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Adaptive Parallel Iterative Learning Control with A Time-Varying Sign Gain Approach Empowered by Expert System

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***Abstract*—This study explores the incorporation of time-varying sign gain into a parallel iterative learning control (ILC) architecture, augmented by an expert system, to enhance the performance and stability of a robotic arm system. The methodology involves iteratively tuning the learning control gains using time-varying sign gain guided by an expert system. Stability analysis, encompassing asymptotic and monotonic convergence, demonstrates promising results across multiple joints, affirming the effectiveness of the proposed control architecture. In comparison with traditional PID control, fixed gain ILC, and ILC with adaptive learning in the expert system, the analysis focuses on stability, precision, and adaptability, using root mean square error (RMSE) as a key metric. The results show that ILC with adaptive learning from the expert system consistently reduces RMSE, even in the presence of learning transients. This adaptability effectively controls the learning transients, ensuring improved performance in subsequent iterations. In conclusion, the integration of time-varying sign gain with expert system assistance in a parallel ILC architecture holds promise for advancing adaptive control in robotic systems. Positive outcomes in stability, precision, and adaptability suggest practical applications in real-world scenarios. This research provides valuable insights into the implementation of dynamic learning mechanisms for enhanced robotic system performance, laying the groundwork for future refinement in robotic manipulator control systems.**

***Keywords*—Robotic; PID Control; ILC; Dynamic Model.**

I. INTRODUCTION

In the contemporary landscape, robotic manipulators play a crucial role in various industries and healthcare, undertaking tasks like welding, gluing, polishing, and neurorehabilitation. Ensuring high precision in repeated executions is paramount for the success of these applications. Traditionally, developers have tackled tracking errors by optimizing both mechanical and electrical hardware. However, there is a growing focus on alternative approaches, specifically on control algorithms, as a means to minimize costs.

Creating a closed-loop control system typically involves the use of fundamental control design approaches such as proportional integral derivative (PID) control, fuzzy logic control (FLC), LQR, or others for the initial system design. The design of control systems using these approaches often follows a developmental pattern, for instance, PID controller design involves the application of techniques to enhance its capabilities, such as gain adjustments [1]-[10]. Additionally, fuzzy logic control (FLC) has become a popular choice [11], [12] for tuning PID gains. Furthermore, significant advancements have been made in control systems through the introduction and application of type-1 and interval Type-2 fuzzy logic systems [13]-[26]. These advancements have practical applications in controlling various systems, including motors, electric carts, robotic systems, and the inverted pendulum. However, these design approaches may not effectively reduce the RMSE in the repetitive motion profiles.

An ILC system is designed to reduce the RMSE in repetitive motions by tuning both closed and open-loop controls. It accomplishes this by generating control input signals to compensate for system errors in repetitive motion patterns. ILC takes an unconventional approach, improving the tracking accuracy without modifying the internal parameters. It dynamically adjusts the control input based on the observed errors and input signals from previous iterations. Practical implementations may face challenges with undesirable learning transients, which robust ILC can address [27]. Two main ILC configurations exist with be serial by control inputs outside the feedback system and parallel by control inputs inside the feedback system [27]–[34]. Serial architectures are common due to limited access to manipulate internal control inputs.

Existing comparisons primarily focus on stability analysis [35]–[36], with limited emphasis on practical implementation. Stability proofs in the frequency domain raise concerns as they may overlook transient effects. Three robust ILC categories include Q-filter design, optimization-based design, and robust learning gain design. Q-filters, designed using low-pass filters [37], eliminate high-frequency disturbances [38]–[41]. Optimization-based designs, including norm-optimal ILC [43], offer a trade-off between tracking error and input updates [43]–[48]. Robust learning control matrices, designed for system robustness, may neglect high-frequency components, leading to non-zero tracking errors [51]–[53].

This study explores the combination of dual integral learners to capitalize on their individual strengths, inspired by previous dual-loop ILC designs [54]–[59]. The dual combining concept, merging fast and slow learners, strikes a balance between tracking performance and system robustness, demonstrating effectiveness across various applications.

Expert systems [60] are pivotal in the realm of robotics, serving as decision-support systems designed akin to human decision-making. They facilitate straightforward design and application in closed-loop control systems. Research efforts have yielded a variety of developments, including collaboration with different control systems such as expert PID intelligent control [61], neural network-based expert systems [62], and fuzzy expert systems [63]-[68]. These systems go beyond mere control functions, making substantial contributions to human decision-making across diverse domains.

