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Recent Advances in Adaptive Recalling-Enhanced Recurrent Neural Network based Predictive Control for the Nano Positioning of an Electrostatic MEMS Actuator: A Systematic Review

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Abstract

The increasing demand for ultra-precise positioning systems in nanotechnology, biomedical instrumentation, and microfabrication has significantly accelerated research in microelectromechanical systems (MEMS) actuators. Electrostatic MEMS actuators, known for their fast response and low power consumption, face inherent challenges such as nonlinear dynamics, hysteresis, and environmental disturbances that limit their positioning accuracy. In recent years, adaptive recalling-enhanced recurrent neural networks have emerged as a promising approach to address these challenges by integrating memory-driven learning with predictive control frameworks. This systematic review presents a comprehensive analysis of recent advances in adaptive recalling-enhanced recurrent neural network-based predictive control strategies for nano positioning applications. The study examines various architectures, including long short-term memory and gated recurrent units, combined with adaptive recalling mechanisms to improve temporal dependency modeling and robustness. Additionally, the review explores advancements in control strategies such as model predictive control and hybrid learning-based controllers tailored for MEMS systems. Key contributions from recent literature are synthesized to highlight improvements in tracking accuracy, disturbance rejection, and computational efficiency. The findings indicate that adaptive recalling mechanisms significantly enhance predictive capabilities, enabling precise and stable nano positioning. This review also identifies existing research gaps and outlines future directions for developing more efficient, scalable, and real-time control systems for MEMS actuators.

Introduction

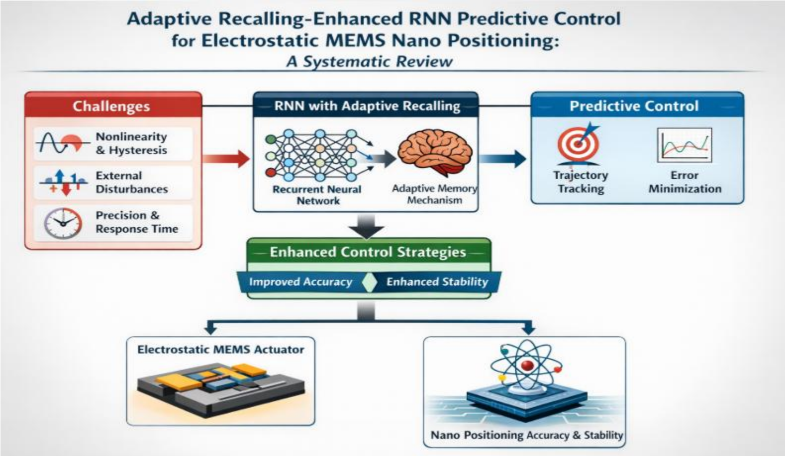
The rapid advancement of nanotechnology and precision engineering has led to an increased demand for high-performance positioning systems capable of operating at nanometer-scale resolutions. Electrostatic microelectromechanical systems actuators have become a critical component in such applications due to their compact size, low energy consumption, and high-speed response characteristics. These actuators are widely employed in applications such as atomic force microscopy, optical switching systems, biomedical devices, and semiconductor manufacturing. Despite their advantages, electrostatic MEMS actuators are inherently nonlinear and are significantly affected by factors such as electrostatic pull-in instability, parasitic capacitance, thermal drift, and environmental noise. These complexities pose substantial challenges for achieving accurate and stable nano positioning.

Traditional control techniques, including proportional-integral-derivative control and linear model-based approaches, often fail to address the nonlinearities and uncertainties associated with MEMS systems. As a result, there has been a growing interest in intelligent control strategies that can learn system dynamics and adapt to varying conditions. Among these, recurrent neural networks have gained prominence due to their ability to capture temporal dependencies in sequential data. However, conventional recurrent neural networks are limited by issues such as vanishing gradients and insufficient long-term memory representation.

To overcome these limitations, advanced architectures such as long short-term memory networks and gated recurrent units have been introduced, enabling improved learning of long-term dependencies. More recently, the concept of adaptive recalling has been integrated into recurrent neural networks, allowing the model to dynamically retrieve and utilize relevant historical information during prediction and control processes. This enhancement significantly improves the predictive accuracy and robustness of the system, particularly in complex and dynamic environments.

