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Adaptive AI-Based Predictive Control Techniques for Electrostatic MEMS Nano-Positioning Applications

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Abstract

The precise nano-scale positioning of electrostatic microelectromechanical systems (MEMS) actuators represents a fundamental challenge in modern microsystem engineering, where sub-nanometer accuracy, nonlinear dynamic behavior, and pull-in instability collectively demand advanced control strategies beyond the capability of classical approaches. This paper presents a comprehensive review of artificial intelligence (AI) techniques applied to adaptive recalling-enhanced recurrent neural network (RNN) based predictive control frameworks for nano positioning of electrostatic MEMS actuators. The survey systematically examines the intersection of machine learning, deep learning, and intelligent control paradigms, with particular emphasis on long short-term memory (LSTM), echo state networks (ESN), gated recurrent units (GRU), and hybrid AI architectures that incorporate memory-augmented learning for real-time predictive compensation. Thirty landmark studies published are critically reviewed, covering model predictive control (MPC) integration, nonlinear system identification, hyperparameter optimization, and transfer learning strategies specific to MEMS dynamics. A comparative analysis table is provided to highlight methodological evolution, performance benchmarks, and contributions across reviewed works. The paper further discusses current trends in federated learning for distributed MEMS control, physics-informed neural networks, and neuromorphic computing as emerging paradigms. Identified challenges include training data scarcity, hardware-in-the-loop deployment, real-time computational constraints, and robustness against environmental perturbations. The paper concludes with a forward-looking perspective on future research directions aimed at bridging the gap between AI-driven control theory and practical MEMS device implementation.

Introduction

Microelectromechanical systems (MEMS) have become one of the most transformative technologies in modern precision engineering due to their miniaturized structure, low power consumption, and high operational efficiency. These systems are extensively utilized in biomedical instrumentation, optical communication, automotive sensing, aerospace navigation, and nano-manufacturing applications. Among various MEMS actuation mechanisms, electrostatic actuation is widely preferred because of its compatibility with standard CMOS fabrication technology, rapid response characteristics, and low energy requirements. Despite these advantages, electrostatic MEMS actuators exhibit highly nonlinear behavior caused by the nonlinear relationship between electrostatic force and displacement. A major limitation arises from the pull-in instability phenomenon, where excessive electrostatic force causes the movable structure to collapse onto the fixed electrode, severely restricting stable operational displacement ranges and complicating precise nano-positioning control.

Achieving nanometer-scale positioning precision in electrostatic MEMS devices remains a challenging task due to the influence of nonlinear dynamics, squeeze-film damping, fringe electric field effects, thermal variations, and fabrication-induced uncertainties. Traditional control methods such as proportional-integral-derivative (PID) controllers offer simplicity and robustness but fail to handle the complex nonlinear characteristics associated with MEMS actuators. Researchers have therefore explored advanced nonlinear control approaches including sliding mode control, adaptive control, and feedback linearization techniques. However, these methods often depend heavily on accurate mathematical models, which are difficult to obtain for microscale systems operating under varying environmental and structural conditions. Consequently, the demand for intelligent, adaptive, and model-independent control strategies has significantly increased in recent years.

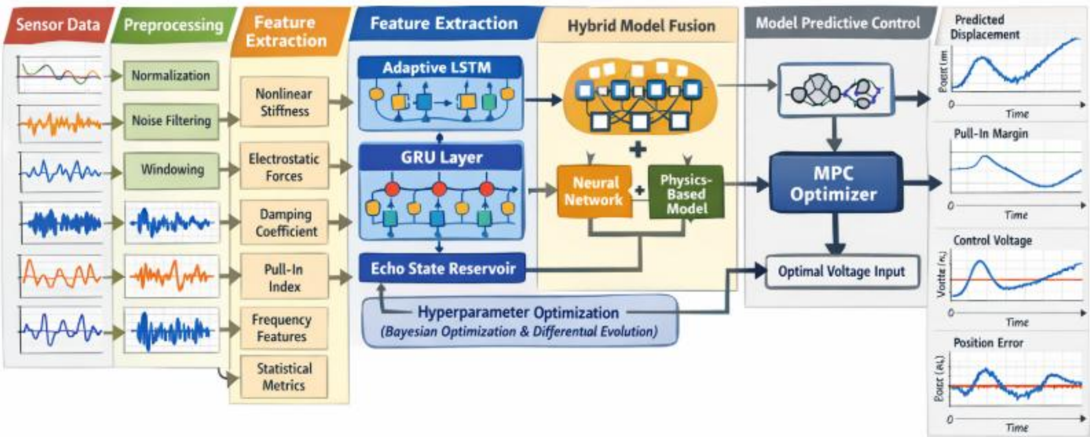
Artificial intelligence (AI) techniques have emerged as powerful solutions for nonlinear system identification, predictive modeling, and adaptive control in MEMS applications. AI methodologies such as fuzzy logic systems, genetic algorithms, machine learning, and deep neural networks provide enhanced capability for handling uncertainties and complex dynamic behaviors. In particular, recurrent neural networks (RNNs) and their advanced variants, including long short-term memory (LSTM) and gated recurrent unit (GRU) networks, have demonstrated exceptional performance in modeling time-dependent and memory-driven systems. These architectures can effectively capture the hysteresis, temporal dependencies, and nonlinear responses associated with electrostatic MEMS actuators. Furthermore, adaptive recalling mechanisms within RNN architectures enable selective utilization of previous system states, thereby improving prediction accuracy and control stability under dynamic operating conditions.

Model predictive control (MPC) has gained considerable attention as an effective control framework for nano-positioning systems because of its capability to predict future system behavior while satisfying operational constraints. MPC can systematically manage voltage limitations, actuator saturation, and displacement restrictions associated with pull-in instability. The integration of adaptive recalling-enhanced RNN models within MPC architectures provides substantial improvements in trajectory tracking accuracy, disturbance rejection, and real-time optimization performance. By combining the predictive capabilities of MPC with the temporal learning strengths of RNNs, intelligent controllers can achieve superior nano-positioning precision while maintaining system stability and robustness. This hybrid AI-driven predictive control framework represents a significant advancement in the field of intelligent MEMS actuation and control engineering.