The continuous pursuit of achieving precise robotic movement with minimal error has been a central focus of research. Extensive investigations into the Seiko D-Tran RT3200 robotic manipulator [50], [53], [59], [69], [70] have paved the way for the development of ILC [40], [71], [72], and repetitive control systems (RC), aiming to minimize the RMSE within the system. This research specifically utilized the system equation of the Seiko D-Tran RT3200 robotic manipulator to formulate an effective control system. The system equation has been trended to design the ILC system by comparing the performance of serial ILC architectures and parallel ILC architecture [51]. The system's actual behavior and simulation results align in the same direction. In designing the test system, fixed gain values were assigned in formulating the learning control matrix, and time-varying sign gains were adjusted in the learning control matrix using fuzzy logic to approximate the gain values. However, there are drawbacks in terms of processing time and limited reduction in RMSE. Furthermore, the development of collaborative dual ILC designs [54] poses challenges in designing numerous gains, requiring advanced mathematical foundations for system design, making it difficult to implement ILC systems practically. Hence, there is a need to develop control systems that intelligently select gains in the time-varying sign gain format to enhance the initial ILC system performance.

This study focuses on the design of a controller for robotic manipulator applications, utilizing ILC to mitigate errors in repetitive movements. An expert system is employed to generate a learning control matrix for ILC controllers. The effectiveness of the system is evaluated through tests involving smooth function-based movements, and a case study is conducted for a comprehensive performance assessment. The findings suggest that employing an expert system to create a learning control matrix for ILC controllers demonstrates the ability to reduce RMSE in robotic systems. The results align with the research objectives, highlighting the potential of applying expert systems in ILC controllers to enhance system performance in robotic manipulator applications and mitigate motion-related errors.

II. RESEARCH METHOD

In this research, emphasis is placed on studying the ILC system, incorporating the use of expert systems to adjust the learning rate of the system. The control system traditionally employs a PID control system for applications in robotics, specifically for controlling the motion of robots in various mission scenarios. The system can be designed ILC with an overall conceptual framework as depicted in Fig. 1.

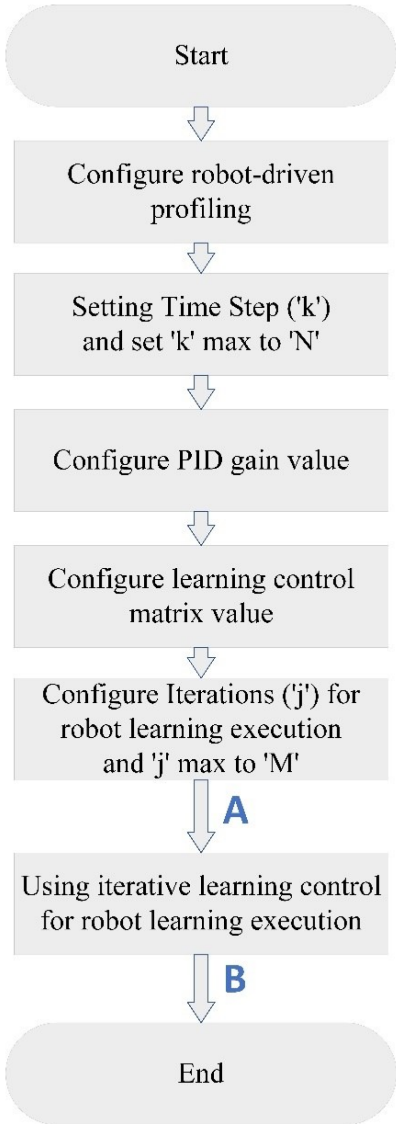
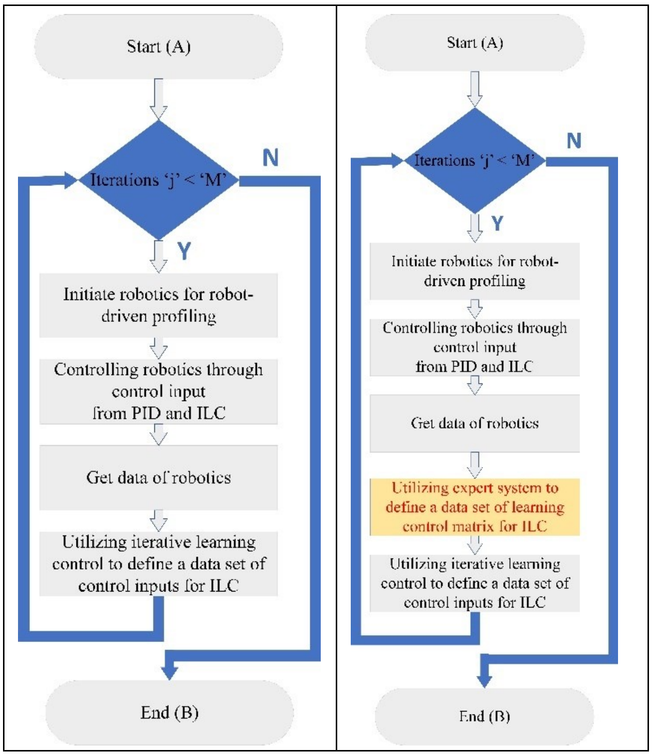


Fig. 1. Flowchart of the overall system design

Fig. 1 depicts a block diagram that illustrates the operational flowchart of a control system, outlining the procedural steps of the ILC system. The initial step involves defining the robot's motion pattern and establishing time values in a non-continuous time equation format. Subsequently, the time step 'k' is recorded, with the highest value being stored in the variable 'N'. Following this, the appropriate PID gain values are determined to the control the system, encompassing the specification of learning control matrix values for the ILC control system. Lastly, the number of learning iterations 'j' for the ILC control system is specified, and the highest value is stored in the variable 'M'.

