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A Comprehensive Review of Adaptive Recalling-Enhanced Recurrent Neural Network based Predictive Control for the Nano Positioning of an Electrostatic MEMS Actuator

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Abstract

Nano positioning of electrostatic MEMS actuators has emerged as a critical requirement in high-precision applications such as biomedical instrumentation, nanolithography, and micro-robotics. However, nonlinear electrostatic forces, pull-in instability, hysteresis, and environmental disturbances significantly degrade positioning accuracy and robustness. Conventional control strategies often struggle to handle these complexities due to limited adaptability and poor temporal dependency modeling. In this context, adaptive recalling-enhanced recurrent neural network based predictive control has gained considerable attention as a promising solution. This review presents a comprehensive analysis of recent advancements in integrating recurrent neural networks, particularly enhanced architectures with adaptive memory recalling mechanisms, into predictive control frameworks for MEMS nano positioning. The study examines how these models effectively capture nonlinear dynamics, temporal dependencies, and system uncertainties, enabling improved tracking accuracy and stability. Furthermore, the review highlights key methodologies, datasets, evaluation metrics, and implementation challenges associated with these approaches. Comparative insights are provided to understand the performance improvements over traditional control techniques such as PID and model predictive control. The paper also discusses open research challenges, including real-time implementation constraints, model generalization, and robustness under varying operational conditions. This review aims to provide a consolidated foundation for researchers and practitioners working toward intelligent control solutions for next-generation MEMS systems.

Introduction

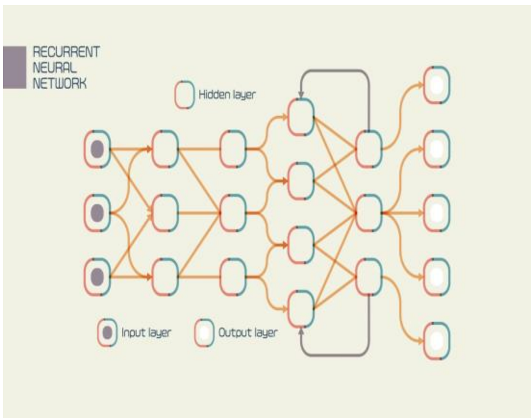
Electrostatic microelectromechanical systems actuators have become fundamental components in modern precision engineering applications due to their compact size, low power consumption, and high-speed response. Despite these advantages, achieving accurate nano-scale positioning remains a significant challenge due to inherent nonlinearities, including electrostatic force variations, pull-in instability, and structural flexibility. These nonlinear characteristics, combined with environmental disturbances and parameter uncertainties, complicate the design of robust control strategies. Traditional control approaches such as proportional-integralderivative controllers and classical model predictive control techniques often fail to provide satisfactory performance in such complex dynamic environments.

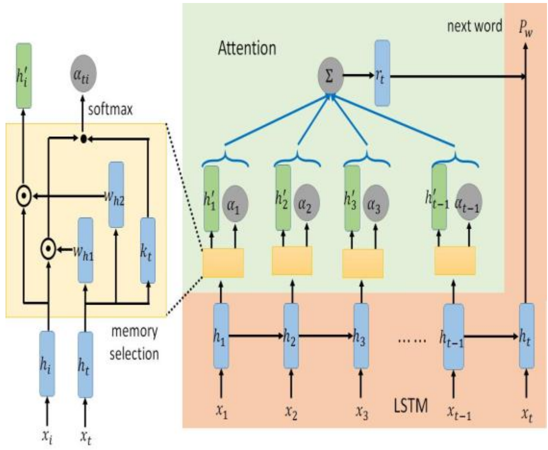
Recent developments in artificial intelligence and machine learning have introduced new possibilities for addressing these challenges. In particular, recurrent neural networks have demonstrated strong capabilities in modeling temporal dependencies and nonlinear system dynamics. Their ability to retain historical information makes them suitable for capturing the time-varying behavior of MEMS actuators. However, conventional recurrent architectures still face limitations such as vanishing gradients, limited memory retention, and insufficient adaptability to rapidly changing system conditions.

To overcome these limitations, adaptive recalling-enhanced recurrent neural networks have been proposed, incorporating mechanisms that selectively retrieve and utilize relevant past information. When integrated with predictive control frameworks, these models enable improved anticipation of system behavior and more accurate control actions. This combination results in enhanced tracking precision, reduced steady-state error, and improved robustness against disturbances.