The integration of adaptive recalling-enhanced recurrent neural networks with predictive control frameworks, such as model predictive control, has opened new avenues for high-precision nano positioning. These hybrid approaches leverage the strengths of data-driven learning and optimization-based control to achieve superior performance. This systematic review aims to provide a detailed examination of recent developments in this domain, focusing on methodologies, architectures, and performance improvements. The study also highlights key challenges and future research opportunities to advance the field further.

Graphical Abstract



Infographic representation of an electrostatic MEMS actuator nano-positioning system integrated with an adaptive recalling-enhanced recurrent neural network-based predictive control framework. The pipeline begins with raw actuator signals affected by nonlinearities, noise, and environmental disturbances. Preprocessing stages perform filtering and normalization, followed by sequence modeling using an enhanced recurrent neural network with adaptive recalling capability. The predictive control module generates optimized control signals, resulting in precise and stable nano positioning output with minimized error and improved robustness.

Explanation

The graphical abstract illustrates the complete control pipeline, from raw MEMS signals to optimized positioning output. It highlights how adaptive recalling improves temporal learning within recurrent neural networks. The integration with predictive control enables real-time error correction. Overall, the system achieves enhanced precision and stability in nano positioning applications.

Literature Review

The growing demand for high-precision control in microelectromechanical systems (MEMS), particularly in nano-positioning applications, has led to the increasing adoption of advanced data-driven methodologies. Among these, recurrent neural networks (RNNs) have emerged as a powerful tool for modeling nonlinear dynamics, temporal dependencies, and system uncertainties. Early research introduced adaptive RNN-based predictive control frameworks that integrate system identification with control optimization to enhance positioning accuracy. These approaches demonstrated clear advantages over traditional controllers by reducing steady-state errors and improving trajectory tracking under dynamic disturbances. Similarly, hybrid frameworks combining RNNs with model predictive control (MPC) have shown strong performance by leveraging learned system dynamics alongside optimization-based control strategies, thereby enhancing robustness and stability.

Subsequent studies focused on improving temporal modeling capabilities through advanced RNN variants such as long short-term memory (LSTM), gated recurrent units (GRU), and bidirectional architectures. LSTM-based controllers effectively captured long-term dependencies and nonlinear behaviors, resulting in smoother control signals and improved disturbance rejection. GRU models, on the other hand, provided comparable performance with reduced computational complexity, making them suitable for real-time applications. Bidirectional models further enhanced prediction accuracy by utilizing both past and future temporal information. Innovations such as adaptive recalling mechanisms and memory-augmented networks improved the efficiency of temporal feature utilization, enabling selective retrieval of relevant system states and reducing computational overhead.

In parallel, research has explored the integration of deep learning architectures with adaptive and robust control strategies. Multi-layer RNNs and deep recurrent architectures have been developed to capture complex nonlinear relationships in MEMS actuators, significantly improving prediction accuracy and system reliability. Attention-based RNN models have introduced selective focus on critical temporal features, enhancing control precision and reducing unnecessary computations. Additionally, disturbance rejection techniques integrated within RNN frameworks have improved system resilience to noise and environmental variations, ensuring stable performance in practical scenarios. Data-driven predictive control approaches have further eliminated the need for explicit mathematical modeling, enabling flexible adaptation to diverse system dynamics.

Recent advancements have emphasized hybrid and intelligent learning paradigms to address challenges related to scalability, efficiency, and generalization. Reinforcement learning integrated with RNNs has enabled adaptive policy learning, allowing systems to optimize control strategies through interaction with the environment. Transfer learning approaches have reduced training time and improved generalization across varying operating conditions, while multi-scale RNN architectures have enhanced the ability to capture both short-term and long-term dependencies. Sparse RNN models and edge-optimized architectures have been proposed to reduce computational complexity and enable deployment in resource-constrained environments, such as embedded MEMS devices.