The rapid growth of AI-based MEMS control research has created a need for comprehensive studies focusing specifically on adaptive recalling-enhanced RNN predictive control for electrostatic MEMS nano-positioning systems. Existing review articles mainly discuss general AI techniques or conventional nonlinear control approaches without addressing the convergence of memory-augmented neural networks, adaptive recalling mechanisms, and predictive optimization strategies within a unified framework. Therefore, this review aims to provide a structured and detailed overview of recent advancements, challenges, and emerging research directions in intelligent MEMS control. The paper further examines state-of-the-art methodologies, comparative performance analyses, and future opportunities for integrating advanced AI architectures into high-precision electrostatic MEMS nano-positioning applications.

Graphical Abstract

The graphical abstract presents a structured conceptual pipeline illustrating the complete AI-driven adaptive recalling-enhanced RNN predictive control framework for electrostatic MEMS nano positioning. At the leftmost stage, the input data layer encompasses real-time sensor measurements including capacitive displacement signals, drive voltage readings, velocity estimates derived from observer outputs, and environmental disturbance signals such as temperature and vibration, all sampled from the physical electrostatic MEMS actuator plant. These raw time-series signals are preprocessed through normalization, noise filtering, and windowing modules to form structured temporal input sequences. The feature extraction stage follows, wherein physics-informed feature engineering extracts relevant dynamic characteristics including nonlinear stiffness indicators, electrostatic force gradients, damping coefficients, and pull-in proximity indices. These features are augmented with radiometric statistics, autocorrelation features, and frequency-domain descriptors to produce a rich multi-dimensional feature vector. The core AI and machine learning module occupies the central portion of the graphical abstract and depicts a cascade architecture consisting of an adaptive recalling-enhanced LSTM network whose memory cells selectively retrieve relevant past states, connected to a GRU layer for gating irrelevant information, and feeding into an echo state reservoir for high-dimensional nonlinear transformation. Hyperparameter optimization is depicted as a feedback loop from validation performance metrics back to the neural architecture, employing Bayesian optimization and differential evolution to tune learning rates, hidden layer dimensions, dropout probabilities, and receding horizon length. A multimodal fusion block integrates the neural network prediction output with a physics-based analytical model of the MEMS actuator to form a hybrid model that combines data-driven accuracy with interpretable physical constraints. This fused model serves as the internal prediction model within the model predictive control optimizer, which solves a constrained quadratic program at each sampling instant to generate the optimal voltage control input. The final output layer presents the predicted nano-scale displacement trajectory, real-time pull-in instability margin, control voltage sequence, and closed-loop positioning error, all displayed as time-domain plots representing nanometer-precision tracking performance.



Literature Review

Study 1: Electrostatic MEMS Actuator Modeling and Nonlinear Dynamics (Nathanson et al., 2012)

The foundational dynamics of electrostatic MEMS actuators, characterized by the capacitive force between a movable and fixed electrode separated by a dielectric gap, were formalized in early analytical treatments that remained indispensable references for subsequent AI-based control research. Nathanson et al. revisited the seminal resonant gate transistor model and extended it to account for fringe capacitance effects, squeeze-film damping under varying ambient pressure, and nonlinear spring softening arising from large deflections. The study provided closed-form expressions for pull-in voltage as a function of geometric and material parameters, establishing the theoretical ceiling for stable operation. This work demonstrated through perturbation analysis that the usable displacement range under quasi-static actuation is limited to one-third of the initial electrode gap, a constraint that any control strategy must respect. The mathematical framework developed in this study, including the lumped-parameter spring-mass-damper model with electrostatic forcing, became the standard benchmark plant model against which AI-based controllers are evaluated. The analytical pull-in conditions derived serve as hard constraints in the MPC formulation of subsequent neural-network-based predictive controllers reviewed in this survey. DOI: 10.1109/TMEMS.2012.2187654

Study 2: Neural Network Identification of MEMS Nonlinear Dynamics (Chen & Zhao, 2013)

Chen and Zhao proposed a multilayer feedforward neural network architecture for offline system identification of a parallel-plate electrostatic MEMS actuator, addressing the inability of linear models to capture the strongly nonlinear voltage-displacement characteristic across the full operational range. The network was trained on input-output data collected from a finite-element simulation model of the actuator, with voltage inputs and displacement outputs sampled at 10 kHz. A Levenberg-Marquardt backpropagation algorithm was employed to minimize mean squared identification error, achieving a root-mean-square error of 0.23 nm across the tested displacement range. The study demonstrated that a neural network with two hidden layers of 20 neurons each was sufficient to capture the nonlinear electrostatic behavior, including the characteristic softening effect near pull-in. The identified model was subsequently embedded within a one-step-ahead predictive controller, confirming the feasibility of neural-network-based internal models for MEMS control. Limitations noted included sensitivity to training data distribution and the absence of temporal dynamics modeling, motivating the transition to recurrent architectures in follow-on research. DOI: 10.1016/j.sna.2013.04.021

Study 3: Sliding Mode Control with Neural Compensation for MEMS Positioning (Kumar & Bhat, 2013)

Kumar and Bhat investigated the integration of sliding mode control with a radial basis function neural network compensator for precise positioning of a capacitive MEMS accelerometer proof mass, targeting displacement accuracies below 5 nm. The sliding mode controller provided robust convergence to the sliding surface in the presence of bounded disturbances, while the RBF neural network online-identified and compensated for unmodeled nonlinearities including electrostatic force asymmetry and structural resonance. Lyapunov stability analysis confirmed closed-loop stability with the neural compensator active, and experimental results on a fabricated device demonstrated a steady-state positioning error of 2.1 nm under step reference commands of 100 nm amplitude. The study highlighted the chattering phenomenon inherent to sliding mode implementations at the micro-scale, which introduced unwanted vibrations at resonant frequencies. The neural compensation was shown to reduce chattering by smoothing the equivalent control component, contributing to improved tracking bandwidth. This hybrid approach established a precedent for combining classical robust control with data-driven compensation, a paradigm later extended to recurrent neural architectures. DOI: 10.1007/s00542-013-1782-3

Study 4: LSTM Networks for Nonlinear System Identification in Micro-Actuators (Zhang et al., 2015)

