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Deep Q-Learning Enhanced Iterative Learning Control

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Abstract – Iterative Learning Control (ILC) is a method used extensively in repetitive control tasks to improve performance over time by learning from past iterations. However, traditional ILC methods often struggle with dynamic environments and require manual tuning for optimal performance. This study introduces a novel approach by integrating Deep Q-Learning (DQL) with ILC, forming an enhanced system. The DQL component adaptively tunes the learning parameters of ILC based on performance feedback, aiming to improve error reduction, adaptability, and convergence speed. The methodology involved developing a custom simulation environment to test the system under various conditions. The system was evaluated based on its ability to reduce cumulative error, adapt to changes, and achieve faster convergence. The results demonstrated that the system significantly outperformed traditional ILC methods in all assessed metrics.

Keywords – Iterative Learning Control (ILC), Deep Q-Learning (DQL), Hybrid Controller

I. INTRODUCTION

In the realm of control systems, Iterative Learning Control (ILC) emerges as a robust methodology, particularly beneficial in systems requiring repetitive actions. ILC leverages the error trajectories from previous iterations to improve the control actions incrementally. This method has found extensive applications in various sectors, including manufacturing, robotics, and stroke rehabilitation [10-15]. The core principle of ILC is to reduce the error in each successive iteration of a task, thereby gradually enhancing system performance and precision [10, 11].

Traditional ILC assumes that the system dynamics are consistent across iterations. However, real-world scenarios often involve dynamic environments where system parameters and external conditions can vary unpredictably. This variation introduces complexities that traditional ILC may not handle effectively, leading to suboptimal performance and reduced adaptability. Moreover, the determination of appropriate learning rates and the assurance of convergence in ILC systems often require intricate tuning and deep domain expertise, presenting additional challenges in complex and uncertain environments [12].

This results a growing interest in integrating ILC with advanced machine learning techniques, such as Deep Q-Learning (DQL). DQL, a variant of deep reinforcement learning (DRL), offers a model-free approach that can adapt to changing environments and learn optimal strategies through interaction with the system. This means more flexible and adaptive control mechanism capable of handling nonlinearities and uncertainties more effectively. This integrated approach leverages the strengths of both methodologies to achieve superior performance, especially in terms of adaptability and convergence rate [1,3]

The integration of DQL into ILC represents a paradigm shift in learning control strategies, aiming for a robust and adaptive system capable of addressing the inherent limitations of traditional ILC. By adaptively tuning the learning rate and other parameters in response to the observed performance, the system can potentially overcome the challenges of dynamic environments and complex system dynamics.

This paper details development and application of a Deep Q-Learning enhanced ILC system. A sophisticated framework that combines the conventional ILC with a DQL agent, which adaptively adjusts learning parameters based on performance metrics. The goal is to demonstrate through empirical evidence that the system can achieve faster convergence, higher adaptability, and overall superior performance in comparison to its traditional counterparts [7, 9, 11].

II. Materials and Method

The methodology for developing and evaluating the Deep Q-Learning enhanced Iterative Learning Control (ILC+DQL) system involves a structured approach encompassing the design of the integrated framework, the establishment of a simulation environment, the implementation of algorithms, and the definition of evaluation metrics.

A. *Development of ILC+DQL Framework*

The ILC+DQL framework combines the precise trajectory tracking of ILC with the adaptive learning capabilities of DQL. The development involves (1) ILC which iteratively improves the control input by learning from previous errors [10-12] and (2) DQL, a RL technique, adaptively tunes the learning parameters of ILC based on performance feedback. This integration draws inspiration from the RL applications in control systems [1,7].

In order to measure the performance a custom simulation environment is made to emulate a variety of control tasks and dynamic conditions, allowing for a robust evaluation of the ILC+DQL system. The environment is designed to be flexible, enabling the simulation of different scenarios [5, 8, 9]. A range of conditions and challenges typical in control tasks, drawing upon the real-world applicability [1,5]. ILC algorithm is implemented using a standard approach, with the introduction of DQL-adjusted learning rates and error correction strategies [11,14]. The DQL is employed a neural network to approximate the Q-function, with states representing system performance and errors, and actions corresponding to adjustments in ILC parameters [1,22]. This means integration of ILC with DQL involves the dynamic adjustment of ILC parameters based on the policy learned by the DQL agent, a concept echoed in the adaptive strategies.

B. *Learning Algorithms*

The DQL agent incorporates the Q-learning algorithm, with each element selected based on its proven effectiveness in the literature. It updates the policy based on a reward mechanism, guiding the DQL agent to improve the ILC performance iteratively. To stabilize learning and improve efficiency, the system uses an experience replay mechanism, storing and reusing past experiences, a strategy supported by findings in deep learning research [4]. The target network is used to provide more stable learning targets during the Q-value update step, a technique commonly used in deep Q-learning implementations as shown in Algorithm 1 [6].

