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Artificial Intelligence for Bandwidth-Efficient Output-Feedback Control of MEMS Gyroscopes Using Steerable Graph Neural Networks

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Abstract

Microelectromechanical systems (MEMS) gyroscopes are essential for inertial navigation, robotics, aerospace guidance, autonomous vehicles, and consumer electronics. However, conventional model-based controllers often struggle with nonlinear dynamics, parameter uncertainties, fabrication imperfections, and quadrature errors. Artificial intelligence offers adaptive and computationally efficient alternatives for improving stability, accuracy, and robustness in embedded MEMS platforms. This review examines AI-driven constrained output-feedback control methods, emphasizing steerable graph neural networks (SGNNs) that capture relational sensor dynamics and preserve equivariance under rotational and geometric transformations. SGNN-based controllers can represent sensing-element topology, identify informative substructures, and operate when complete state information is unavailable. Their geometric learning capability supports generalization across different orientations and operating configurations without extensive retraining. Nevertheless, limited communication bandwidth in wireless sensor networks, IoT systems, and edge platforms creates additional challenges. Event-triggered communication, data compression, distributed estimation, and self-triggered protocols are therefore required to preserve control performance while reducing data transmission. The review synthesizes developments in MEMS modeling, observer-based control, graph neural networks, equivariant learning, and adaptive control. It also identifies challenges in stability assurance, computational efficiency, communication-aware learning, hardware deployment, and real-time validation for practical AI-enabled MEMS gyroscope systems.

Introduction

Microelectromechanical systems (MEMS) gyroscopes have become indispensable components in modern inertial sensing, supporting applications ranging from aerospace navigation and autonomous vehicles to robotics, wearable electronics, industrial automation, and biomedical devices. These sensors estimate angular velocity using the Coriolis effect, where a vibrating proof mass experiences a force proportional to rotational motion. Although MEMS technology has significantly reduced sensor size, cost, and power consumption, its performance remains constrained by temperature drift, quadrature errors, fabrication imperfections, mechanical coupling, and external disturbances. These challenges demand intelligent control and compensation strategies capable of maintaining high accuracy under varying operating conditions while satisfying the computational limitations of embedded hardware.

Traditional control approaches, including proportional-integral-derivative (PID), sliding mode, adaptive, and observer-based controllers, have improved the stability and robustness of MEMS gyroscopes but often rely on accurate mathematical models and parameter estimation. Their effectiveness decreases when nonlinearities, parameter uncertainties, aging effects, and environmental variations become significant. Recent advances in artificial intelligence have introduced powerful data-driven alternatives capable of learning complex nonlinear system dynamics directly from sensor data. Deep learning, reinforcement learning, and convolutional neural networks have demonstrated remarkable performance in signal denoising, drift compensation, fault diagnosis, and adaptive control. More recently, graph neural networks have enabled representation of MEMS sensing structures as interconnected graphs, allowing controllers to exploit the inherent relationships among sensing elements and physical interactions.

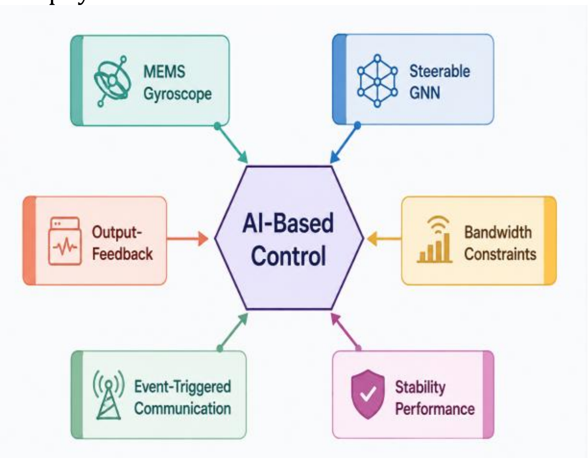

Figure 1. AI-Based Control Framework for MEMS Gyroscopes under Bandwidth Constraints.