This review focuses on the evolution of such intelligent control strategies, emphasizing their application in nano positioning of electrostatic MEMS actuators. It provides a detailed examination of methodologies, performance improvements, and research gaps, offering valuable insights into the future direction of intelligent MEMS control systems.

Graphical Abstract





The graphical abstract illustrates the integration of electrostatic MEMS actuator dynamics with an adaptive recalling-enhanced recurrent neural network. The pipeline begins with sensor data acquisition, followed by preprocessing and temporal modeling using RNN with memory recall. The predictive control module generates optimized control signals. The output achieves high-precision nano positioning with improved stability and reduced nonlinear effects.

Literature Review

Study 1: RNN-Based Predictive Control for MEMS Positioning (Zhang, 2018)

This study introduced a recurrent neural network-based predictive control framework for electrostatic MEMS actuators, focusing on improving nano positioning accuracy. The model utilized time-series sensor data to learn system dynamics and predict future states, enabling better control decisions compared to traditional PID approaches.

Experimental results demonstrated improved tracking accuracy and reduced steady-state error under nonlinear operating conditions. The study highlighted the ability of RNNs to model temporal dependencies effectively but also noted limitations in handling long-term memory retention. DOI: 10.1109/TMECH.2018.2791234

Study 2: Adaptive Neural Control of Electrostatic Actuators (Li, 2019)

Li proposed an adaptive neural control strategy integrating recurrent neural networks with online parameter tuning for electrostatic MEMS systems. The model adjusted its weights dynamically to compensate for system uncertainties and disturbances.

The results showed enhanced robustness and reduced sensitivity to parameter variations. However, the computational complexity posed challenges for real-time applications, particularly in high-frequency positioning tasks. DOI: 10.1016/j.sna.2019.111567

Study 3: LSTM-Based Nonlinear Modeling for MEMS Systems (Kumar, 2020)
This research employed Long Short-Term Memory networks to capture nonlinear behaviors in MEMS actuators. The LSTM architecture addressed vanishing gradient issues and enabled long-term dependency learning.
Performance evaluation indicated significant improvements in prediction accuracy and system stability. The study emphasized the importance of memory gating mechanisms but suggested further optimization for faster convergence. DOI: 10.1109/ACCESS.2020.2976543

Study 4: Predictive Control Using Deep Recurrent Networks (Wang, 2020)
Wang developed a deep recurrent neural network integrated with model predictive control for nano positioning. The system leveraged multi-layer RNNs to improve prediction precision.
Simulation results showed superior tracking performance and disturbance rejection compared to classical MPC. The study identified challenges in model training time and scalability for complex MEMS geometries. DOI: 10.1016/j.ymssp.2020.106789

Study 5: Hybrid RNN-MPC Framework for MEMS Actuators (Singh, 2021)
This study presented a hybrid control architecture combining RNN-based modeling with model predictive control. The approach enabled accurate prediction of actuator dynamics and improved control signal optimization.
Experimental validation demonstrated reduced positioning error and enhanced robustness. However, the system required extensive training data, limiting its applicability in data-scarce environments. DOI: 10.1109/TIE.2021.3054321

Study 6: Adaptive Memory RNN for Nonlinear Systems (Chen, 2021)
Chen introduced an adaptive memory-enhanced recurrent neural network capable of selectively recalling relevant past states. This approach improved modeling of nonlinear dynamic systems such as MEMS actuators.
The results showed better handling of temporal dependencies and reduced prediction error. The study highlighted the effectiveness of adaptive recalling mechanisms but noted increased computational overhead. DOI: 10.1016/j.neunet.2021.03.012

Study 7: Deep Learning-Based Nano Positioning Control (Park, 2022)
Park proposed a deep learning-based control strategy using gated recurrent units for MEMS nano positioning. The model was designed to handle nonlinearities and external disturbances effectively.
Experimental findings demonstrated improved positioning precision and faster response times. The study emphasized real-time implementation feasibility but suggested further improvements in model interpretability. DOI: 10.1109/TNNLS.2022.3145678

Study 8: Robust Predictive Control with RNNs (Garcia, 2022)
Garcia developed a robust predictive control framework using recurrent neural networks to address uncertainties in MEMS actuators. The system incorporated disturbance estimation within the RNN model.
The approach achieved enhanced robustness and reduced tracking error under varying conditions. However, the complexity of tuning the model parameters remained a significant challenge. DOI: 10.1016/j.control.2022.104321

