also, heuristic algorithms are used to save tuning time and get better performances (C. Wei and D. Söffker, 2016). The neural network is developed to auto-tuning the AMB PID controller parameters as well (Y. Li, et al., 2023). However, these methods depend on the accurate AMB model, which is costly (H. Jiang, et al., 2023). Some researchers design a heuristic algorithm combining with the prior physical knowledge to transfer an unstable AMB system to a stable AMB system without the model of the target AMB system (M. Zhou, et al., 2024). The fuzzy logic controllers are also used to reduce the requirement of the parameter tuning (S. Gupta, et al., 2019). Nevertheless, these methods are not simple enough for AMB users to use. An easier way to help tune the AMB PID parameters is needed to be explored.

Recently, large language models (LLMs) have developed a lot. These non-human agents can work much more like humans. Thus, artificial intelligence technologies are applied to programming (R. Ma, et al., 2024), smart grid designing (K. Shahzad, et al., 2023), and so on. LLMs can help users solve problems in the natural language, which is effortless to understand. However, LLMs' performances in the AMB PID controller parameters tuning area are little tested and are concerned by the AMB engineers. Also, the AMB system is a system with simple basic

In this article, the reasoning LLMs, including Deepseek-r1 and ChatGPTo3-mini, are tested in AMB PID controller parameters tuning tasks. The tasks are designed in Section 2. Experiments and the results are listed in Section 3. Section 4 concludes this article.

2. Task design

The target plant used in the following tasks is a linear single-axis AMB system with a PID displacement controller, which is implemented in the MATLAB/Simulink simulation environment. Because the parameter I does not influence the stability and the dynamic performance of the AMB system, parameter I is set as a fixed value and will not be changed by the LLMs.

The first task is that the reasoning LLMs need to provide PD parameters tuning advice for four typical combinations of PD parameters, including small P, large P, small D and large D. The displacement waveforms of these four typical situations are shown in Fig. 1. The four typical waveforms will be sent to the LLMs in order, and the ture answer will be provided whether the answer of the LLMs is correct or not. This task is an annotation task and is used to test the normal reasoning LLMs' prior knowledge about the AMB system and the PID controller.

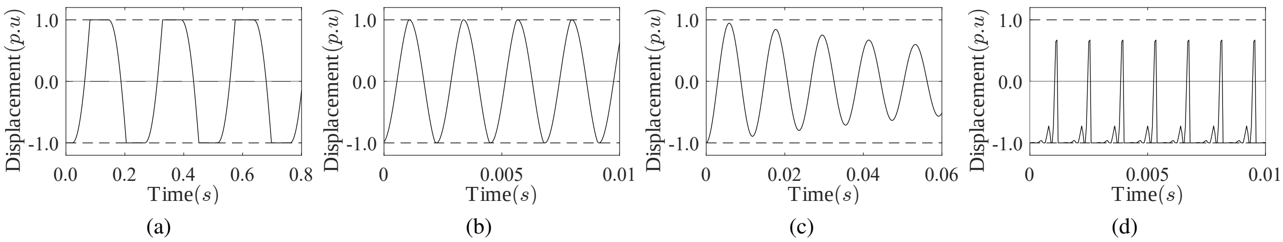

Fig. 1 Typical displacement waveforms with different combinations of parameters PD. (a) Small P. (b) Large P. (c) Small D. (d) Large D.

The second task is that the reasoning LLMs need to tune the PD parameters continuously with displacement waveforms feedback. The PID displacement controller of the target AMB system is set as small parameter P and small parameter D, whose waveform is similar to Fig. 1(a). This task is used to test the reasoning ability of LLMs with varying displacement in the context.

3. Experiments and results

In experiments, all the waveforms are supplied in text files to focus on the knowledge and reasoning ability but not the image recognition capability. The data of displacement waveforms is also downsampled to save token and ensure the conversations be long enough for the tasks. The down sampling will not affect the understanding of displacement waveforms. Figure 2 shows one example of the downsampled waveforms, where the blue line is the original waveforms and the orange circles are the downsampled waveforms. The diagram of the experiment environment is shown as Fig. 3.

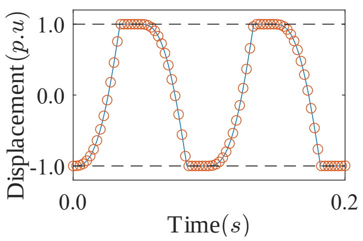

Fig. 2 Down sampling example.

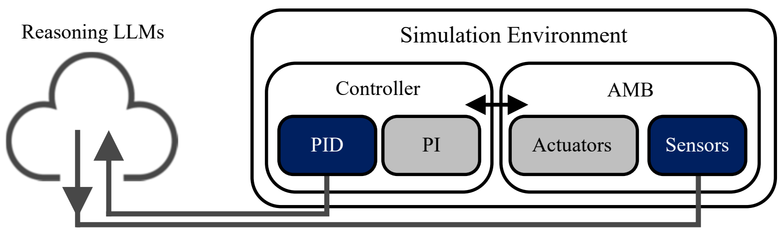

Fig. 3 Diagram of the experiment environment.