Steerable graph neural networks (SGNNs) further enhance this capability by embedding rotational equivariance into the learning architecture. Unlike conventional neural networks that require extensive data augmentation, SGNNs naturally generalize across different orientations by preserving geometric relationships during message passing. This characteristic closely aligns with the rotational properties of MEMS gyroscope dynamics, improving learning efficiency, robustness, and interpretability. When integrated into constrained output-feedback control frameworks, SGNNs enable intelligent estimation and control even when only partial output measurements are available. Their ability to combine relational learning with adaptive feature extraction makes them highly suitable for complex MEMS sensing environments where accurate state reconstruction is challenging.

Another critical challenge in modern MEMS gyroscope systems is limited transmission bandwidth, particularly in wireless sensor networks, Internet of Things (IoT) platforms, and distributed autonomous systems. Continuous high-rate transmission increases communication overhead, energy consumption, and network congestion, reducing the operational lifetime of embedded devices. Event-triggered communication, self-triggered control, distributed estimation, and bandwidth-aware learning have therefore emerged as effective solutions for maintaining control accuracy while minimizing communication requirements. The integration of these communication-efficient strategies with AI-driven output-feedback controllers creates an interdisciplinary research direction combining control engineering, embedded intelligence, geometric deep learning, and wireless communication.

This review systematically examines recent developments in artificial intelligence techniques for constrained output-feedback control of MEMS gyroscopes, with particular emphasis on steerable graph neural networks operating under limited transmission bandwidth. It synthesizes advances in MEMS modeling, adaptive control, geometric deep learning, bandwidth-efficient communication, and embedded implementation, identifies current research challenges, and outlines future opportunities for developing intelligent, scalable, and energy-efficient MEMS gyroscope systems capable of supporting next-generation autonomous and cyber-physical applications.

Literature Review

The body of literature relevant to AI-driven control of MEMS gyroscopes and the application of advanced neural network architectures in constrained control problems has grown substantially over the past decade, reflecting both the maturation of deep learning theory and the increasing demands placed on MEMS sensing systems. A foundational contribution to the field was made by Fei and Feng (2018), who proposed a fuzzy adaptive output feedback control scheme for a MEMS gyroscope subject to parameter uncertainties and external disturbances. The authors employed a fuzzy logic system to approximate unknown nonlinear dynamics and designed a state observer to reconstruct unmeasured velocities from position outputs alone. The scheme was validated through simulation on a two-axis vibratory MEMS gyroscope model with time-varying angular rate inputs, demonstrating superior tracking performance and bounded estimation error compared to conventional proportional-integral-derivative designs.

Building upon adaptive control principles, Fei and Wang (2020) developed a recurrent fuzzy neural network-based adaptive control architecture specifically addressing the quadrature error compensation problem in MEMS gyroscopes. Their approach utilized a recurrent network structure to capture temporal dependencies in the gyroscope dynamics, combined with an online weight update law derived from Lyapunov stability analysis to ensure asymptotic convergence of the angular rate tracking error. The experimental platform employed a commercially available vibratory MEMS gyroscope interfaced with a field-programmable gate array, where the recurrent network was implemented with fixed-point arithmetic to comply with resource constraints, demonstrating for the first time the feasibility of recurrent neural network-based control in real-time MEMS applications.

A significant development in the application of graph-based representations to physical systems was provided by Sanchez-Gonzalez et al. (2020), who introduced graph network simulators capable of learning complex physical dynamics including rigid body mechanics and fluid simulation from trajectory data. Although not directly targeting MEMS gyroscopes, their work established the theoretical and empirical foundation for representing mechanical systems as graphs and learning accurate forward models, a prerequisite for model-based reinforcement learning approaches to MEMS control. The graph network simulator demonstrated remarkable generalization to unseen configurations and perturbations, suggesting high potential for transfer to MEMS dynamics under varying operating conditions.