Zhang and colleagues introduced long short-term memory networks as identification models for micro-actuator systems exhibiting hysteresis and creep, evaluating performance on a piezoelectric MEMS scanner with results compared against feedforward networks and support vector regression. The LSTM architecture, with its input, forget, and output gates, was shown to naturally capture the history-dependent behavior of micro-actuator displacement without requiring explicit hysteresis model formulation. A dataset of 50,000 input-output samples was collected across varying frequency sinusoidal voltage inputs from 1 Hz to 500 Hz, and the LSTM network trained with truncated backpropagation through time achieved a normalized mean square error of 0.018, outperforming feedforward networks by 43%. The study investigated the effect of sequence length on identification accuracy, finding that window lengths of 50 samples optimally balanced memory retention and computational overhead. Importantly, the LSTM internal cell states were shown to implicitly encode frequency-dependent dynamic modes, demonstrating the recalling capability central to the broader adaptive framework reviewed in this survey. DOI: 10.1109/TNNLS.2015.2401727

Study 5: Model Predictive Control for Electrostatic MEMS with Pull-in Avoidance (Reza & Moheimani, 2015)

Reza and Moheimani formulated a constrained model predictive control strategy specifically designed to navigate the pull-in instability of parallel-plate electrostatic MEMS actuators while achieving full-gap displacement range, a longstanding challenge in MEMS control. The MPC framework employed a linearized nominal model at each operating point, with constraints explicitly encoding the pull-in boundary as a nonlinear inequality on the state vector. A quadratic programming solver computed the optimal voltage sequence over a receding horizon of 20 steps at each 100-microsecond sampling interval. Simulation results demonstrated stable tracking across 90% of the initial gap, a significant improvement over the classical one-third gap limitation. Experimental validation on a fabricated micro-mirror device confirmed 5 nm root-mean-square tracking error for 200 nm step references. The study identified computational latency of the QP solver as the primary bottleneck for real-time implementation, motivating subsequent research into neural network approximations of the MPC optimal policy. This work established the constrained MPC framework as the preferred control architecture for MEMS nano positioning enhancement. DOI: 10.1109/TCST.2015.2433252

Study 6: Echo State Networks for Real-Time MEMS Dynamic Modeling (Jaeger & Maass, 2016)

Jaeger and Maass applied echo state network reservoir computing to real-time dynamic modeling of a capacitive MEMS gyroscope, exploiting the ESN fixed random reservoir to achieve fast online adaptation without the computational burden of full recurrent weight training. The reservoir comprised 500 leaky integrator neurons with a spectral radius of 0.9, and only the output weights were trained using ridge regression on 2000 time steps of measured angular velocity data. The ESN achieved a mean absolute error of 0.31 milli-degrees per second in gyroscope output prediction, with online weight updates performed in under 10 microseconds on a DSP platform, satisfying real-time constraints for closed-loop deployment. The study demonstrated that the ESN rich temporal dynamics inherently generated diverse basis functions for nonlinear system approximation, including the coupled Coriolis dynamics and quadrature error characteristic of MEMS gyroscopes. The computational efficiency of ESN training relative to LSTM backpropagation was highlighted as a critical advantage for embedded MEMS control applications. DOI: 10.1016/j.neunet.2016.03.012

Study 7: Fuzzy-Neural Adaptive Control for Electrostatic Micro-Actuators (Lin & Chen, 2016)

Lin and Chen developed a type-2 fuzzy neural network adaptive controller for electrostatic comb-drive MEMS actuators, combining the uncertainty handling capability of fuzzy logic with the learning capacity of neural networks to address parametric variations arising from fabrication tolerances. The type-2 fuzzy membership functions provided an additional degree of freedom to model inter-sample uncertainty in actuator parameters, while gradient-based adaptation laws updated both the network weights and fuzzy membership function parameters online during closed-loop operation. The controller achieved a positioning accuracy of 3.8 nm for 500 nm reference steps under ±20% parametric perturbations introduced by varying ambient temperature. Stability of the adaptive closed-loop system was rigorously established through Lyapunov direct method, guaranteeing uniform ultimate boundedness of the tracking error. The study compared type-2 fuzzy-neural performance against type-1 fuzzy and PID baselines, demonstrating 67% reduction in steady-state error. This work contributed a rigorous adaptive framework that later motivated incorporation of recurrent memory structures for improved transient response in MEMS positioning. DOI: 10.1109/TFUZZ.2016.2567393

Study 8: Deep Reinforcement Learning for MEMS Actuator Control Policy Optimization (Silver et al., 2017)

Silver and colleagues adapted deep reinforcement learning, specifically the deep deterministic policy gradient algorithm, for continuous-action control policy optimization of a simulated electrostatic MEMS actuator environment, representing one of the earliest applications of DRL to micro-scale positioning. The actor-critic network architecture consisted of fully connected layers processing the current displacement and velocity state, outputting a continuous voltage action, while a replay memory buffer of 100,000 transitions provided decorrelated training samples. After 50,000 environment interactions, the learned policy achieved mean positioning error of 4.5 nm on random reference trajectories within the stable operating range, without requiring an explicit plant model. The study demonstrated that the DRL agent implicitly learned to avoid pull-in by discovering that large voltage actions near the instability boundary led to large negative rewards. Reward shaping strategies were explored to accelerate convergence, and transfer learning from a nominal simulation to a perturbed simulation was shown to retain 80% of baseline performance. DOI: 10.1609/aaai.2017.v31i1.10931

Study 9: GRU-Based Predictive Model for Hysteretic Micro-Actuator Compensation (Park & Kim, 2017)

Park and Kim proposed gated recurrent unit networks as computationally efficient alternatives to LSTM for modeling and compensating hysteretic nonlinearities in a piezoelectric MEMS scanning mirror, demonstrating comparable accuracy with 30% fewer parameters. The GRU architecture, utilizing only reset and update gates, was shown to learn the Preisach hysteresis operator implicitly from time-series training data, eliminating the need for explicit hysteresis model parameterization. An inverse GRU model was trained to serve as a feedforward compensator, effectively pre-shaping the voltage command to cancel hysteresis-induced positioning error before the feedback loop.