In the section titled "Using iterative learning control for robot learning execution", both the PID control system and the ILC control system collaborate to coordinate the system's movement and minimize errors in each iteration. The overarching objective is to attain the lowest possible error values in each iteration of the ILC system. Fig. 2 offers an expanded perspective on "Using iterative learning control for robot learning execution", illustrating the standard system operation in Fig. 2 (a) and showcasing the enhanced system with additional adjustments in Fig. 2 (b).



(a) (b)

Fig. 2. Control system process

Fig. 2 explains the control process of the "Using iterative learning control for robot learning execution" box. In this section, the focus is on Fig. 2 (a), illustrating the original design of the ILC system. This involves setting the initial values of the system, consistently initiating the system at a designated point.

Following this, the system's motion is controlled by utilizing the estimated values of the PID and ILC control systems fed into the robot system. At the end of each movement cycle, motion data is collected for system analysis. The estimation of control input values for the ILC control system initiates a new process until the specified cycles are completed, concluding the operation of the ILC control system for system improvement.

Fig. 2 (b) depicts the system's enhancement by incorporating an expert system to refine the selection of the learning control matrix for ILC. It receives the values obtained from the system's operation in the previous iteration and sets the learning control matrix values for ILC at each time step. These values are then applied to the system's operation in the subsequent cycle.

III. Robotic Manipulator

In the realm of industrial applications, robotic manipulators find widespread use in diverse operations, including welding, assembly, and painting. Various types of industrial robots cater to these tasks, encompassing scara robots, cartesian robots, cylindrical robots, spherical robots, and delta robots. A representative robotic manipulator is illustrated here. Specifically, an illustrative application featuring the Seiko D-Tran RT3200 robotic manipulator, categorized as a cylindrical robot, will be showcased.

A. *Robotic Manipulator Seiko D-Tran RT3200*

The study employed a Seiko D-Tran RT3200 robot controller, featuring a Cartesian robot arm with four joints facilitating movement along the X-axis (joint R), rotation within the X-Y plane (joints T and A), and elevation or descent along the Z-axis (joint Z). To regulate the rotation of the four motors, a control unit was devised using a cRIO-9075 and programmed using LabVIEW. The configuration of the control unit is depicted in both Fig. 3 and Fig. 4.

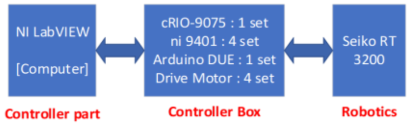


Fig. 3. Block diagram of the overall system

Fig. 4. Seiko D-Tran RT3200 and device for controller

B. *Dynamic Model of the Robotic Manipulator System*

The Seiko D-Tran RT3200 robot employed in this investigation, as depicted in Fig. 3 and Fig. 4, is defined by a system equation in discrete time, featuring a sampling rate of 0.055 seconds. Numerous explorations have been conducted regarding the regulation of this robotic system, as demonstrated by the scholarly contributions of P. Chotikunnan et al. [59], [70], [73], [74]. These scholarly efforts present a model for the system equation, identified as (1), incorporating the coefficients explicated in Table I. The data within the table corresponds to the variables associated with the manipulator arm.

$$P(z) = \frac{\gamma_1 z}{z^2 + \beta_1 z + \beta_0} \tag{1}$$

TABLE I. Parameterss Used in the Open-Loop System

Joint	γ_1	β_1	β_0
Joint R	0. 0333	-1. 6871	0. 6884
Joint T	0. 0162	-1. 7077	0. 7111
Joint Z	0. 0140	-1. 7519	0. 7526

IV. Parallel ILC Architecture

The parallel ILC architecture design [53] encompasses the development of an ILC control system that concurrently introduces the control input signal into the system alongside the existing control system. This architecture is compatible with any control system and is essentially termed feedback control, as depicted in Fig. 5. The figure offers a summary of the functioning of the parallel ILC outlined in this study.

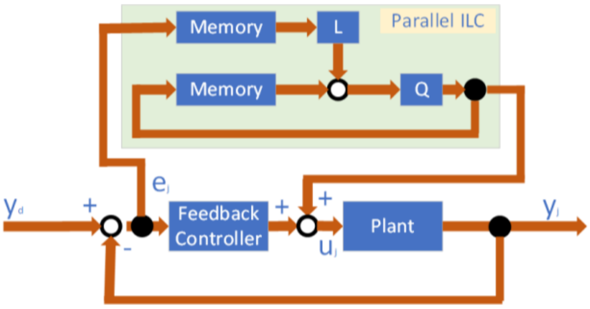


Fig. 5. Block diagram of Parallel ILC architecture

In Fig. 6, the section that removes the ILC control system is presented to illustrate the original structure in this study. A PID control system has been designed to transform it into a feedback controller system. In this study, a discrete-time PID controller system is designed, as depicted in (2), representing the estimated control input for the system.