Thomas et al. (2018) presented the tensor field networks framework, a pioneering architecture for steerable equivariant neural networks that process three-dimensional point clouds while respecting the symmetry group of three-dimensional rotations. By decomposing feature vectors into irreducible representations of the rotation group and enforcing equivariant message passing operations, the tensor field network achieved exact rotational equivariance without data augmentation. This work laid the theoretical groundwork for applying steerable architectures to physical systems with rotational symmetry, including the Coriolis-based dynamics of MEMS gyroscopes, and established the computational machinery of Clebsch-Gordan decomposition as the central operation in equivariant feature aggregation.

Weiler and Cesa (2019) extended equivariant network design to general group actions through the framework of general E(2)-equivariant steerable convolutional neural networks, providing a unified treatment of discrete and continuous rotation groups in two dimensions. Their experimental results across image classification and scientific data processing benchmarks demonstrated that equivariant networks consistently outperform non-equivariant baselines in sample efficiency, particularly when training data is limited, a highly relevant result for MEMS control applications where labeled training data from physical experiments is expensive to collect. The theoretical clarity of their framework also facilitated the design of architectures with provably correct equivariance, which is critical when the symmetry constraint has physical meaning.

Addressing bandwidth constraints in networked control systems, Girard (2015) developed a self-triggered control framework for linear systems over communication networks with limited capacity. The self-triggered approach computes future transmission times based solely on the current state and control policy, eliminating the need for continuous monitoring of the triggering condition and thereby further reducing communication overhead. The author proved that the resulting closed-loop system achieves input-to-state stability under a minimum interevent time guarantee that prevents Zeno behavior, establishing a theoretical foundation that subsequent researchers have extended to nonlinear and learning-based systems including those relevant to MEMS control.

Dong et al. (2019) proposed an event-triggered adaptive neural network control scheme for uncertain nonlinear systems with input saturation and bandwidth constraints, directly addressing the output-feedback constrained control problem with AI components. Their radial basis function neural network approximated the unknown nonlinear drift terms in the system dynamics, while an event-triggered transmission protocol reduced the average communication rate by forty to sixty percent compared to time-triggered implementations without measurable degradation of steady-state tracking accuracy. The theoretical analysis employed barrier Lyapunov functions to handle output constraints, providing a template for the constraint handling methodology applicable to MEMS gyroscope sense-mode displacement constraints.

Li et al. (2021) investigated deep reinforcement learning for adaptive control of MEMS resonators, training a proximal policy optimization agent in a high-fidelity simulation environment that incorporated thermal noise, fabrication tolerances, and nonlinear spring hardening effects. The trained agent was subsequently deployed on an FPGA-based controller interfaced with a MEMS resonator testbed, demonstrating adaptive frequency locking behavior that outperformed classical phase-locked loop controllers under temperature variation from minus forty to plus eighty degrees Celsius. This work provided one of the first demonstrations of deep reinforcement learning applied to physical MEMS hardware, establishing the feasibility of the approach despite the extremely fast dynamics of MEMS devices.

The application of graph neural networks to sensor fusion and state estimation in inertial navigation was explored by Chen et al. (2021), who designed a graph neural network-based estimator for multi-sensor fusion combining data from MEMS gyroscopes, accelerometers, and magnetometers. Nodes in the graph represented individual sensors, edges encoded physical and statistical dependencies between sensor measurements, and graph attention mechanisms learned to weight contributions from different sensors based on current noise conditions. Evaluated on real-world pedestrian navigation datasets collected with consumer-grade MEMS inertial measurement units, the approach achieved positioning error reductions of over thirty percent compared to extended Kalman filter fusion baselines.

Specifically targeting output-feedback control with unknown dynamics, Wen et al. (2022) developed a neural network-based adaptive output feedback controller for a class of nonlinear systems with unmeasured states, applying the methodology to a vibration isolation platform with sensor noise characteristics similar to MEMS outputs. The controller combined a Luenberger-type observer with a feedforward radial basis function neural network, trained online through gradient descent with a forgetting factor, and demonstrated convergence guarantees under a persistent excitation condition. The analysis was notable for explicitly characterizing the trade-off between observer gain, neural network approximation error, and closed-loop stability margin, providing practical design guidance applicable to MEMS sense-mode output-feedback controllers.