The test results of the task 1 are listed in Table 1. According to Table 1, Deepseek-r1 hardly tells the real state of parameters except situation large P. The reason of wonderful accuracy in situation large P is that the displacement of the AMB system is similar with conventional PID controlled system when the parameters P is extremely large. When the parameter D is small, the accuracy of Deepseek-r1 also exceeds 50.0%. Because the waveform has a trend of convergence, Deepseek-r1 sometimes prefer to increase parameter P first but not parameter D, causing the little wrong answer.

Table 1 Accuracy of LLMs in the task 1.

Situation	Accuracy of Deepseek-r1	Accuracy of ChatGPTo3-mini
Small P	25.0% (total 8)	50.0% (total 8)
Large P	100% (total 8)	50.0% (total 8)
Small D	62.5% (total 8)	62.5% (total 8)
Large D	12.5% (total 8)	0.00% (total 8)

When comes to situation small P or large D, Deepseek-r1 always finds that there is a collision and suggests to increase the system's damping, which lead to wrong answers. In this situation, the collision frequency is ignored by Deepseek-r1 totally.

ChatGPTo3-mini seems to have better accuracy when parameter P is small. However, the answers still seems to be coincidentally correct. In the situation large P, ChatGPTo3-mini prefers to increase parameter D and keep parameter P same, causing its low accuracy. For the same reason, ChatGPTo3-mini could not provide any correct advice when the parameter D is large.

As a result, Deepseek-r1 performs little better than ChatGPTo3-mini in the task 1, which has more knowledge about the PID controller. However, none of them could really provide available suggestions for tuning AMB displacement controller parameters directly.

Table 2 Parameters tuning log from Deepseek-r1.

Trial	Parameter P	Parameter D
1	1 (base)	1 (base)
2	0.5	2
3	0.3	3
4	0.15	4.5
5	1	1
6	0.8	2.5
7	0.55	3.8
8	0.407	5.13
9	0.36	5.6

The tuning suggestions from Deepseek-r1 in task 2 are listed in Table 2, where the AMB displacement controller is initialized with small parameter P and small parameter D. Deepseek-r1 keeps believing in increasing the parameter D can eliminate collisions, which is true in normal system. Some waveforms are shown in Fig. 4. These waveforms are similar because the AMB displacement controller cannot provide effective control current command. In this case, the increase in parameter D affects less due to the main electromagnetic is generated by the I controller, which changes slowly, making the output of the D controller small and hardly eliminates collisions. Deepseek-r1 notices that the collisions still exist after the $4th$ trial, which shows its capability to compare and evaluate. However, after resetting parameters, Deepseek-r1 cannot supply different suggestions.

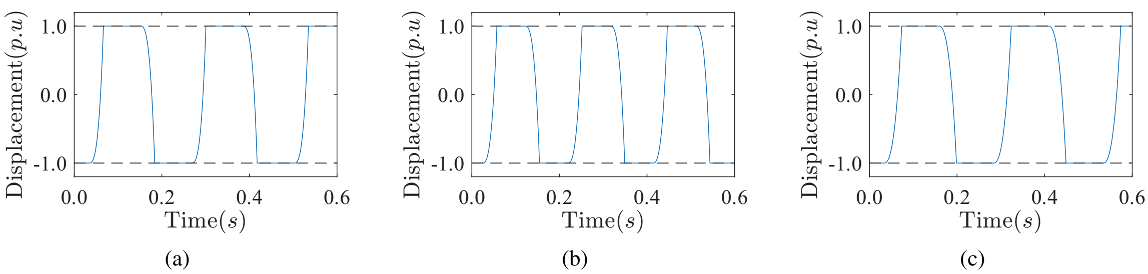

Fig. 4 Unconverged displacement waveforms after some specific trials of Deepseek-r1. (a) After trial 3, $P = 0.3$, $D = 3$. (b) After trial 6, $P = 0.8$, $D = 2.5$. (c) After trial 9 (final), $P = 0.36$, $D = 5.6$.

The way to help Deepseek-r1 is easy. The waveforms and their tags in Fig. 1 are provided before the continuous tuning task. This time, Deepseek-r1 compares the new unknown waveform with the four known waveforms and finds that the new waveform is mostly similar to the small P waveform. The new tuning suggestions from Deepseek-r1 with reference waveform are listed in Table 3. The waveforms after some specific trials are shown in Fig. 5. The collision frequency

Table 3 Parameters tuning log from Deepseek-r1 with reference waveforms.

Trial	Parameter P	Parameter D
1	1 (base)	1 (base)
2	2.5	0.6
3	2.25	1.32
4	2.25	1.98
5	2.48	5.55
6	4.95	4.44
7	7.92	1.78

Table 4 Parameters tuning log from ChatGPTo3-mini.