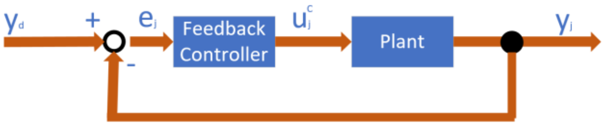


Fig. 6. Block diagram of feedback controller

$$u_j^C(k) = K_p e_j(k) + K_i \sum_{k-N}^{k} e_j(k) + K_d \left(e_j(k) - e_j(k-1)\right) \tag{2}$$

where, the control inputs, u_j^C, in this study, consist of the proportional gain (K_p), integral gain (K_i), and derivative gain (K_d).

In this investigation, a PID controller was formulated to govern the motor system in joints R, T, and Z, employing CHR tuning to minimize overshooting. The system design was explored in the works of P. Chotikunnan and R. Chotikunnan [70]. The parameters utilized in the system are detailed in Table II.

TABLE II. P Gain Values of Joint R

Joint	Joint R	Joint T	Joint Z
P controller	4. 25	8. 00	6. 70

The utilization of ILC [75]-[80] aims to eradicate tracking errors by assimilating insights from historical data. Presuming that a control system consistently generates the same tracking error when executing identical commands, it becomes apparent that the error and control input signals from previous iterations need to learn and adapt, generating a more suitable control input signal to minimize the tracking errors in the current execution.

In a broader context, the learning control law of ILC can be articulated as follows

$$u_{j+1}(k) = Q(u_j(k) + Le_j(k+1)) \tag{3}$$

where L denotes a learning control matrix, and Q represents a low-pass filter designed to prevent amplification of the learning control input. Given that the closed-loop system incurs a one-time-step delay, the control input $u(k)$ endeavors to nullify the error $e(k+1)$. In order to eliminate $e_j(k), k \in [1, N]$, the array of control inputs for iteration j is expressed as $u_j = \begin{bmatrix} u_j(0) & u_j(1) & \dots & u_j(N-1) \end{bmatrix}^T$.

The Parallel ILC architecture illustrates a block diagram depicting the transition from iterations j to $j+1$. The learning mechanism follows the same concept as the serial structure, wherein it records the learning control input and the corresponding errors from the preceding iteration to adjust the learning control signal in the ongoing execution. However, in contrast to modifying the external command in the feedback control system, as seen in the serial structure, the internal control input u_j^{int} within the feedback loop is iteratively updated following (3). In simpler terms, $u_j^{int} = u_j$ in this configuration. It is essential to highlight that this accomplishment is feasible when the feedback control system is manipulable.

As the control input is a summation of the learning control input and the output from the feedback controller, a generalization can be made by updating only the learning control input, similar to the approach in the structure outlined in (3). During the initial execution, the learning control input is initialized to zero, resulting in $u_0 = u_0^C$. Upon activation of the learning mechanism, the control input is subsequently updated according to $u_j = u_j^L + u_j^C$, where u_j^L is derived from the update specified in (5).

$$u_{j+1}(k) = ((u_j^L(k) + u_j^C(k)) + Le_j(k+1)) \tag{4}$$

$$u_{j+1}^{int}(k) = (u_j^{int}(k) + Le_j(k+1)) \tag{5}$$

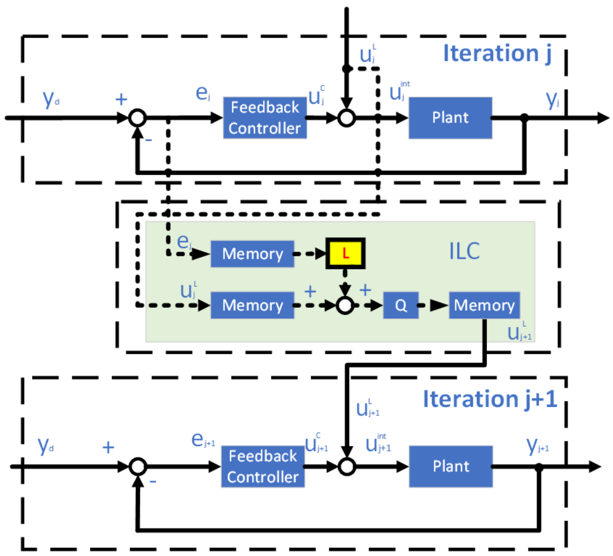


Fig. 7. Block diagram of the parallel ILC architecture

A. Stability Analysis of Parallel ILC Architecture

The error employed within the feedback control loop corresponds to the one utilized in the learning mechanism, incremented by a single time step.

$$e_{j+1} = (I + \mathbb{P}_o\mathbb{C})^{-1}(I - P_o L + \mathbb{P}_o\mathbb{C})\ e_j \tag{6}$$

where I denotes an identity matrix with dimensions equivalent to P_0, $\mathbb{P}_o$ signifies the plant with a delay of two-time steps, and $\mathbb{C}$ represents the feedback controller.