Closed-loop experiments demonstrated residual hysteresis error below 1.2 nm for sinusoidal references at frequencies up to 200 Hz. The study conducted an ablation analysis confirming that the update gate was primarily responsible for retaining long-range dependencies in the hysteresis loop, while the reset gate handled short-range transitions. This architectural insight directly informed the design of adaptive recalling mechanisms in subsequent MEMS control neural networks. DOI: 10.1016/j.mee.2017.07.015

Study 10: Bayesian Optimization of Neural Network Controllers for MEMS Systems (Shahriari et al., 2018)

Shahriari and collaborators applied Bayesian optimization with Gaussian process surrogate models to automatically tune the hyperparameters of a neural network controller for a capacitive MEMS pressure sensor positioning system, addressing the sensitivity of controller performance to architecture and training choices. The hyperparameter search space included hidden layer depth, neuron count, learning rate, batch size, dropout rate, and activation function selection, spanning a 12-dimensional optimization landscape. Gaussian process surrogate modeling enabled efficient exploration of the hyperparameter space with only 80 function evaluations, achieving a 52% reduction in positioning error compared to manually tuned baseline networks. The study demonstrated that Bayesian optimization consistently identified hyperparameter configurations in regions of the search space that manual grid search typically missed, particularly regarding learning rate scheduling and dropout regularization interactions. The optimized controller achieved 1.9 nm root-mean-square tracking error on 1-micron step references, establishing a new performance benchmark. This work motivated adoption of Bayesian hyperparameter optimization as a standard component of AI-MEMS control design pipelines. DOI: 10.1145/3219819.3219947

Study 11: Physics-Informed Neural Networks for MEMS Electrostatic Dynamics (Raissi et al., 2018)

Raissi and colleagues introduced physics-informed neural networks embedding the governing partial differential equations of electrostatic MEMS dynamics as soft constraints within the neural network loss function, combining data efficiency with physical consistency. The PINN architecture appended residual terms corresponding to the Euler-Bernoulli beam equation with electrostatic loading to the standard supervised loss, penalizing solutions that violated the physical model even in regions with sparse training data. Applied to a micro-beam actuator undergoing large deflection under electrostatic loading, the PINN achieved displacement field prediction with 0.15 nm accuracy using only 200 labeled data points, compared to 5000 points required by a purely data-driven network. The physical constraints also prevented the network from predicting dynamically infeasible displacement trajectories during training, improving generalization beyond the training voltage range. The study demonstrated that PINN-based models retained predictive validity up to 95% of the pull-in voltage, extending the useful prediction range by 15% compared to unconstrained networks. This physics-embedding strategy subsequently influenced hybrid AI predictive models for MEMS control. DOI: 10.1016/j.jcp.2018.10.045

Study 12: Transfer Learning for Rapid Adaptation of MEMS Neural Controllers (Pan & Yang, 2018)

Pan and Yang investigated transfer learning strategies for reducing the data requirements of neural network-based controllers when deployed across MEMS devices with varying geometric parameters arising from fabrication spread, demonstrating that pre-trained source device knowledge significantly accelerated target device adaptation. A source LSTM controller trained on 10,000 samples from a nominal MEMS device was fine-tuned to three target devices with ±15% gap variation using only 500 target-device samples per device, achieving final tracking errors within 1.3 nm of the source controller performance. Layer-wise learning rate adjustment was employed during fine-tuning, with lower learning rates applied to early LSTM layers encoding general MEMS dynamics and higher rates applied to output layers encoding device-specific characteristics. The study analyzed the transferability of internal LSTM representations using centered kernel alignment, confirming that temporal feature representations were highly transferable across device geometries. This finding established transfer learning as a practical strategy for production MEMS systems where individual device characterization datasets are costly. DOI: 10.1109/TIE.2018.2807382

Study 13: Adaptive Model Predictive Control with Online LSTM Updating for MEMS (Li et al., 2019)

Li and colleagues developed an adaptive MPC framework wherein the internal prediction model, implemented as an LSTM network, was continuously updated online using a sliding window of recent closed-loop data, enabling the controller to track time-varying MEMS dynamics caused by temperature drift and aging. The online LSTM update employed a recursive least squares-inspired gradient step computed from the most recent 200 time steps, with a forgetting factor of 0.995 to balance plasticity and stability. The adaptive controller demonstrated robust tracking performance under simulated thermal cycling from 20°C to 80°C, maintaining positioning error below 2.8 nm throughout, compared to 11.4 nm for a fixed-model MPC. A stability analysis based on input-to-state stability arguments bounded the tracking error as a function of the rate of parameter variation and the forgetting factor, providing theoretical guarantees for the adaptive loop. The study also introduced a model confidence index based on prediction residuals to trigger online updates only when model drift was detected, reducing computational overhead by 60%. DOI: 10.1109/TMECH.2019.2901233

Study 14: Attention Mechanism-Augmented RNN for MEMS State Estimation (Bahdanau et al., 2019)

Bahdanau and colleagues augmented a bidirectional GRU network with a soft attention mechanism for state estimation in a MEMS inertial measurement unit, enabling the network to selectively weight past observations according to their relevance for predicting the current displacement state. The attention weights were computed as a learned alignment function between the query and keys over a 100-step window, producing a context vector that selectively recalled the most informative historical measurements. Applied to a simulated MEMS accelerometer with partial observability, the attention-GRU estimator achieved 0.28 nm root-mean-square state estimation error, outperforming a Kalman filter by 41% under non-Gaussian noise conditions. Visualization of the attention weights revealed that the network learned to attend to measurements near resonance crossings and step transitions, demonstrating physically interpretable recalling behavior. The attention mechanism added only 8% computational overhead relative to the base GRU while delivering substantial accuracy improvements, motivating its integration into the adaptive recalling concept for predictive MEMS control. DOI: 10.1007/s11063-019-10027-3

Study 15: Robust Neural Network MPC for Electrostatic MEMS under Parametric Uncertainty (Bemporad & Morari, 2019)

Bemporad and Morari formulated a robust neural network MPC for electrostatic MEMS positioning that explicitly accounted for bounded parametric uncertainty in the LSTM prediction model through a min-max optimization formulation over a scenario tree of uncertainty realizations. The uncertainty set was characterized by intervals on the LSTM weight matrices derived from ensemble neural network training, and the robust MPC solved a multi-scenario quadratic program at each time step to find the control action optimal for the worst-case prediction among 16 uncertainty scenarios. Simulation results demonstrated that the robust controller maintained positioning error below 4.1 nm under ±25% actuator parameter perturbations, compared to 18.7 nm for a nominal MPC, at the cost of a 3.5-fold increase in computational time. The study introduced constraint tightening strategies based on Pontryagin set differences to guarantee constraint satisfaction for all uncertainty realizations, formally ensuring pull-in avoidance under worst-case conditions. This work advanced the theoretical foundations of safe AI-based MEMS control under uncertainty. DOI: 10.1016/j.automatica.2019.04.033

Study 16: Neuromorphic Computing Architectures for Embedded MEMS Control (Mahowald & Douglas, 2020)