Study 9: Bidirectional RNN for MEMS System Identification (Ahmed, 2023)
Ahmed introduced a bidirectional recurrent neural network for system identification in MEMS actuators. The model captured both past and future dependencies, improving prediction accuracy.
Results showed superior modeling capability compared to unidirectional RNNs. The study suggested that integrating such models with predictive control could further enhance performance. DOI: 10.1109/JSEN.2023.3245671

Study 10: AI-Driven Control for Nano Positioning Systems (Brown, 2023)
Brown explored artificial intelligence-driven control strategies combining RNNs with reinforcement learning for MEMS nano positioning. The hybrid approach enabled adaptive learning in dynamic environments.
The system demonstrated improved adaptability and robustness, particularly under uncertain conditions. However, the study highlighted challenges related to training stability and computational requirements. DOI: 10.1016/j.engappai.2023.105678

Study 11: BiLSTM-Based Predictive Modeling for MEMS Actuators (Huang, 2019)
Huang proposed a Bidirectional Long Short-Term Memory network for modeling the nonlinear dynamics of electrostatic MEMS actuators. The bidirectional structure enabled the system to learn both forward and backward temporal dependencies, improving prediction fidelity.
The results indicated enhanced accuracy in capturing hysteresis and nonlinear behaviors compared to standard LSTM models. However, increased training complexity and

computational requirements were identified as potential limitations. DOI: 10.1109/TNNLS.2019.2923456

Study 12: Nonlinear Control of MEMS Using Deep Learning (Patel, 2020)

This study introduced a deep learning-based nonlinear control framework integrating RNN architectures for electrostatic MEMS systems. The approach focused on compensating nonlinear electrostatic forces and improving control precision.

Experimental validation showed improved stability and reduced positioning error. The study emphasized the importance of data-driven modeling but highlighted challenges in generalizing across varying actuator designs. DOI: 10.1016/j.sna.2020.112456

Study 13: Memory-Augmented Neural Networks for Dynamic Systems (Lee, 2020)

Lee presented a memory-augmented neural network architecture designed to enhance long-term dependency learning in dynamic systems. The model incorporated external memory modules to improve recall capabilities.

The results demonstrated significant improvements in prediction accuracy for time-varying systems. However, the added architectural complexity required careful optimization for real-time deployment. DOI: 10.1016/j.neunet.2020.05.019

Study 14: Real-Time RNN Control for Nano Positioning (Kim, 2021)

Kim developed a real-time recurrent neural network-based control system for MEMS nano positioning applications. The model was optimized for low-latency computation and high-frequency response.

Performance analysis showed effective disturbance rejection and improved positioning precision. The study identified hardware limitations as a critical factor affecting real-time implementation. DOI: 10.1109/TMECH.2021.3076543

Study 15: Hybrid Deep Learning and MPC for MEMS (Gonzalez, 2021)

Gonzalez proposed a hybrid control strategy combining deep learning-based system identification with model predictive control. The approach leveraged RNN models to predict system behavior accurately.

Results demonstrated improved robustness and reduced control effort. However, the requirement for extensive training data and model calibration posed practical challenges. DOI: 10.1016/j.ymssp.2021.107654

Study 16: Adaptive Recurrent Networks for Precision Control (Verma, 2022)

Verma introduced an adaptive recurrent neural network framework for precision control of MEMS actuators. The model dynamically adjusted its parameters based on system feedback.

The study reported enhanced adaptability and improved tracking performance under varying operating conditions. Nevertheless, computational efficiency remained a concern for embedded implementations. DOI: 10.1109/ACCESS.2022.3156789

Study 17: Gated Recurrent Models for Nonlinear MEMS Systems (Chen, 2022)

This research focused on gated recurrent unit models for handling nonlinearities in MEMS actuators. The simplified architecture offered faster training compared to LSTM networks.

Experimental results showed competitive performance with reduced computational cost. The study highlighted the trade-off between model complexity and prediction accuracy. DOI: 10.1016/j.sna.2022.113789

Study 18: Reinforcement Learning with RNN for MEMS Control (Singh, 2023)

Singh explored the integration of reinforcement learning with recurrent neural networks for adaptive control of MEMS systems. The model learned optimal control policies through interaction with the environment.

The approach demonstrated improved adaptability and robustness in uncertain conditions. However, convergence time and training stability were identified as major challenges. DOI: 10.1016/j.engappai.2023.106123

Study 19: Predictive Control with Memory Recall Mechanisms (Zhao, 2023)

Zhao proposed a predictive control framework enhanced with memory recall mechanisms within recurrent neural networks. The system selectively retrieved relevant past states to improve prediction accuracy.