Asymptotic convergence, the parallel ILC system is asymptotically stable for any initial iteration error, denoted as e_0, if

$$\rho((I + \mathbb{P}_o\mathbb{C})^{-1}(I - P_o L + \mathbb{P}_o\mathbb{C})\ ) < 1 \tag{7}$$

Since the matrix $(I + \mathbb{P}_o\mathbb{C})^{-1}(I - P_o L + \mathbb{P}_o\mathbb{C})$ for the parallel structure is equivalent to the matrix $(I - PL)$ in the parallel structure.

Monotonic convergence, the error norm for the parallel ILC system, decays monotonically if

$$\max_i \sigma_i((I + \mathbb{P}_o\mathbb{C})^{-1}(I - P_o L + \mathbb{P}_o\mathbb{C})) < 1 \tag{8}$$

essentially the same as that by substituting $(I + \mathbb{P}_o\mathbb{C})^{-1}(I - P_o L + \mathbb{P}_o\mathbb{C})$ to $(I - PL)$.

V. Adaptive Parallel Iterative Learning Control with A Time-Varying Sign Gain Approach Empowered by Expert System

An expert system is a computer program that utilizes artificial intelligence (AI) to replicate human judgments using specialized knowledge. It is crafted to tackle problems through if-then rules and encompasses a knowledge base, inference tools, and user interface. In this research instance, the expert system fine-tunes the adjustable gain on the learning control matrix of the ILC controller. The expert system's design for the adjusted gain of the learning control matrix is illustrated in Fig. 8 and Fig. 9, presenting the pseudocode for the time-varying sign gain optimization with the expert system, where l_{kk} serves as the output for adjusting the learning control matrix of the ILC controller.

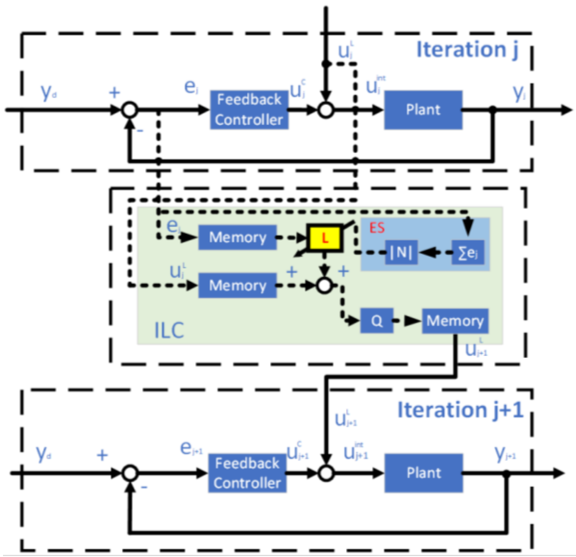


Fig. 8. Parallel structure block diagram of an ILC with the expert system

if $\left|\sum_{k-N}^{k}\left(G_{ki}e_j(k)\right)\right| > integral\_error\_ck$
 then $l_{kk} = 0$
else
 then $l_{kk} = Gain\_ILC$
end

Fig. 9. Pseudo code of the expert system for ILC controller

where G_{ki} represents the gain of integral, and $integral\_error\_ck$ assigned a value of limit summation of error.

Each block diagram reveals the addition of an extra box, highlighted in orange, to the structure. This box represents a gain adjustment mechanism facilitated by the expert system to iteratively fine-tune the learning control gains $l_{11}, \dots, l_{NN}$ within the learning control matrix in (9).

$$L = \begin{bmatrix} l_{11} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & l_{NN} \end{bmatrix} \tag{9}$$

From Fig. 8 and Fig. 9, it can be observed that the operation of the pseudo code of the expert system for the ILC controller involves adjusting the values of L when completing one cycle of operation. It sequentially updates the values from l_{11} to l_{NN} according to the number of time steps designed in the system's motion path. The maximum number of time steps ('N') is determined to utilize the learning control matrix values in the next iteration.

VI. Simulation Results

In designing the simulation system, the testing of the simulated motion of the Seiko D-Tran RT3200 robot arm was conducted using the system in (1) and the parameter values from Table II. The testing of the simulation system was divided into four parts, including 1. Stability analysis verification, 2. Motion of the original ILC system, 3. Motion of the ILC system with the expert system, and 4. Summary of overall results of the simulation system testing.

Simulation tests were performed to evaluate the simulated robotic arm control system's performance. Stability was ensured using the PID controller system, and the precision of motion was improved with the ILC control system. Parameters for the simulations, including the maximum allowable values as outlined in Table III, were defined in the research. The subsequent sections analyze and present the results of the system simulation.