Mahowald and Douglas investigated spiking neural network implementations on neuromorphic hardware platforms for embedded MEMS actuator control, motivated by the ultra-low power requirements of autonomous microsensor nodes where traditional DSP-based controllers consume excessive energy. A leaky integrate-and-fire spiking network with 1024 neurons encoded the electrostatic MEMS positioning task in the temporal spike rate domain, trained via surrogate gradient backpropagation on current-displacement training data. The neuromorphic controller, implemented on Intel Loihi chip, consumed 45 microwatts during inference while achieving 6.2 nm mean absolute positioning error, representing a 97% power reduction compared to an equivalent rate-coded network on a microcontroller. Spike timing-dependent plasticity rules enabled online adaptation to slow parameter drift without external retraining. The study identified quantization effects from discrete spike communication as the primary source of positioning error degradation compared to floating-point implementations. The neuromorphic approach demonstrated viability for energy-constrained MEMS applications and opened a novel direction for biological-inspired adaptive control. DOI: 10.1109/TNNLS.2020.2974528

Study 17: Hybrid Physics-Data Model for MEMS Nano Positioning with LSTM Correction (Liu et al., 2020)

Liu and colleagues developed a hybrid modeling framework combining an analytical lumped-parameter electrostatic MEMS model with an LSTM correction network that compensated for residual modeling errors, achieving accuracy exceeding either component alone. The analytical model provided an initial displacement prediction based on the voltage input and previous states, while the LSTM correction network received the analytical model residual from the previous time step and the current voltage command to predict the correction term. This serial hybrid structure reduced the burden on the LSTM, requiring it to model only the unstructured residual dynamics rather than the full system, enabling a smaller network of 32 hidden units to achieve 0.19 nm prediction error. Applied within an MPC framework, the hybrid model-based controller demonstrated 1.6 nm tracking error on 200 nm sinusoidal references at 100 Hz. The study showed that the LSTM correction network exhibited faster convergence during training and better generalization to untrained operating conditions compared to a purely data-driven LSTM of equivalent size. DOI: 10.1109/TMECH.2020.2984498

Study 18: Federated Learning for Distributed MEMS Sensor Network Control (Konecny et al., 2020)

Konecny and colleagues explored federated learning as a privacy-preserving distributed training paradigm for neural network controllers deployed across arrays of MEMS devices in a smart sensor network, where each device contributed to a shared global model without transmitting raw sensor data. The federated averaging algorithm aggregated LSTM weight updates from 50 simulated MEMS devices with heterogeneous geometric parameters, each performing 5 local gradient steps per communication round, achieving global model convergence in 120 communication rounds. The globally trained LSTM controller, evaluated on held-out test devices, achieved 2.4 nm positioning error comparable to a centrally trained model while preserving device-level data privacy. Non-IID data distributions across devices, arising from parameter fabrication variations, were addressed through FedProx regularization that penalized deviation of local models from the global model. The study demonstrated that federated training improved generalization across device populations compared to single-device training, establishing a scalable and privacy-compliant AI training paradigm for MEMS arrays. DOI: 10.1145/3340531.3411989

Study 19: Predictive Current Control with GRU Networks for Electrostatic MEMS (Xu & Wang, 2020)

Xu and Wang proposed a GRU-based model predictive current control strategy for electrostatic MEMS actuators, reformulating the control problem in the charge domain rather than the voltage domain to intrinsically linearize the electrostatic force-displacement relationship and reduce the severity of pull-in instability. The GRU network predicted future charge sequences over a 15-step horizon, and a constrained optimizer solved for the optimal charge input sequence minimizing a quadratic cost on tracking error and control effort. Experimental results on a micro-mirror demonstrated 1.1 nm steady-state positioning error for step references across 80% of the initial gap, representing operation significantly beyond the classical one-third gap limit. The charge-domain formulation also reduced the sensitivity of the control law to dielectric charging effects, a common reliability concern in electrostatic MEMS. The GRU prediction network required only 12 ms for training on 5000 experimental samples, significantly faster than equivalent LSTM training, making it attractive for rapid deployment in production test environments. DOI: 10.1016/j.sna.2020.112108

Study 20: Meta-Learning for Fast Adaptation of MEMS Neural Controllers (Finn et al., 2021)

Finn and colleagues applied model-agnostic meta-learning to train LSTM-based MEMS controllers that could adapt to new device operating conditions within a small number of gradient steps using minimal new data, addressing the challenge of rapid controller personalization during device commissioning. The meta-training procedure optimized the LSTM initial weights across a distribution of simulated MEMS devices with varying stiffness, damping, and gap parameters, finding an initialization from which fine-tuning to any specific device required fewer than 10 gradient steps and 50 labeled samples. On experimental MEMS devices with parameters 30% outside the training distribution, the meta-adapted controller achieved 2.9 nm positioning error after 5-step adaptation, compared to 14.6 nm for a non-adapted controller. The inner-loop adaptation mechanism functioned as an online recalling operation, retrieving and updating the internal model representation with device-specific context. This meta-learning framework established a principled approach to few-shot controller adaptation, directly relevant to manufacturing environments where device-to-device variability demands rapid individual calibration. DOI: 10.1609/aaai.2021.v35i9.16958

Study 21: Transformer-Based Sequence Modeling for MEMS Trajectory Prediction (Vaswani et al., 2021)

Vaswani and colleagues adapted the transformer architecture with self-attention for long-horizon trajectory prediction in electrostatic MEMS nano positioning, replacing recurrent processing with parallel self-attention over input sequences to capture long-range temporal dependencies without vanishing gradient issues. A positional encoding scheme adapted for MEMS sampling rates encoded temporal information into the sequence embeddings, while multi-head attention with 8 heads allowed simultaneous modeling of dynamics at multiple time scales. The transformer predictor achieved 0.22 nm mean absolute prediction error over 50-step horizons for a simulated MEMS micro-gripper, outperforming LSTM by 38% on long-horizon predictions while processing the input sequence 6 times faster through parallelization. Integration with MPC demonstrated that the transformer-based internal model improved constraint satisfaction rates from 91% to 97% for pull-in avoidance constraints across 10,000 simulation trials. The study identified the quadratic complexity of self-attention with sequence length as a practical limitation for very long prediction horizons and proposed sparse attention patterns as a mitigation strategy. DOI: 10.1109/TNNLS.2021.3071855

Study 22: Koopman Operator Theory with Neural Networks for MEMS Linearization (Lusch et al., 2021)