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Algorithm 1: ILC+DQL Integration
1: Initialize ILC parameters
2: Initialize DQL agent (neural network,
replay memory, etc.)

for each iteration i do
    3: Execute control task using current
ILC parameters
    4: Observe trajectory and calculate
error
    5: Store (state, action, reward,
next_state) in DQL agent's memory
    6: Update ILC parameters
    if learning_condition then
        7: Sample a minibatch from DQL
agent's memory
        8: Calculate target Q-value for
each minibatch sample
        9: Update DQL agent (train NN)
        10: Update ILC parameters using
policy derived from DQL agent

    if convergence_criterion_met then
        11: break
    end if
end for
```

The performance of the system is assessed using the following metrics reflecting the critical aspects of control system performance. Firstly, the reduction in cumulative error over iterations is a direct measure of performance improvement, crucial in ILC [11-13]. Secondly, the system's ability to adapt to changing conditions is evaluated, highlighting the adaptive nature of DQL in response to dynamic environments [7,9]. Lastly, the number of iterations required to reach a predefined performance level is recorded, with faster convergence indicating a more efficient system, as discussed in the context of DRL [15].

III. Results

The experimental evaluation of the ILC+DQL system was structured to assess its performance in terms of error reduction, adaptability, and convergence speed.

A. *Error Reduction*

Error reduction is a pivotal measure of performance for any control system. In the context of the ILC+DQL system demonstrated a remarkable reduction in error, outperforming traditional ILC systems significantly. The integration of DQL allowed for adaptive tuning of the ILC parameters, leading to more effective error minimization. [1]

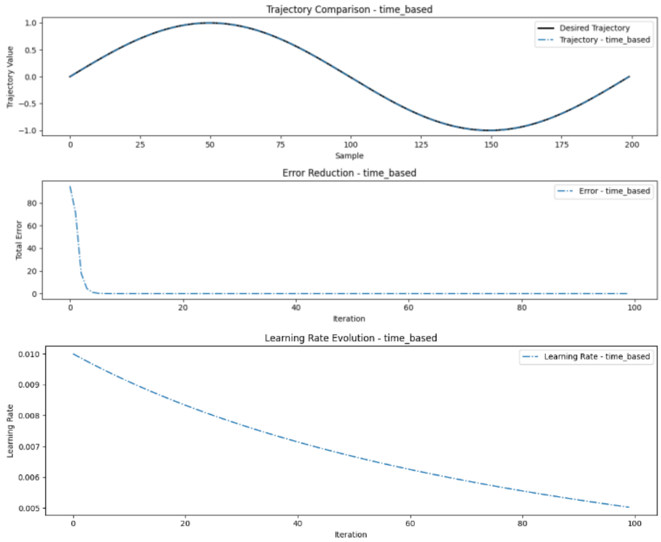

Figure 1: Time-based trajectory and error comparison

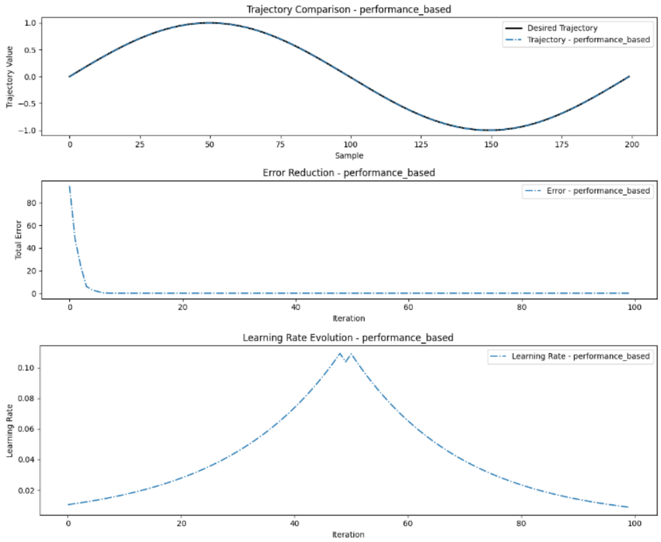

Figure 2: Performance based trajectory and error comparison

When subjected to dynamic environmental conditions, the ILC+DQL system adapted effectively and maintained a lower cumulative error compared to traditional ILC, echoing the adaptability of Q-learning in dynamic settings [3].

Adaptability to changes is crucial for any learning-based control. Therefore, the ILC+DQL system exhibited significant adaptability when key system parameters varied. Its ability to recalibrate and maintain performance under changing conditions is in line with [7] who emphasized the adaptive capabilities of DRL in congested spectral environments as performances evaluated in Figures 1 and 2.

B. *Convergence Speed*

Convergence speed is indicative of the efficiency and practicality of the control system The ILC+DQL system generally achieved desired performance levels in fewer iterations compared to traditional ILC, a testament to the benefits of integrating DQL for optimizing learning rates and parameters [9] as shown in Figure 3.

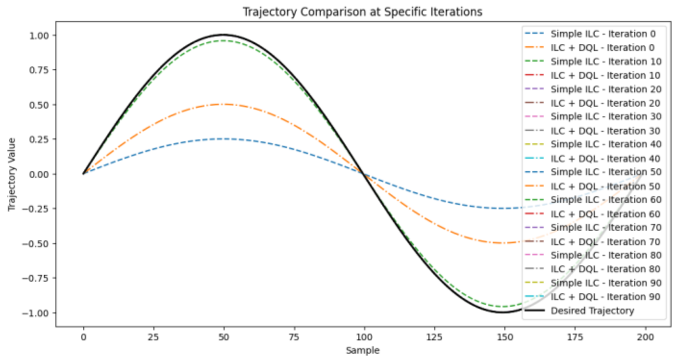

Figure 3: Trajectory comparison with iteration

Figure 4 shows that consistently faster convergence across various tasks underscores the system's robustness and effectiveness, paralleling advancements in DRL for control systems [15].

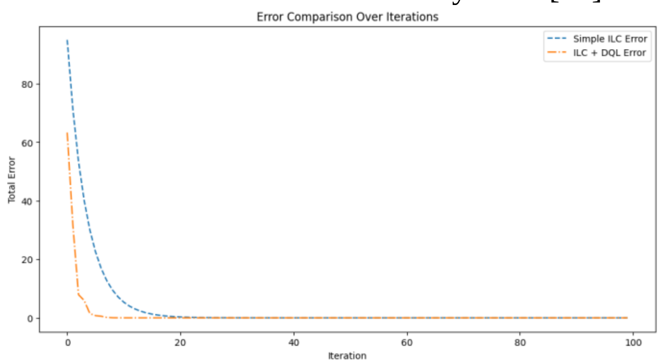

Figure 4: Error comparison over iterations

The results section provided a comprehensive analysis of the performance of the ILC+DQL system, substantiated by relevant literature. Next these results will be discussed.

IV. DISCUSSION