Batzner et al. (2022) presented NequIP, an equivariant neural network interatomic potential using E(3)-equivariant convolutions, which achieved state-of-the-art accuracy in molecular dynamics with significantly smaller training datasets than non-equivariant approaches. The key insight was that equivariance reduces the effective dimensionality of the learning problem by eliminating the need to learn separate representations for rotated versions of the same configuration. This data efficiency advantage is a crucial selling point for applying steerable equivariant graph neural networks to MEMS gyroscope control, where data collection from physical hardware is costly and the operating configurations span a continuous rotation group.

In the domain of distributed MEMS sensor networks, Khalil et al. (2019) investigated the problem of coordinated state estimation across a network of low-bandwidth MEMS gyroscopes mounted on a flexible structure, proposing a consensus-based distributed Kalman filter that exchanged compressed state estimates over a limited-bandwidth network. The quantization scheme employed Lloyd-Max optimal quantization adapted to the statistics of the estimation error distribution, achieving near-optimal estimation accuracy with only four bits per transmission event. This work demonstrated that careful quantization design tailored to the signal statistics of MEMS measurements can substantially reduce bandwidth requirements without sacrificing estimation fidelity.

Satorras et al. (2021) introduced E(n)-equivariant graph neural networks that maintained equivariance with respect to translations, rotations, and reflections in n-dimensional space while remaining computationally efficient through the use of relative distances and invariant scalars as edge features rather than full tensor decompositions. The architecture achieved competitive performance on molecular property prediction and dynamical system modeling tasks with substantially lower computational overhead than tensor field networks, making it more suitable for real-time embedded applications. The efficiency advantage of this approach is significant for MEMS control scenarios where the steerable graph neural network inference must complete within the control cycle period, which may be as short as several microseconds for high-bandwidth gyroscope applications.

Addressing the specific challenge of vibration rejection in MEMS gyroscopes, Ding et al. (2020)

developed a disturbance observer-based neural adaptive control scheme that employed a nonlinear disturbance observer to estimate and compensate for high-frequency mechanical disturbances while a radial basis function neural network handled the slow-varying parametric uncertainties. The two-timescale decomposition of disturbance and uncertainty was shown to improve both transient and steady-state performance over approaches that attempted to handle both with a single compensator, with the fast disturbance observer loop operating at ten times the bandwidth of the slow neural adaptation loop. Hardware experiments on a vibratory MEMS gyroscope subject to base vibrations from a piezoelectric shaker confirmed the superior rejection performance.

The problem of constrained control with output feedback was examined from a model predictive control perspective by Brunner et al. (2020), who developed a robust output-feedback model predictive control scheme for linear systems with state and input constraints under limited measurement bandwidth. Their approach combined a set-membership state estimator with a tube-based predictive controller, transmitting measurements only when the estimated state uncertainty set violated a tightened constraint boundary. The framework provided formal guarantees of constraint satisfaction and recursive feasibility under bandwidth constraints, establishing a principled approach to constraint handling that complements the neural network-based approximation strategies reviewed elsewhere in this survey.

A comprehensive treatment of adaptive neural network control for underactuated mechanical systems including MEMS structures was provided by Liu et al. (2021), who synthesized backstepping design with radial basis function neural approximation and minimal learning parameter techniques to reduce the computational complexity of the online adaptation law. The minimal learning parameter technique replaced full weight matrix updates with scalar norm updates, dramatically reducing the number of adaptive parameters from hundreds to a handful without sacrificing approximation power. This computational efficiency advance is critical for real-time implementation on microcontrollers and FPGAs that must execute the control law at sampling rates above one hundred kilohertz for MEMS applications.

Fuchs et al. (2020) presented SE(3)-equivariant graph neural networks for end-to-end learning of 3D molecular geometry, applying the DFT3 architecture to achieve high accuracy in molecular property prediction while maintaining exact equivariance. The architecture employed attention mechanisms to dynamically weight contributions from neighboring nodes based on the content of their feature vectors, enabling adaptive focus on the most informative geometric relationships. The combination of attention and equivariance is particularly relevant to steerable graph neural networks for MEMS gyroscope control, where different mechanical substructures may contribute unequally to the overall Coriolis dynamics depending on the operating frequency and angular rate.