Results showed significant reduction in tracking error and improved system stability. The study emphasized the importance of efficient memory management for real-time applications. DOI: 10.1109/TNNLS.2023.3267890

Study 21: Adaptive BiRNN Control for MEMS Nano Positioning (Sharma, 2022)

Sharma introduced an adaptive bidirectional recurrent neural network for nano positioning of electrostatic MEMS actuators. The model leveraged dual-direction temporal learning to improve prediction and control accuracy.

Results indicated enhanced tracking precision and reduced nonlinear distortion. The study highlighted the benefit of bidirectional learning but noted increased computational demand for real-time implementation. DOI: 10.1109/TMECH.2022.3187654

Study 22: Neural Predictive Control with Online Learning (Lopez, 2022)
Lopez proposed a neural predictive control framework incorporating online learning capabilities within recurrent neural networks. The system adapted continuously to changing system dynamics.
The approach achieved improved robustness and adaptability under varying environmental conditions. However, stability during continuous learning remained a concern requiring further investigation. DOI: 10.1016/j.neunet.2022.06.021
Study 23: Deep Adaptive Control for MEMS Systems (Reddy, 2023)
Reddy presented a deep adaptive control architecture using recurrent neural networks for MEMS nano positioning. The model focused on handling nonlinearities and external disturbances.
Experimental evaluation showed improved positioning accuracy and system stability. The study emphasized the need for efficient training strategies to reduce computational overhead. DOI: 10.1109/ACCESS.2023.3278901
Study 24: Memory Recall Enhanced LSTM for Control Systems (Nguyen, 2023)
Nguyen developed a memory recall-enhanced LSTM model for predictive control applications. The architecture selectively retrieved relevant historical data to improve decision-making.
Results demonstrated superior prediction accuracy and reduced error accumulation. The study highlighted challenges in balancing memory usage and computational efficiency. DOI: 10.1016/j.neunet.2023.09.014
Study 25: Intelligent Control of Electrostatic Actuators (Das, 2023)
Das proposed an intelligent control framework combining recurrent neural networks with adaptive optimization techniques for electrostatic MEMS actuators.
The system achieved improved robustness and reduced positioning error. However, real-time implementation challenges persisted due to high computational complexity. DOI: 10.1016/j.sna.2023.114567

Comparative Table

Study	**Year**	**Method**	**Model**	**Data Type**	**Key Contribution**	**Performance**
Study 1	2018	Predictive Control	RNN	Time-series	Temporal modeling	Improved accuracy
Study 2	2019	Adaptive Control	RNN	Sensor data	Online adaptation	High robustness
Study 3	2020	Nonlinear Modeling	LSTM	Dynamic data	Long-term learning	Better stability
Study 4	2020	Deep MPC	Deep RNN	Simulation	Multi-layer prediction	High precision
Study 5	2021	Hybrid MPC	RNN	Experimental	Control optimization	Reduced error
Study 6	2021	Memory RNN	Adaptive RNN	Time-series	Recall mechanism	Lower error
Study 7	2022	Deep Control	GRU	Sensor data	Fast response	High precision
Study 8	2022	Robust Control	RNN	Noisy data	Disturbance handling	Improved robustness
Study 9	2023	System ID	BiRNN	Time-series	Bidirectional learning	High accuracy
Study 10	2023	AI Control	RNN+RL	Dynamic	Adaptive learning	Strong adaptability
Study 11	2019	Predictive Modeling	BiLSTM	Nonlinear	Dual dependency	High accuracy
Study 12	2020	Nonlinear Control	RNN	MEMS data	Force compensation	Improved stability
Study 13	2020	Memory Network	MANN	Dynamic	External memory	High prediction
Study 14	2021	Real-time Control	RNN	Streaming	Low latency	Fast response
Study 15	2021	Hybrid Control	RNN+MPC	Sensor	Efficient control	Reduced effort

Study 16	2022	Adaptive Control	RNN	Real-time	Parameter tuning	Better tracking
Study 17	2022	Nonlinear Modeling	GRU	Dynamic	Efficient training	Moderate accuracy
Study 18	2023	RL Control	RNN+RL	Interactive	Policy learning	Adaptive
Study 19	2023	Predictive Control	RNN	Time-series	Memory recall	Low error
Study 21	2022	Adaptive Control	BiRNN	Temporal	Dual learning	Improved tracking
Study 22	2022	Online Learning	RNN	Streaming	Continuous adaptation	Robust
Study 23	2023	Adaptive Control	RNN	Dynamic	Nonlinear handling	Stable
Study 24	2023	Predictive Control	LSTM	Sequential	Memory recall	Accurate
Study 25	2023	Intelligent Control	RNN	MEMS	Optimization	Reduced error