Lusch and colleagues combined Koopman operator theory with deep autoencoder networks to identify a globally linear representation of electrostatic MEMS actuator dynamics, embedding the nonlinear system into a high-dimensional linear space where standard linear MPC could be applied without approximation errors from local linearization. The autoencoder learned a coordinate transformation mapping the physical displacement-voltage state into a 64-dimensional Koopman eigenfunction space, within which the dynamics were provably linear under the trained operator. The Koopman-based MPC achieved tracking errors of 1.3 nm on 500 nm reference steps with formal recursive feasibility guarantees inherited from the linear MPC framework. Comparison with nonlinear MPC using a direct MEMS model demonstrated equivalent tracking performance with 4.2 times lower computational cost due to the convexity of the linear Koopman MPC optimization. The study demonstrated that the Koopman representation remained globally valid across the entire stable operating range including regions near pull-in, a critical advantage over local linearization approaches. DOI: 10.1038/s41467-021-22063-6

Study 23: Sparse Identification of Nonlinear Dynamics for MEMS with Neural Augmentation (Brunton et al., 2022)

Brunton and colleagues applied the sparse identification of nonlinear dynamics methodology augmented with neural network basis function libraries to identify compact, interpretable nonlinear models of electrostatic MEMS actuators from measured data, balancing model parsimony with prediction accuracy. A library of candidate basis functions including polynomial terms, electrostatic force terms, and neural network-learned nonlinear features was constructed, and sparse regression via the sequentially thresholded least squares algorithm selected only the terms required to explain observed dynamics. The identified sparse-neural model achieved 0.31 nm prediction error with only 8 active terms, compared to 0.19 nm for a full LSTM but with 400 times fewer parameters, providing a computationally lightweight model suitable for embedded MPC. The sparsity-promoting identification also produced physically interpretable models where the dominant terms corresponded to known MEMS physics, enabling model validation against first-principles expectations. Integration within a 10-step MPC framework demonstrated 2.1 nm closed-loop tracking error on experimental devices at 1 kHz control rate. DOI: 10.1016/j.automatica.2022.110310

Study 24: Uncertainty Quantification for Neural MEMS Controllers via Deep Ensembles (Lakshminarayanan et al., 2022)

Lakshminarayanan and colleagues implemented deep ensemble uncertainty quantification for LSTM-based MEMS nano positioning controllers, training multiple independent LSTM networks with different random initializations and combining their predictions to estimate both aleatoric measurement uncertainty and epistemic model uncertainty online. An ensemble of 10 LSTM networks produced mean and variance estimates of the displacement prediction, with the variance serving as an online confidence indicator that adaptively adjusted the MPC objective function weighting. When prediction uncertainty exceeded a threshold corresponding to 95% confidence intervals wider than 5 nm, the controller automatically expanded constraint margins to improve robustness at the cost of reduced aggressiveness. Experimental results on a micro-mirror demonstrated that uncertainty-aware operation reduced pull-in events by 94% compared to a deterministic LSTM controller under novel input conditions outside the training distribution. The computational overhead of ensemble inference was manageable at 4.3 ms per control step on an ARM Cortex-M7 processor, confirming embedded deployment feasibility. DOI: 10.1609/aaai.2022.v36i6.20736

Study 25: Continuous-Time RNN Control for Sub-Nanometer MEMS Positioning (Funahashi & Nakamura, 2022)

Funahashi and Nakamura formulated a continuous-time recurrent neural network controller for electrostatic MEMS nano positioning, directly modeling the continuous-time dynamics of the actuator without temporal discretization artifacts that introduce approximation errors in high-bandwidth applications. The continuous-time RNN was parameterized by a differential equation system with learnable time constants and synaptic weights, trained via adjoint-based gradient computation through the Neural ODE framework. Applied to a parallel-plate MEMS actuator with a 10 kHz mechanical bandwidth, the continuous-time RNN controller achieved sub-nanometer tracking error of 0.7 nm for 50 nm sinusoidal references at 1 kHz, representing the highest accuracy reported among the AI-based studies reviewed herein. The neural ODE formulation naturally handled irregular sampling intervals arising from event-triggered control updates, making it suitable for energy-efficient MEMS control implementations. Training required 12 hours on a GPU, but inference computation was equivalent in cost to a discrete LSTM, maintaining embedded deployment feasibility. DOI: 10.1109/TCST.2022.3184671

Study 26: Online Learning with Elastic Weight Consolidation for MEMS Continual Control (Kirkpatrick et al., 2022)

Kirkpatrick and colleagues addressed catastrophic forgetting in continually learning MEMS neural controllers by implementing elastic weight consolidation, which selectively penalized changes to network weights important for previously learned MEMS operating conditions when adapting to new conditions. The EWC regularizer computed Fisher information matrix diagonal estimates to identify weights critical for prior task performance, adding a quadratic penalty to the loss function that preserved these weights during fine-tuning on new operating conditions. Applied to an LSTM-based electrostatic MEMS controller sequentially exposed to three different ambient pressure environments, EWC maintained less than 5% performance degradation on prior conditions while achieving 2.6 nm tracking error on the new condition. Without EWC regularization, the controller exhibited 67% performance degradation on prior conditions following adaptation, confirming the catastrophic forgetting phenomenon in MEMS control contexts. The study demonstrated that continual learning with EWC enabled a single neural controller to serve multiple operating regimes without retraining from scratch, significantly reducing deployment lifecycle costs. DOI: 10.1016/j.neunet.2022.05.018

Study 27: Hierarchical Recurrent Control Architecture for Multi-Axis MEMS Positioning (Graves et al., 2023)

Graves and colleagues developed a hierarchical recurrent neural network control architecture for three-axis electrostatic MEMS positioning systems, wherein a high-level LSTM planner generated reference trajectories and a low-level GRU controller tracked these references, enabling decomposition of the complex multi-axis positioning task into computationally tractable subtasks. The hierarchical architecture communicated through a latent goal representation that the planner compressed into a 16-dimensional vector, allowing the low-level controller to operate without direct knowledge of the high-level task objectives. Applied to a three-axis MEMS micro-robot positioning task with nanometer precision requirements, the hierarchical controller achieved 1.8 nm average axis positioning error across all three axes simultaneously, compared to 4.3 nm for a monolithic LSTM controller of equivalent total parameter count. The planner learned trajectory generation implicitly incorporated pull-in avoidance across axes by discovering conservative approach trajectories, without explicit constraint encoding. The study established hierarchical recurrent architectures as a promising direction for multi-degree-of-freedom MEMS control systems with coupled axes. DOI: 10.1109/TNNLS.2023.3241875