TABLE III. Maximum of Learning Control Gains

Learning control gains value	Joint R	Joint T	Joint Z
learning control gains using	4	4	3
Gki	0.055	0.055	0.055
integral_error_ck	0.001	0.001	0.001
maximum of learning control gain	30.0300	61.7284	71.4286

Table III outlines the variables with specified conditions for simulating the system. "*Learning control gain using*" sets the initial values for the learning control matrix in the ILC system. "$integral\_error\_ck$" represents the sum of error values, a user-defined parameter for system testing. "*Maximum of learning control gains*" is the highest value allowed for the learning control matrix in the stability analysis condition, determined by matrix P_o.

A. Stability Analysis Verification

Stability analysis was performed to examine the values of asymptotic convergence and monotonic convergence, as presented in Table IV. It was observed that the values of asymptotic convergence for Joint R, Joint T, and Joint Z are less than 1, indicating that the ILC control system with the learning control gains from Table III can effectively stabilize the system. However, the presence of monotonic convergence values greater than 1 suggests the potential occurrence of learning transients in the system. These learning transients may be manageable in computer simulation systems but could pose challenges in real-world control scenarios if the development of the learning control matrix adjustment system is not sufficiently optimized.

TABLE IV. STABILITY ANALYSIS

Stability analysis	Joint R	Joint T	Joint Z
Asymptotic convergence	0.8833	0.9426	0.9616
Monotonic convergence	1.0907	1.0380	1.0537

B. Motion of The Original ILC System

In the simulation of the robotic arm to motion of the original ILC system, the results are depicted in Fig. 10 to Fig. 12. The topmost image in each axis illustrates the specified motion of the robotic arm in that axis. For the middle image, it displays the control input values obtained from the system estimation. The bottommost image represents the RMSE for each axis. The simulation was 9,600 iterations under the condition of $integral\_error\_ck$ set at 0.001 for all three axes, as detailed below.

For joint R, As shown in Fig. 10, during the first iteration, the RMSE is observed to be 4.027 mm. With the ILC learning system, the RMSE consistently decreases until 5 iterations, reaching a value of 0.1681 mm. Subsequently, a learning transient occurs, with the highest value at 403 iterations is 2.2708×10^{13} mm. before decreasing again, approaching zero around 1,504 iterations. The minimum RMSE over 9,600 iterations is 1.8167×10^{-12} mm.

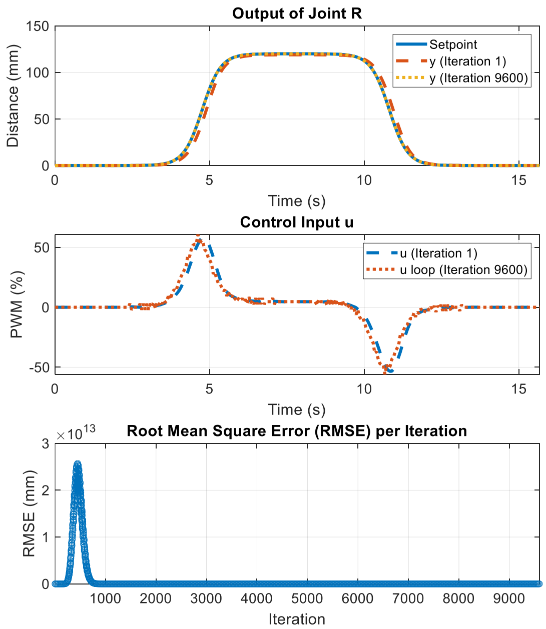


Fig. 10. Results of original ILC system in Joint R

Joint T, As shown in Fig. 11, during the first iteration, the RMSE is observed to be 0.5394 deg. With the ILC learning system, the RMSE consistently decreases until 8 iterations, reaching a value of 0.0279 deg. Subsequently, a learning transient occurs, with the highest value at 1,003 iterations is 1.5854×10^{11} deg. before decreasing again, approaching zero around 2,901 iterations. The minimum RMSE over 9,600 iterations is 3.7505×10^{-14} deg.

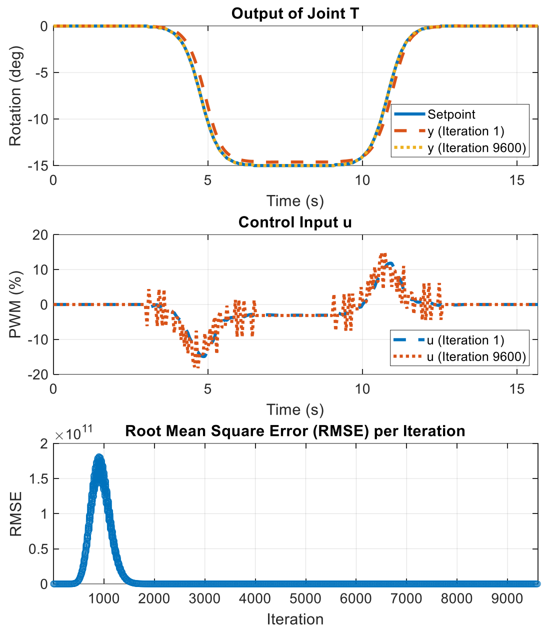


Fig. 11. Results of original ILC system in Joint T

For joint Z, As shown in Fig. 12, during the first iteration, the RMSE is observed to be 1.7695 mm. With the ILC learning system, the RMSE consistently decreases until 5 iterations, reaching a value of 0.5909 mm. Subsequently, a learning transient occurs, with the highest value at 1,600 iterations is 6.3173×10^{18} mm. before decreasing again, approaching zero around 1,504 iterations. The minimum RMSE over 9,600 iterations is 0.8469 mm.