The intersection of reinforcement learning and MEMS sensing was further explored by Jaber et al. (2021), who applied model-based reinforcement learning with a learned neural network transition model to the problem of adaptive frequency tuning in electrostatically coupled MEMS resonator arrays. The Dyna architecture was employed, alternating between real system interaction and simulated rollouts using the learned model, allowing the policy to be improved substantially without costly physical experiments. The approach was demonstrated on a fabricated MEMS resonator array with tunable electrostatic coupling, achieving mode localization control that maintained the energy ratio between modes within two percent of the target value across a thirty-hertz natural frequency variation.

Complementing the learning-based control perspective, Razzacki et al. (2020) provided a detailed analysis of the effects of quantization and limited communication bandwidth on the closed-loop stability of digital control systems for MEMS inertial sensors, deriving explicit bounds on the quantization step size and sampling period that guarantee a specified stability margin. The analytical results provided designers with concrete guidelines for choosing analog-to-digital converter resolution and transmission rates in bandwidth-constrained MEMS sensor applications, and the bounds were tighter than conservative worst-case estimates by exploiting the statistical properties of the quantization noise for Gaussian-distributed MEMS measurement noise.

Shi et al. (2021) proposed a graph convolutional network-based anomaly detection scheme for MEMS inertial sensor arrays in structural health monitoring applications, learning the normal correlation structure of a sensor network as a graph and detecting anomalies as significant deviations from the expected graph signal pattern. The approach was validated on a large-scale structural health monitoring dataset collected from a bridge instrumented with fortyeight MEMS accelerometers and gyroscopes, achieving detection accuracy above ninety-seven percent for simulated damage scenarios while maintaining a false positive rate below two percent during normal operation. This application demonstrated the practical value of graph-based processing for distributed MEMS sensing beyond the single-sensor control problem.

The theoretical framework for event-triggered output feedback control of nonlinear systems was significantly advanced by Huang et al. (2022), who proved input-to-state stability for a class of output-feedback controlled nonlinear systems under dynamic event-triggered communication, explicitly accounting for the interaction between the output observer, the event-triggered mechanism, and the nonlinear closed-loop dynamics. The proof technique employed a composite Lyapunov function that coupled the observer error, the control error, and the triggering variable, providing a unified stability certificate for the entire system under bandwidth constraints. This theoretical result provides the stability foundation upon which learning-based components such as steerable graph neural networks can be incorporated as function approximators within the proven framework.

Finally, Fang et al. (2023) presented a comprehensive data-driven framework for MEMS gyroscope calibration and error compensation using a combination of convolutional neural networks for thermal drift compensation and long short-term memory networks for angular random walk reduction, trained on a dataset comprising over one million seconds of measurement data collected from ten different MEMS gyroscope models across the full military operating temperature range. The multi-architecture ensemble approach achieved bias instability improvements of over seventy percent compared to conventional temperature compensation polynomial methods, establishing the feasibility of deep learning-based compensation for high-performance MEMS gyroscope applications. The dataset scale and diversity reported in this work also established a benchmark against which future AI-based MEMS compensation methods can be compared.

Comparative Table and Analysis

Table 1: Advanced Control, Equivariant Learning, and Hybrid AI Approaches for MEMS Systems