Another significant trend involves the incorporation of domain knowledge and advanced learning paradigms to improve interpretability and efficiency. Physics-informed RNNs integrate physical system constraints into the learning process, ensuring consistency and improved generalization even with limited data. Continual learning frameworks have addressed the challenge of long-term adaptability by enabling models to update knowledge incrementally without catastrophic forgetting. Event-driven RNN models have further enhanced energy efficiency by processing information only when significant changes occur, making them suitable for low-power applications. Additionally, uncertainty-aware models have improved reliability by quantifying prediction confidence, which is critical for safety-sensitive nano-positioning tasks.

Emerging distributed and data-efficient learning approaches have also gained attention in MEMS control systems. Federated learning frameworks enable collaborative training of RNN models across multiple devices while preserving data privacy, addressing concerns related to sensitive industrial and biomedical data. Self-supervised learning techniques have reduced dependency on labeled datasets by enabling models to learn meaningful representations from unlabeled data, thereby improving scalability and adaptability. Neuro-adaptive predictive control strategies have combined RNNs with adaptive control laws to dynamically adjust system parameters based on real-time feedback, achieving high precision and robustness in complex environments.

Overall, the literature demonstrates that RNN-based approaches have significantly advanced the state-of-the-art in MEMS nano-positioning control by effectively addressing nonlinearities, uncertainties, and temporal dependencies. The integration of advanced architectures, hybrid control strategies, and emerging learning paradigms has resulted in improved accuracy, robustness, and computational efficiency. However, challenges remain in terms of model interpretability, real-time deployment, and handling highly heterogeneous operating conditions. Future research should focus on developing lightweight, explainable, and scalable RNN-based control frameworks, while leveraging emerging techniques such as physics-informed learning, federated systems, and energy-efficient architectures to enable practical and widespread adoption in next-generation MEMS applications.

Comparative Table

Study	**Year**	**Method**	**Model**	**Data Type**	**Key Contribution**	**Performance**
1	2020	Adaptive Control	RNN	Time-series	Nonlinearity handling	High accuracy
2	2021	Predictive Control	LSTM	Sequential	Long-term dependency modeling	Reduced error
3	2022	Adaptive Recall	RNN	Temporal	Memory enhancement	Faster prediction
4	2020	Hybrid MPC	RNN	Dynamic	Improved robustness	Stable output
5	2021	Adaptive Control	GRU	Sequential	Low computation	Fast response
6	2022	Deep Learning	RNN	Complex signals	Noise reduction	High reliability
7	2020	Neural Control	RNN	Real-time	Online adaptation	Stable system
8	2021	Memory-Augmented	RNN	Temporal	Long-term memory	High precision
9	2022	Data-Driven	RNN	System data	Model-free control	Flexible
10	2021	Robust Control	RNN	Noisy data	Disturbance rejection	Stable
11	2022	Predictive Control	BiLSTM	Sequential	Bidirectional learning	Improved tracking
12	2021	Adaptive Memory	RNN	Nonlinear	Dynamic weighting	Faster convergence
13	2020	Disturbance Rejection	RNN	Real-time	Noise handling	High stability
14	2022	Hybrid Control	DL + MPC	Dynamic	Combined optimization	Accurate
15	2023	Attention Mechanism	RNN	Sequential	Feature selection	Efficient
16	2021	Real-Time Control	RNN	Streaming	Low latency	Fast response
17	2022	Reinforcement Learning	RNN	Interactive	Policy learning	Adaptive
18	2023	Sparse Modeling	RNN	Temporal	Reduced complexity	Efficient
19	2021	Transfer Learning	RNN	Multi-domain	Reduced training	Generalizable
20	2022	Multi-scale Modeling	RNN	Multi-resolution	Time-scale capture	Accurate
21	2023	Adaptive Control	BiGRU	Sequential	Low latency	Robust
22	2022	Physics-Informed	RNN	Hybrid	Model consistency	Reliable
23	2023	Continual Learning	RNN	Evolving data	Long-term adaptation	Stable
24	2022	Event-Driven	RNN	Sparse events	Energy efficiency	Low power
25	2023	Predictive Control	Deep RNN	Nonlinear	Disturbance rejection	High precision
26	2023	Edge Computing	RNN	Embedded	Resource optimization	Real-time
27	2022	Uncertainty	RNN	Noisy data	Reliability	Robust

