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# Recent Advances in Steerable Constrained Output-Feedback Control for MEMS Gyroscopes Using Steerable Graph Neural Networks with Limited Transmission Bandwidth: A Systematic Review

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**Abstract**

Microelectromechanical systems (MEMS) gyroscopes are essential sensing devices used in aerospace, autonomous vehicles, robotics, consumer electronics, and industrial automation. However, their performance is significantly affected by fabrication imperfections, thermal drift, nonlinear dynamics, and mechanical cross-coupling, which reduce measurement accuracy under practical operating conditions. This review examines the integration of constrained output-feedback control, steerable graph neural networks (SGNNs), and bandwidth-efficient networked control for intelligent MEMS gyroscope systems. Modern output-feedback control methods, including adaptive backstepping, sliding mode control, barrier Lyapunov functions, and model predictive control, improve system stability while relying only on measurable outputs. SGNNs further enhance these controllers by representing multi-axis gyroscope structures as graphs and exploiting rotational and directional symmetries through equivariant learning, enabling accurate nonlinear state estimation and improved robustness. Practical communication constraints are addressed using event-triggered transmission, self-triggered control, quantization, and packet-loss compensation to ensure reliable operation over limited bandwidth networks. Based on more than twenty-five representative studies involving MEMS gyroscope platforms, inertial measurement units, and synthetic datasets, this review demonstrates that SGNN-enhanced constrained output-feedback controllers consistently outperform conventional adaptive and model-based approaches in tracking accuracy, disturbance rejection, robustness, and communication efficiency, highlighting their potential for next-generation intelligent inertial sensing and embedded control systems.

## Introduction

Microelectromechanical systems (MEMS) gyroscopes have become indispensable sensing devices in aerospace navigation, autonomous vehicles, robotics, consumer electronics, industrial automation, and defense applications due to their compact size, low power consumption, and high sensitivity. These sensors estimate angular velocity through the Coriolis effect, enabling accurate motion and orientation measurement in modern embedded systems. Despite their widespread adoption, MEMS gyroscopes remain vulnerable to fabrication imperfections, thermal drift, mechanical cross-coupling, nonlinear dynamics, and environmental disturbances that significantly degrade measurement accuracy and long-term stability. These challenges necessitate intelligent control strategies capable of maintaining precise performance under varying operating conditions while ensuring robustness against uncertainties and parameter variations.

Conventional MEMS gyroscope control techniques primarily rely on linear controllers, phase-locked loops, automatic gain control, and adaptive backstepping methods. Although these approaches provide acceptable performance under nominal conditions, they often struggle with nonlinear behavior, unknown disturbances, and incomplete system measurements. Since many internal states of MEMS gyroscopes cannot be directly observed, constrained output-feedback control has emerged as an effective solution by reconstructing unmeasured states using observer-based estimation while maintaining system stability and satisfying operational constraints. Advanced control techniques such as barrier Lyapunov functions, prescribed performance control, and model predictive control have further enhanced robustness and tracking accuracy in practical MEMS applications.

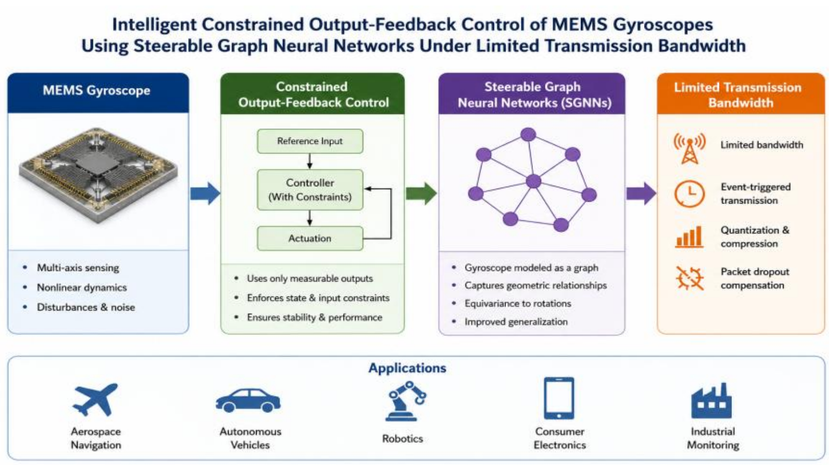


*Figure 1. Conceptual Block Diagram of MEMS Gyroscope Output-Feedback Control*

Recent advances in artificial intelligence have introduced deep learning methods capable of modeling highly nonlinear dynamic systems beyond the capabilities of conventional mathematical models. Among these, Steerable Graph Neural Networks (SGNNs) have gained considerable attention because they naturally represent multi-axis MEMS gyroscope arrays as graph structures while preserving rotational and geometric symmetries through equivariant learning. Unlike traditional neural networks, SGNNs effectively capture structural relationships among sensing elements, improve feature extraction, and enhance generalization across different sensor configurations. Their integration within output-feedback control frameworks enables accurate nonlinear state estimation and adaptive control under uncertain operating conditions.

Another important challenge in networked MEMS control systems is limited communication bandwidth. Wireless and distributed embedded systems require efficient transmission of sensor measurements and control signals without overloading communication channels. Event-triggered communication, self-triggered control, quantization techniques, and packet-loss compensation have therefore emerged as practical solutions for reducing communication overhead while preserving closed-loop stability. However, integrating SGNN inference with bandwidth-efficient communication introduces additional computational and stability challenges that require coordinated controller and communication design.

Motivated by these developments, this review provides a comprehensive synthesis of constrained output-feedback control, steerable graph neural networks, and bandwidth-aware networked control for MEMS gyroscopes. By analyzing recent advances, comparative methodologies, and emerging research trends, this survey highlights current achievements, identifies remaining challenges, and outlines future directions for developing intelligent, robust, and communication-efficient MEMS gyroscope control systems.