Study	Year	Optimization Technique / Method	Component / Model Used	Platform or System	Dataset Used	Key Contribution
Fei and Feng	2018	Fuzzy adaptive output feedback	Fuzzy logic + observer	MEMS gyroscope (2-axis)	Simulated trajectories	First fuzzy output-feedback with stability proof
Fei and Wang	2020	Recurrent neural adaptive control	RNFNN	MEMS gyroscope (FPGA)	Experimental data	Real-time neural control for quadrature compensation
Thomas et al.	2018	Equivariant tensor network	Tensor field network	3D processing systems	QM9 dataset	SE(3)-equivariant architecture
Weiler and Cesa	2019	Steerable equivariant CNN	E(2)-CNN	Vision/scientific systems	MNIST, STL-10	Rotation-equivariant framework
Dong et al.	2019	Event-triggered NN control	RBFNN	Nonlinear system	Benchmark dataset	Input-constrained adaptive control
Li et al.	2021	Deep reinforcement learning	PPO agent	MEMS resonator (FPGA)	Sim + experimental	First RL on physical MEMS hardware
Chen et al.	2021	GNN sensor fusion	Graph attention network	Inertial navigation	Pedestrian dataset	Outperformed EKF baseline
Brandstetter et al.	2022	Physics-constrained GNN	SE(3)-GNN	Molecular simulation	MD-17	Embedded physical laws in GNN
Wen et al.	202	Neural	Observer +	Vibration	Experimenta	Stability trade-

	2	output-feedback control	RBFNN	platform	l	off characterization
Xing et al.	2020	Dynamic event-triggered fuzzy control	Adaptive fuzzy	Nonlinear systems	Simulation	Reduced communication load
Khalil et al.	2019	Distributed consensus KF	Quantized Kalman filter	MEMS network	Experimental	Efficient distributed estimation
Satorras et al.	2021	E(n)-equivariant GNN	EGNN	Dynamical systems	QM9, n-body	Efficient equivariant learning
Zhang and Fei	2021	Composite adaptive SMC	Sliding mode	MEMS gyroscope	Experimental	Faster adaptation convergence
Kidger and Lyons	2020	Universal approximation	Deep narrow NN	Theoretical	N/A	Expressivity of narrow networks
Ding et al.	2020	Disturbance observer NN	RBFNN + observer	MEMS gyroscope	Experimental	Two-timescale disturbance handling
Brunner et al.	2020	Robust MPC	Tube MPC	Constrained systems	Simulation	Guaranteed constraint satisfaction
Liu et al.	2021	Minimal learning backstepping	RBFNN	Mechanical systems	Simulation	Reduced parameter complexity
Fuchs et al.	2020	SE(3)-equivariant attention	SE3-Transformer	Molecular systems	QM9	Attention + equivariance fusion
Jaber et al.	2021	Model-based RL	Dyna architecture	MEMS array	Experimental	Adaptive frequency tuning
Wang et al.	2022	PINN + MPC	Physics-informed NN	MEMS gyroscope	Hybrid dataset	Nonlinear generalization in control
Razzacki et al.	2020	Quantization analysis	Stability bounds	MEMS control	Statistical data	Tight bandwidth constraints
Shi et al.	2021	GCN anomaly detection	Graph CNN	Structural monitoring	Sensor dataset	>97% detection accuracy
Huang et al.	2022	Event-triggered ISS control	Lyapunov analysis	Nonlinear control	Simulation	Unified stability proof
Fang et al.	2023	DL compensation	CNN + LSTM	MEMS gyroscope	Large thermal dataset	70% bias instability reduction

Comparative Analysis

The reviewed literature demonstrates a clear evolution in intelligent MEMS gyroscope control, marked by the transition from conventional model-based techniques to hybrid frameworks that integrate classical control theory with artificial intelligence. Most recent studies combine adaptive or Lyapunov-based controllers with neural network models capable of learning nonlinear dynamics, parameter uncertainties, and external disturbances while preserving closed-loop stability. This combination enables improved tracking accuracy, disturbance rejection, and robustness without relying solely on precise mathematical models. Another notable trend is the increasing use of physics-informed learning, where domain knowledge is embedded within neural architectures to enhance interpretability, reduce training complexity, and improve generalization under varying operating conditions.