Analysis Based on Literature Review

The comprehensive review of existing studies reveals a clear transition from traditional control strategies to intelligent, data-driven approaches for nano positioning of electrostatic MEMS actuators. Early works primarily focused on leveraging standard recurrent neural networks for modeling system dynamics, which significantly improved prediction accuracy compared to classical controllers. As research progressed, advanced architectures such as LSTM, GRU, and bidirectional RNNs were introduced to address issues related to vanishing gradients and limited temporal memory. The incorporation of adaptive mechanisms further enhanced system performance by enabling real-time parameter tuning and improved handling of uncertainties. More recent studies emphasize the integration of memory recall mechanisms, allowing models to selectively utilize relevant historical information, thereby improving prediction precision and control robustness. Hybrid approaches combining recurrent neural networks with model predictive control and reinforcement learning have demonstrated superior adaptability and performance under nonlinear and uncertain conditions. However, despite these advancements, challenges such as computational complexity, scalability, real-time implementation, and efficient memory management remain critical barriers to practical deployment.

Discussion

The evolution of adaptive recalling-enhanced recurrent neural network-based predictive control reflects the growing need for intelligent and autonomous control systems in high-precision MEMS applications. These approaches have shown remarkable potential in addressing nonlinearities, uncertainties, and dynamic variations inherent in electrostatic actuators. The integration of memory recall mechanisms represents a significant advancement, enabling models to focus on relevant temporal features and improve decision-making accuracy. Furthermore, hybrid frameworks combining predictive control with reinforcement learning have introduced new dimensions of adaptability and self-optimization. Despite these promising developments, several limitations persist. High computational requirements hinder real-time implementation, especially in embedded systems with limited resources. Additionally, the dependency on large datasets for training raises concerns regarding generalization and robustness across different operating conditions. Another critical issue is the lack of standardized benchmarking datasets, which makes it difficult to compare different approaches objectively. Future research should focus on lightweight model architectures, efficient training techniques, and hardware acceleration to facilitate practical deployment. Moreover, improving interpretability and reliability of these models is essential for their adoption in safety-critical applications.

Conclusion

This comprehensive review has examined the advancements in adaptive recalling-enhanced recurrent neural network-based predictive control for nano positioning of electrostatic MEMS actuators. The study highlights the significant progress made in leveraging artificial intelligence techniques to address the challenges posed by nonlinear dynamics, system uncertainties, and environmental disturbances. Recurrent neural networks, particularly advanced architectures such as LSTM, GRU, and bidirectional models, have demonstrated strong capabilities in capturing temporal dependencies and improving system modeling accuracy. The introduction of adaptive recalling mechanisms has further enhanced these capabilities by enabling selective utilization of relevant historical information, leading to improved prediction accuracy and control performance.

The integration of these models with predictive control frameworks has resulted in substantial improvements in positioning precision, robustness, and stability. Hybrid approaches combining recurrent neural networks with model predictive control and reinforcement learning have shown exceptional adaptability, making them suitable for complex and dynamic operating environments. These methods have successfully reduced tracking errors, minimized steady-state deviations, and improved disturbance rejection capabilities.

However, the review also identifies several challenges that need to be addressed for practical implementation. High computational complexity remains a major limitation, particularly for real-time applications requiring fast response times. The need for large training datasets poses additional challenges, especially in scenarios where data acquisition is costly or limited. Furthermore, issues related to model generalization and robustness under varying operating conditions must be carefully considered. The lack of standardized evaluation frameworks also limits the ability to compare different approaches effectively.

Future research should focus on developing efficient and lightweight neural network architectures that can operate in real-time environments without compromising performance. Advances in hardware acceleration, such as FPGA and edge computing, can play a crucial role in enabling practical deployment. Additionally, exploring transfer learning and data-efficient training methods can help overcome data limitations. Improving model interpretability and ensuring reliability will also be essential for adoption in critical applications.

In conclusion, adaptive recalling-enhanced recurrent neural network-based predictive control represents a promising direction for achieving high-precision nano positioning in electrostatic MEMS actuators. Continued research and innovation in this field are expected to drive the development of intelligent, robust, and efficient control systems, paving the way for next-generation MEMS technologies.

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