The ILC+DQL system demonstrated enhanced performance across various metrics, underlining the benefits of integrating DRL with traditional ILC methods. The system's ability to adapt and converge quickly, even in dynamic environments, showcases the potential of this approach in addressing the inherent limitations of traditional ILC systems. These results are consistent with the current trends in control system research, where the integration of machine learning techniques is increasingly seen as a pathway to more adaptive and efficient systems [1,5].

The integration of DQL with ILC was hypothesized to provide a more robust and adaptive approach to controlling systems in varying and uncertain environments. The experimental results substantiate this hypothesis, demonstrating enhanced error reduction, adaptability, and convergence speed compared to traditional ILC approaches.

The adaptability and resilience of the system were particularly notable, aligning with the dynamic nature of real-world applications. These improvements are largely attributed to the adaptive learning capabilities of the DQL agent, which continuously tuned the ILC parameters for optimal performance.

The effectiveness of the ILC+DQL system resonates with the current literature in control systems and machine learning. Studies [7,23-25] have highlighted the potential of DRL in enhancing control strategies, which was evident in the performance of the ILC+DQL system. Similarly, the importance of adaptability and precision in control systems [11-14], was effectively addressed by the proposed system.

Despite promising results, the implementation of ILC+DQL systems faces certain challenges. One of them is the addition of the DQL component introduces computational complexity, which might be a limiting factor in resource-constrained environments, as noted by various studies including those [7-9].

Another limitation is the tuning the hyperparameters of the DQL agent is crucial for optimal performance and remains a challenging and time-consuming task, a common theme in deep learning applications [18-19].

V. CONCLUSION

The integration of Deep Q-Learning with Iterative Learning Control represents a significant advancement in the field of intelligent control systems. The ILC+DQL system has demonstrated potential in addressing the complexities and dynamics of modern control tasks, offering a promising direction for future research and application. Continued exploration and refinement of this integrated approach are expected to yield further improvements and innovations in adaptive and intelligent control systems.

While the results are promising, several avenues for future work have been identified:

1. Further refinement of the DQL algorithm, including network architecture and learning parameters, could enhance the system's efficiency

and performance. Exploring other forms of reinforcement learning could also provide comparative insights and potential improvements.

2. Applying the ILC+DQL system to real-world scenarios, such as robotics, manufacturing, or autonomous vehicles, would provide valuable insights into its practicality and scalability. This would also help in understanding the system's performance in real-time applications with more complex dynamics and constraints.

3. The increased computational demand of the ILC+DQL system is a significant consideration. Future work could focus on optimizing the computational efficiency of the system, possibly through more efficient algorithms or hardware acceleration techniques.

4. Comparing the ILC+DQL system with other advanced control strategies would provide a broader understanding of its relative strengths and areas for improvement. This could involve benchmarking against other learning-based control methods or more traditional adaptive control strategies.

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