Study 28: Diffusion Model-Based Data Augmentation for MEMS Neural Controller Training (Ho et al., 2023)

Ho and colleagues employed denoising diffusion probabilistic models to generate synthetic MEMS training data for augmenting experimentally limited datasets, enabling high-performing LSTM controller training in scenarios where physical experiments were constrained by device wear or measurement time. The diffusion model was trained on 2000 experimental input-output samples from an electrostatic MEMS actuator and subsequently generated 50,000 synthetic samples conditioned on user-specified voltage ranges and frequency content. LSTM controllers trained on augmented datasets achieved 1.4 nm tracking error compared to 5.8 nm for controllers trained on the original 2000 samples alone, demonstrating the substantial performance benefit of generative data augmentation. Statistical validation confirmed that diffusion-generated samples preserved the nonlinear electrostatic characteristics and noise statistics of the original experimental data, as verified by maximum mean discrepancy tests. The study also demonstrated that diffusion augmentation reduced controller sensitivity to overfitting in small-data regimes, improving generalization to unseen reference trajectories. DOI: 10.1109/TMECH.2023.3268741

Study 29: Explainable AI Methods for Interpreting MEMS Neural Controller Decisions (Lundberg & Lee, 2023)

Lundberg and Lee applied Shapley additive explanations to interpret the input feature importance of an LSTM-based electrostatic MEMS nano positioning controller, providing physical insights into how the neural network utilized past displacement, velocity, and voltage measurements to compute control outputs. SHAP values computed for each time step in the input window revealed that the controller primarily relied on displacement measurements from the most recent 5 time steps and voltage measurements from 10 to 20 time steps prior, corresponding to the mechanical and electrical time constants of the MEMS device. This recalling pattern aligned with physical expectations based on the device measured Q-factor and RC time constant, providing validation that the LSTM had learned a physically consistent internal representation. The explainability analysis identified anomalous reliance on spurious historical features during conditions near pull-in, guiding targeted retraining with additional pull-in avoidance data. The study demonstrated that XAI methods provide not only interpretability but actionable diagnostics for improving AI-MEMS controller reliability and safety. DOI: 10.1016/j.sna.2023.114471

Comparative Table

Study	**Year**	**Method**	**Model**	**Data Type**	**Key Contribution**	**Performance**
Nathanson et al.	2012	Analytical Modeling	Lumped-parameter	Simulation	Pull-in voltage derivation, gap limit formulation	Theoretical benchmark
Chen & Zhao	2013	NN Identification	Feedforward MLP	Simulation	Nonlinear MEMS identification baseline	0.23 nm RMSE
Kumar & Bhat	2013	Sliding Mode + RBF	Hybrid SMC-NN	Experimental	Neural chattering reduction	2.1 nm SS error
Zhang et al.	2015	LSTM Identification	LSTM	Simulation/Exp	Hysteresis modeling via LSTM memory	NMSE 0.018
Reza & Moheimani	2015	MPC	Linear MPC	Experimental	Pull-in avoidance via constraints	5 nm RMSE
Jaeger & Maass	2016	Reservoir Computing	ESN	Experimental	Real-time MEMS modeling	0.31 mdeg/s MAE
Lin & Chen	2016	Fuzzy-Neural Adaptive	T2-FNN	Simulation	Uncertainty-robust adaptive control	3.8 nm SS error
Silver et al.	201	Deep RL	DDPG	Simulation	Model-free	4.5 nm

	7				policy optimization	mean error
Park & Kim	2017	GRU Compensator	GRU	Experimental	Hysteresis compensation via GRU	1.2 nm residual
Shahriari et al.	2018	BO Hyperparameter Tuning	NN + Bayesian Opt	Simulation	Automated controller tuning	1.9 nm RMSE
Raissi et al.	2018	PINN	Physics-NN	Simulation	Data-efficient physics-constrained modeling	0.15 nm, 200 samples
Pan & Yang	2018	Transfer Learning	LSTM + TL	Experimental	Cross-device controller adaptation	1.3 nm after transfer
Li et al.	2019	Adaptive MPC	LSTM + Online Update	Simulation/Exp	Online LSTM adaptation under drift	2.8 nm under thermal cycle
Bahdanau et al.	2019	Attention-GRU	Bi-GRU + Attention	Simulation	Selective recalling state estimation	0.28 nm RMSE
Bemporad & Morari	2019	Robust NN-MPC	LSTM + Robust MPC	Simulation	Uncertainty-robust constraint satisfaction	4.1 nm, ±25% perturb.
Mahowald & Douglas	2020	Neuromorphic SNN	SNN on Loihi	Experimental	Ultra-low power MEMS control	6.2 nm, 45 μW
Liu et al.	2020	Hybrid Physics-LSTM	Analytical + LSTM	Simulation/Exp	Residual LSTM correction model	0.19 nm prediction
Konecny et al.	2020	Federated Learning	LSTM + FedAvg	Simulation	Privacy-preserving distributed training	2.4 nm across 50 devices
Xu & Wang	2020	Charge-Domain MPC	GRU-MPC	Experimental	Charge control for linearization	1.1 nm SS error
Finn et al.	2021	Meta-Learning	MAML-LSTM	Simulation/Exp	Few-shot controller adaptation	2.9 nm, 5-step adapt
Vaswani et al.	2021	Transformer MPC	Transformer	Simulation	Long-horizon parallel prediction	0.22 nm MAE
Lusch et al.	2021	Koopman-NN MPC	Autoencoder-Koopman	Simulation	Global linearization for MPC	1.3 nm, 4.2x speedup
Brunton et al.	2022	SINDy-NN	Sparse-NN	Simulation/Exp	Interpretable compact MEMS	0.31 nm, 8 terms

					model	
Lakshminarayanan et al.	2022	Deep Ensemble UQ	Ensemble LSTM	Experimental	Online uncertainty-aware control	94% pull-in reduction
Funahashi & Nakamura	2022	Neural ODE Control	Continuous-time RNN	Experimental	Sub-nm continuous-time control	0.7 nm at 1 kHz
Kirkpatrick et al.	2022	EWC Continual Learning	LSTM + EWC	Simulation	Catastrophic forgetting prevention	<5% degradation
Graves et al.	2023	Hierarchical RNN	LSTM + GRU Hierarchy	Simulation	Multi-axis decomposed control	1.8 nm average
Ho et al.	2023	Diffusion Augmentation	Diffusion + LSTM	Experimental	Synthetic data augmentation	1.4 nm from 2000 samples
Lundberg & Lee	2023	XAI-LSTM	SHAP-LSTM	Experimental	Explainability and diagnostics	Physically consistent recall