Trial	Parameter P	Parameter D
1	1 (base)	1 (base)
2	1.5	1.5
3	2	2
4	2	2.5
5	2.3	2.7
6	2.5	3
7	2.4	3.5
8	2.6	3

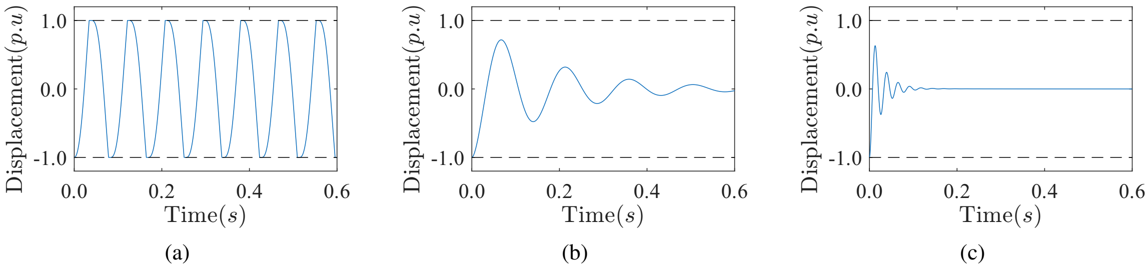

Fig. 5 Displacement waveforms after some specific trials of Deepseek-r1 with reference waveforms. (a) After trial 3. (b) After trial 5. (c) After trial 7 (final).

increases first. Then the system starts to converge. With the great increase in parameter P according to Deepseek-r1, the AMB system can levitate the target rotor quickly at last. This result also indicates that simple prompts can obviously improve the performance of LLMs.

The tuning suggestions from ChatGPTo3-mini are listed in Table 4 and the waveforms after some specific trials are shown in Fig. 6. The tuning process starts similar to the process of Deepseek-r1, the collision frequency increases with the increase of parameter P and D first as Fig. 6(a) shown. Then the AMB system starts to converge. Differently, ChatGPTo3-mini tunes the parameters conservatively, who changes the parameters with small steps. Thus, the AMB system with the final parameters performs only a little better than the AMB system with the mid-term parameters, like Fig. 6(b) and Fig. 6(c) shown.

Compared Fig. 6(c) to Fig. 5(c), the final performance of the AMB tuned by ChatGPTo3-mini is worse than the results of Deepseek-r3, even ChatGPTo3-mini makes more trials. However, the AMB system tuned by ChatGPTo3-mini is stable finally and ChatGPTo3-mini can successfully finish the task 2 without any additional help. This result is consistent with the results of task 1, that ChatGPTo3-mini has higher accuracy when parameter P is small.

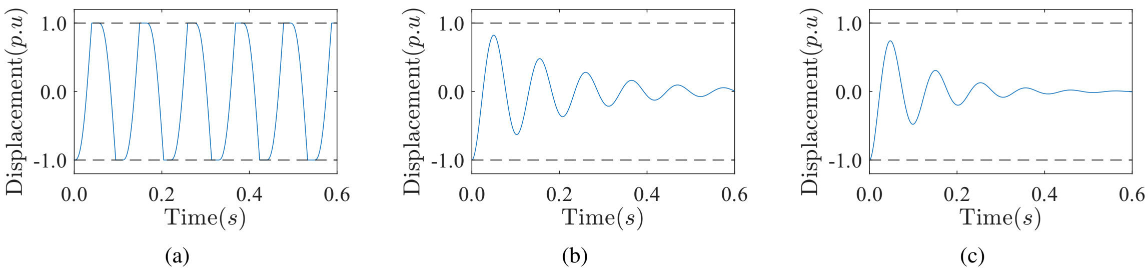

Fig. 6 Displacement waveforms after some specific trials of ChatGPTo3-mini. (a) After trial 3. (b) After trial 6. (c) After trial 8 (final).

According to the results of task 2, ChatGPTo3-mini can tune the AMB displacement controller parameters better. Though both of them can finish the task successfully after finding the true tuning direction, Deepseek-r1 believes its knowledge too much to give up the incorrect answers. However, the reasoning LLMs already can provide practicable suggestions for the single-axis AMB system tuning, greatly demonstrating the potential for actual application of supplying tuning advice to normal users, which may reduce the application cost of the AMB.

4. Conclusion

The AMB system is still not very widely used these days, especially compared to the motor. Thus, LLMs have little prior knowledge about AMB. This makes AMB displacements data annotation task quite difficult. However, LLMs could provide proper tuning advice with comparisons in the early tuning stage directly or with easy prompts. Then, LLMs help the tuning process based on their "experience" in PID controller and comparing ability when the AMB systems start to be stable and perform as other normal systems.

In further work, more tasks will be carried to test the LLMs' performance in the AMB area, especially a multi-axis AMB tuning task and a real AMB tuning task. Though the fine-tuning or other methods may be needed to improve LLMs' performances in the AMB area, we believe that reasoning LLMs would greatly help engineers or normal users in the future.

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