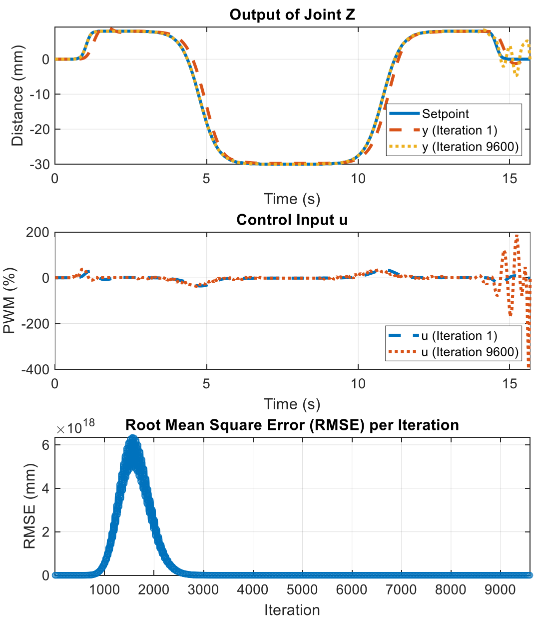


Fig. 12. Results of original ILC system in Joint Z

The trends for Joint R, Joint T, and Joint Z are consistent with control input signals for all three axes exceeding 100% of the system's capability. The robotic arm simulation experiences learning transients during ILC operation due to monotonic convergence values exceeding one. However, the asymptotic convergence values being less than 1 allowing the system to recover after learning transients occur. This suggests that signal improvement cannot effectively control the robotic system, making it impractical for real-world applications.

C. Motion of The ILC System with The Expert System

In the simulation of the robotic arm with ILC system with the expert system, the results are depicted in Fig. 13 to Fig. 15. The topmost image in each axis illustrates the specified motion of the robotic arm in that axis. For the middle image, it displays the control input values obtained from the system estimation. The bottommost image represents the RMSE for each axis. The simulation was 9,600 iterations under the condition of $integral\_error\_ck$ set at 0.001 for all three axes, as detailed below.

Joint R, As shown in Fig. 10, during the first iteration, the RMSE is observed to be 4.027 mm. With the ILC learning system, the RMSE consistently decreases until 2,997 iterations, reaching a value of 0.0609 mm. Subsequently, a learning transient occurs, with the highest value at 3,277 iterations being 0.0257 mm. before decreasing again, approaching zero around 3,340 iterations. The minimum RMSE over 9,600 iterations is 1.5893×10^{-12} mm.

Joint T, Fig. 11 illustrates that in the first iteration, the RMSE is 0.5395 deg. With the ILC learning system, the RMSE consistently decreases until 3,502 iterations, reaching a value of 0.0148 deg. A learning transient occurs, with the highest value at 4,606 iterations, before decreasing again and approaching zero around 5,000 iterations. The minimum RMSE over 9,600 iterations is 7.7899×10^{-15} deg.

For joint Z, In the first iteration, as seen in Fig. 12, the RMSE is 1.7694 mm. With the ILC learning system, The RMSE decrease approaches zero around 7,835 iterations and the minimum RMSE over 9,600 iterations is 0.0035 mm.