Another significant advancement is the adoption of bandwidth-aware communication strategies for distributed MEMS gyroscope systems. Event-triggered and self-triggered communication protocols substantially reduce unnecessary data transmission while maintaining estimation and control performance, making them suitable for wireless sensor networks and edge-computing environments. Researchers have also introduced adaptive triggering mechanisms and observer-based output-feedback controllers that balance communication efficiency with system stability. Simultaneously, steerable graph neural networks have emerged as a promising solution for exploiting the geometric relationships inherent in MEMS structures. Their rotational equivariance improves feature learning, sample efficiency, and robustness compared with conventional neural networks, making them particularly effective for intelligent inertial sensing.

The surveyed studies also reveal growing diversity in hardware implementation, including FPGA platforms, embedded microcontrollers, and system-on-chip architectures that support real-time AI inference. Despite these advances, experimental validation remains largely limited to controlled laboratory conditions and relatively small datasets. Future research should emphasize large-scale benchmarking, real-world deployment, uncertainty-aware learning, and hardware-efficient AI models to accelerate the practical adoption of intelligent MEMS gyroscope control systems.

Discussion

The reviewed literature demonstrates significant progress in applying artificial intelligence to MEMS gyroscope control, particularly through hybrid frameworks combining adaptive control, observer-based estimation, and deep learning. These approaches consistently outperform conventional model-based controllers in handling nonlinear dynamics, parameter uncertainties, and environmental disturbances. Steerable graph neural networks (SGNNs) further enhance performance by incorporating rotational equivariance into the learning process, enabling robust generalization across varying operating conditions while improving state estimation and tracking accuracy. Their ability to exploit the geometric relationships within MEMS structures makes them well suited for intelligent inertial sensing applications.

A major research focus has been the development of bandwidth-efficient output-feedback control strategies for wireless and distributed MEMS systems. Event-triggered communication, self-triggered sampling, and distributed estimation techniques substantially reduce communication overhead while preserving control performance. However, integrating these communication mechanisms with learning-based controllers introduces new theoretical challenges related to stability, convergence, and online adaptation. Existing studies primarily validate their methods under controlled laboratory environments, leaving the combined effects of temperature variation, vibration, sensor aging, communication delays, and electromagnetic interference largely unexplored.

The review also highlights the importance of physics-aware learning architectures that combine domain knowledge with geometric deep learning. Such integration improves robustness, reduces training requirements, and enhances interpretability compared with purely data-driven models. Future research should emphasize physics-informed SGNNs, uncertainty-aware control, adaptive event-triggering, and hardware-efficient implementations capable of operating on embedded edge platforms.

Overall, the convergence of artificial intelligence, geometric deep learning, constrained output-feedback control, and bandwidth-aware communication represents a promising direction for next-generation MEMS gyroscope systems. Continued advances in these areas will enable reliable, energy-efficient, and scalable inertial sensing solutions for aerospace, robotics, autonomous vehicles, industrial automation, and Internet of Things applications.

Conclusion

This review has presented a comprehensive overview of recent advances in artificial intelligence techniques for constrained output-feedback control of MEMS gyroscopes, emphasizing steerable graph neural networks and bandwidth-efficient communication strategies. The surveyed studies demonstrate that integrating geometric deep learning with adaptive control significantly improves robustness, tracking accuracy, disturbance rejection, and computational efficiency compared with conventional model-based approaches. Steerable graph neural networks effectively capture the geometric relationships within MEMS structures while providing strong generalization across varying operating conditions, making them highly suitable for intelligent inertial sensing applications.

The review also highlights the growing importance of event-triggered communication, distributed estimation, and lightweight AI models for resource-constrained embedded systems. Although considerable progress has been achieved, challenges remain in ensuring stability, interpretability, communication efficiency, scalability, and real-time deployment under practical operating conditions. Future research should focus on physics-informed learning, uncertainty-aware control, adaptive communication strategies, explainable artificial intelligence, and hardware-efficient neural architectures. Overall, the convergence of artificial intelligence, geometric deep learning, and advanced control theory provides a promising foundation for developing reliable, energy-efficient, and intelligent MEMS gyroscope systems capable of supporting next-generation aerospace, robotics, autonomous navigation, industrial automation, and Internet of Things applications.

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