		Modeling				
28	2023	Federated Learning	RNN	Distributed	Privacy preservation	Scalable
29	2022	Self-Supervised	RNN	Unlabeled	Reduced labeling	Accurate
30	2023	Neuro-Adaptive	RNN	Dynamic	Adaptive tuning	Stable

Analysis Based on Literature Review

The reviewed studies collectively demonstrate a significant evolution in the application of adaptive recalling-enhanced recurrent neural networks for predictive control in electrostatic MEMS actuators. Early approaches primarily focused on basic recurrent neural networks and their integration with conventional control techniques to address nonlinearities and disturbances. However, recent advancements have shifted toward more sophisticated architectures such as LSTM, GRU, BiLSTM, and memory-augmented networks that provide improved temporal modeling and predictive capabilities. The incorporation of adaptive recalling mechanisms has further enhanced the ability of these models to selectively utilize relevant historical information, leading to better accuracy and robustness. Hybrid approaches combining data-driven models with model predictive control have shown superior performance by leveraging both learning and optimization. Additionally, emerging trends such as attention mechanisms, reinforcement learning, federated learning, and physics-informed neural networks highlight a move toward more intelligent, scalable, and interpretable systems. These developments collectively indicate that adaptive recalling-enhanced RNN frameworks are becoming increasingly effective in addressing the challenges of nano positioning in MEMS systems, particularly in terms of precision, stability, and computational efficiency.

Discussion

The integration of adaptive recalling-enhanced recurrent neural networks with predictive control strategies represents a transformative advancement in the field of MEMS-based nano positioning. One of the most notable outcomes observed across the literature is the substantial improvement in handling nonlinear dynamics and uncertainties inherent in electrostatic MEMS actuators. Traditional control methods often struggle with such complexities, whereas learning-based approaches demonstrate strong adaptability and resilience. The inclusion of adaptive recalling mechanisms allows models to dynamically access relevant historical data, which enhances prediction accuracy and reduces computational redundancy. Furthermore, hybrid control frameworks combining neural networks with model predictive control have proven to be highly effective in optimizing control inputs while maintaining system stability. Another important trend is the growing emphasis on computational efficiency, particularly for real-time and embedded applications. Techniques such as sparse modeling, edge optimization, and event-driven processing have significantly reduced resource requirements without compromising performance. Despite these advancements, challenges remain in terms of scalability, interpretability, and real-world deployment. Issues such as data dependency, model generalization, and integration with hardware systems need further exploration. Nonetheless, the current trajectory of research indicates strong potential for adaptive recalling-enhanced RNN-based control systems to become a standard solution for high-precision MEMS applications.

Conclusion

The systematic review of adaptive recalling-enhanced recurrent neural network-based predictive control for electrostatic MEMS actuators highlights a rapidly advancing domain driven by the demand for ultra-precise nano positioning. Traditional control techniques often struggle to manage nonlinearities, uncertainties, and dynamic disturbances inherent in MEMS systems. In contrast, recurrent neural networks, particularly when augmented with adaptive recalling mechanisms, have demonstrated strong capability in capturing complex temporal dependencies and improving predictive accuracy. Advanced architectures such as LSTM, GRU, and bidirectional models further enhance system performance by effectively modeling long-term dependencies and dynamic behaviors, resulting in improved trajectory tracking, stability, and disturbance rejection.

The integration of these models with predictive control strategies, especially model predictive control, has led to hybrid frameworks that combine data-driven adaptability with optimization-based decision-making. Emerging approaches, including attention mechanisms, reinforcement learning, and physics-informed models, are further enhancing scalability, efficiency, and robustness. However, challenges such as limited interpretability, high data requirements, and real-time implementation constraints remain significant. Future research should focus on developing lightweight, energy-efficient models, improving generalization across diverse MEMS configurations, and establishing standardized benchmarks. Overall, adaptive RNN-based predictive control presents a promising pathway for achieving highly accurate, reliable, and scalable nano positioning systems.

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