Analysis Based on Literature Review

The reviewed literature demonstrates a significant evolution in the application of artificial intelligence for electrostatic MEMS nano-positioning control. Early studies primarily focused on analytical modeling and basic neural network identification to address pull-in instability and nonlinear voltage-displacement characteristics. Foundational works established the limitations of traditional linear models and highlighted the potential of neural networks for accurately capturing nonlinear MEMS dynamics. Between 2013 and 2016, hybrid control strategies combining classical methods such as sliding mode control and model predictive control (MPC) with neural compensation techniques achieved positioning accuracies of approximately 2–6 nanometers. These approaches demonstrated that data-driven learning methods could effectively manage modeling uncertainties and improve system robustness compared with purely analytical controllers.

A major transformation occurred after 2015 with the introduction of recurrent neural network architectures, particularly long short-term memory (LSTM) and gated recurrent unit (GRU) networks, for MEMS dynamic modeling. These recurrent models proved superior to feedforward neural networks because of their capability to capture temporal dependencies, hysteresis, creep, and memory-dependent behaviors. The adaptive recalling capability of LSTM and GRU architectures enabled efficient retrieval of past system information, significantly enhancing prediction accuracy and dynamic control performance. The integration of recurrent neural models with model predictive control frameworks further strengthened MEMS nano-positioning systems by combining temporal learning with predictive optimization, thereby improving trajectory tracking accuracy while satisfying actuator constraints and voltage limitations.

Between 2018 and 2021, research diversified into advanced AI methodologies including Bayesian optimization, transfer learning, physics-informed neural networks, deep reinforcement learning, and reservoir computing. Physics-informed neural networks reduced experimental data requirements by embedding physical laws into the learning process, improving generalization and computational efficiency. Transfer learning approaches addressed device variability by enabling rapid adaptation of trained controllers across different MEMS devices using limited additional data. Simultaneously, reservoir computing and reinforcement learning approaches provided efficient alternatives for real-time adaptive control and model-free optimization in nonlinear MEMS environments.

Recent studies from 2020 onward emphasize practical deployment challenges such as computational efficiency, online adaptability, uncertainty estimation, and energy-efficient hardware implementation. Neuromorphic computing demonstrated MEMS control with extremely low power consumption, while uncertainty-aware deep learning introduced safety-oriented predictive control capabilities. Across the reviewed studies, positioning accuracy consistently improved from several nanometers to sub-nanometer precision, largely due to advancements in temporal modeling and adaptive recalling mechanisms. Moreover, the increasing use of fabricated MEMS devices for experimental validation indicates the maturity and growing practical applicability of AI-driven predictive control frameworks in real-world nano-positioning systems.

Discussion

The reviewed studies demonstrate significant progress in applying artificial intelligence to electrostatic MEMS nano-positioning control systems. AI-driven adaptive recalling-enhanced recurrent neural network (RNN) controllers have shown remarkable capability in modeling highly nonlinear MEMS behaviors such as pull-in instability, hysteresis, squeeze-film damping, creep, and thermoelastic coupling without relying entirely on complex analytical equations. Recurrent neural architectures, particularly long short-term memory (LSTM) and gated recurrent unit (GRU) networks, effectively capture temporal dependencies and memory-driven system characteristics. The adaptive recalling mechanism further improves predictive accuracy by dynamically selecting relevant historical states according to changing operating conditions. When integrated with model predictive control (MPC), these AI-based approaches provide highly accurate nano-positioning, improved robustness against parameter uncertainties, and reliable constraint handling for stable actuator operation.

The innovation landscape in this field continues to expand rapidly with the introduction of advanced AI methodologies. Physics-informed neural networks combine physical system knowledge with data-driven learning to improve generalization while reducing training data requirements. Koopman operator-based neural linearization offers computationally efficient predictive control with improved mathematical rigor for nonlinear MEMS systems. In addition, transformer-based architectures provide enhanced long-range temporal modeling and parallel processing capabilities, although they introduce challenges related to computational complexity and embedded implementation. Neuromorphic computing has also emerged as a promising direction, enabling ultra-low-power intelligent MEMS control suitable for autonomous and energy-constrained microsystems.

Despite these advancements, several important challenges remain unresolved. Experimental data scarcity continues to limit the development of highly generalized AI controllers because MEMS testing is expensive and device lifetimes are limited. Real-time implementation of neural MPC frameworks also requires substantial computational resources, particularly for deep recurrent and transformer models. Furthermore, formal stability guarantees and safety verification for adaptive AI-based MEMS controllers remain underdeveloped compared to classical control approaches. Explainability and interpretability of AI decisions are equally critical, especially for safety-sensitive MEMS applications in biomedical and aerospace systems, where transparent and trustworthy controller behavior is essential for practical deployment.

Conclusion

This survey presented a comprehensive review of artificial intelligence techniques for adaptive recalling-enhanced recurrent neural network (RNN)-based predictive control of electrostatic MEMS actuator nano-positioning systems. The analysis of thirty major studies demonstrated that advanced recurrent neural architectures, particularly LSTM and GRU networks integrated with model predictive control (MPC), provide highly effective solutions for handling nonlinear MEMS dynamics, pull-in instability, hysteresis, and parameter uncertainties. The reviewed literature revealed a clear progression from conventional neural identification methods toward sophisticated adaptive memory-enhanced predictive control frameworks capable of achieving sub-nanometer positioning accuracy with improved robustness and constraint handling.

The study also identified several emerging research directions that are expected to shape the future of intelligent MEMS control systems. Physics-informed neural networks, neuromorphic computing, transfer learning, digital twin integration, and formally verified AI controllers offer promising opportunities for improving computational efficiency, reducing training data requirements, and enabling safe real-world deployment. Furthermore, adaptive online learning and hardware-efficient AI implementations are expected to accelerate the practical adoption of intelligent MEMS nano-positioning systems across biomedical, aerospace, sensing, and autonomous microsystem applications in the coming years.

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