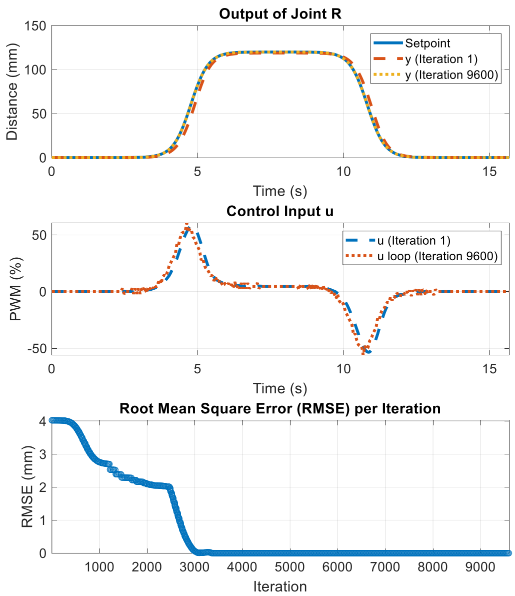


Fig. 13. Results of ILC system with the expert system in Joint R

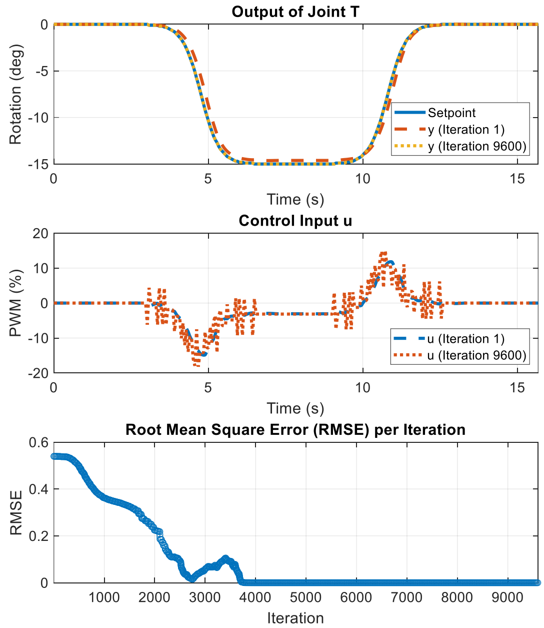


Fig. 14. Results of ILC system with the expert system in Joint T

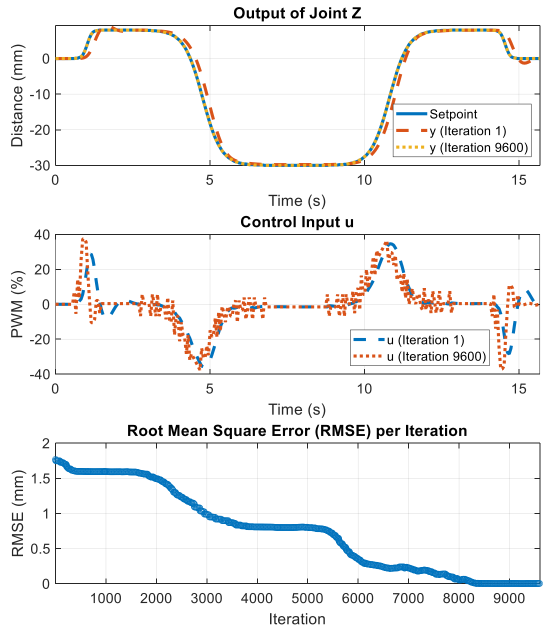


Fig. 15. Results of ILC system with the expert system in Joint Z

The trends for Joint R, Joint T, and Joint Z are consistent, with control input signals for all three axes not exceeding 100% of the system's capability. This suggests that the signal improvement is within the controllable limits of the system. The use of adaptive parallel iterative learning control with a time-varying sign gain approach, empowered by an expert system, effectively manages the occurrence of learning transients in the ILC system. Even when the monotonic convergence values exceed 1, the dynamic operation of the learning control matrix allows for stable control of the robotic system.

D. Summary of Overall Results of The Simulation System Testing

In the overall view of the ILC control system, it has the ability to reduce errors in motion, although designing to check the stability conditions of the ILC control system requires finding the system equations used for control first. Only then can formulas be derived to find the asymptotic convergence and monotonic convergence values.

In testing the simulation of the system using the original ILC system, there are challenges in designing the learning control matrix to have both asymptotic convergence and monotonic convergence values less than 0. Setting the sign gain values in some systems may not be feasible at all. Therefore, it is evident that designing the system can be achieved by simply specifying that the asymptotic convergence values are less than 1, while the monotonic convergence values remain above one. However, to address this issue, a multi-gain system may need to be designed to set values so that both asymptotic convergence and monotonic convergence are less than 0.

For the ILC system with the expert system, which adjusts the learning control matrix, it can control the occurrence of learning transients in the ILC system. Although the asymptotic convergence values are less than 1 and the monotonic convergence values remain above 1, the design of the expert system can help the ILC system operate within the constraints of controlling the motion of the robotic system, using a sign gain approach. Therefore, this serves as a fundamental approach in designing the basic usage of the ILC control system for controlling future systems.

VII. Conclusion

This research delves into the exploration and development of a robotic control system by introducing the adaptive parallel iterative learning control technique, combined with time-varying sign gain and an expert system. The objective is to elevate the performance and stability of the robotic system across diverse scenarios. The simulations outcomes showcase the system's capability to manage and enhance the operations of the robot, as substantiated by the analysis of RMSE, convergence values, and the adept handling of learning transients within the system. Comparative simulations with systems employing PID control and fixed gain ILC underscore the superiority of the proposed system in terms of stability, precision, and adaptability in dynamic learning environments. Moreover, the incorporation of an expert system in the learning control gain adjustment process significantly amplifies the system's efficiency in dealing with learning transients, thereby facilitating a more effective operation. By conducting simulations and analyses, this study proposes a path for developing a robotic control system that is both highly efficient and reliable. It lays the groundwork for pioneering innovations in robotic control for forthcoming applications.

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