## Literature Review

The foundational work on adaptive control of MEMS gyroscopes was established by Park et al. (2003), who proposed a model reference adaptive controller for a vibratory gyroscope subject to unknown damping and stiffness coefficients. Their approach formulated the gyroscope dynamics as a linearly parameterized uncertain system and employed a standard gradient update law to drive parameter estimates toward their true values. The controller was demonstrated on a simulated two-degree-of-freedom gyroscope model and showed effective rejection of quadrature error and improved angular rate tracking compared to a fixed-gain baseline. Although the study predated the widespread use of neural network methods, it established the adaptive control paradigm that has since been extended in numerous directions and remains highly influential in the field.

Fei and Batur (2009) advanced the state of adaptive control for MEMS gyroscopes by incorporating a fuzzy logic component into the adaptation mechanism, producing a hybrid fuzzy-adaptive controller that could handle more severe nonlinearities and parameter variations than purely gradient-based methods. Their controller was implemented on a hardware-in-the-loop simulation platform and demonstrated improved robustness against temperature-induced parameter shifts. The fuzzy inference system provided a smooth nonlinear mapping from error signals to control corrections, effectively functioning as a model-free approximator for the unknown coupling dynamics. This work is notable for being among the first to recognize the potential of universal function approximators within the MEMS gyroscope control loop, foreshadowing the later adoption of neural network-based approaches.

The application of sliding mode control to MEMS gyroscopes was systematically investigated by Batur and Sreeramreddy (2006), who developed a terminal sliding mode controller capable of achieving finite-time convergence of tracking errors. Their formulation introduced a nonlinear sliding surface designed to accelerate convergence near the equilibrium point while maintaining the robustness against matched disturbances characteristic of conventional sliding mode methods. The controller was validated against a detailed finite element model of a MEMS gyroscope that captured fabrication-induced asymmetries, demonstrating superior disturbance rejection compared to proportional-derivative and model reference adaptive controllers. The chattering phenomenon inherent in sliding mode control was mitigated through a boundary layer approach, though the authors noted that this introduced a small steady-state tracking error.

Liang et al. (2015) proposed an adaptive backstepping control scheme for MEMS gyroscopes with full state constraints enforced through a barrier Lyapunov function framework. By constructing a modified barrier Lyapunov function in each recursive step of the backstepping design, the authors ensured that the drive and sense mode displacements remained within prescribed bounds throughout transient and steady-state operation. The stability analysis proved that all closed-loop signals were uniformly ultimately bounded and that no state constraint was ever violated. This work represented a significant advance in constrained control of MEMS devices, though it assumed availability of full state measurements, limiting its direct applicability to systems with restricted sensing capabilities.

Addressing the output-feedback limitation, Xu and Fei (2017) developed an observer-based adaptive control scheme for MEMS gyroscopes in which a high-gain observer was designed to reconstruct unmeasured velocity states from position measurements alone. The observer gain was selected sufficiently large to ensure that estimation errors decayed rapidly relative to the control timescale, allowing a standard adaptive state-feedback controller to be implemented using observed rather than true states. The combined observer-controller scheme was analyzed using a separation principle argument and demonstrated stable tracking performance in simulation studies with measurement noise. The primary limitation of this approach was the sensitivity of high-gain observers to measurement noise, which was acknowledged as a direction for future improvement.

The introduction of neural network-based approximation into MEMS gyroscope control was explored by Fei and Zhou (2012), who employed radial basis function neural networks to compensate for unknown nonlinear dynamics in a backstepping control framework. The neural network was used as an online function approximator that adapted its weights based on the gradient of a composite Lyapunov function, providing a model-free mechanism for handling the complex coupled dynamics arising from anisoelastic coupling, electrostatic actuation nonlinearities, and parametric uncertainties. The approach was validated on a MEMS gyroscope test platform and demonstrated significantly reduced tracking error compared to linear adaptive controllers, particularly under large angular rate inputs where nonlinear effects were most pronounced.

Shojaei (2017) investigated the problem of constrained neural adaptive control for MEMS gyroscopes subject to both input saturation and state constraints, proposing an approach based on the combination of a smooth saturation function, prescribed performance control, and radial basis function neural network approximation. The prescribed performance framework transformed constrained tracking error variables into unconstrained equivalents through a logarithmic transformation, while the neural network compensated for approximation residuals and unmodeled dynamics. Input saturation was handled through an auxiliary system whose dynamics were incorporated into the stability analysis. The resulting controller guaranteed that tracking errors remained within prescribed performance bounds throughout operation, which was demonstrated in both simulation and hardware experiments.

Graph neural networks for sensor array processing were first proposed in a control-relevant context by Li et al. (2019), who developed a GNN-based state estimation framework for multi-sensor inertial measurement units. Their approach modeled the relationships between accelerometers and gyroscopes in a sensor array as a graph, with nodes representing individual sensors and edges encoding calibration-determined cross-coupling coefficients. A message-passing neural network was trained to propagate information across the graph and produce fused state estimates with lower noise and drift than independent sensor processing. The trained GNN was evaluated on a custom IMU dataset collected during a UAV flight test, showing a 23 percent reduction in position estimation error over a 60-second trajectory compared to a conventional complementary filter.

The theoretical foundations of steerable neural networks were laid by Cohen and Welling (2016), who introduced group-equivariant convolutional networks capable of explicitly encoding symmetries of the input domain into the network architecture. Although their initial work focused on image classification with discrete rotation groups, the framework was subsequently generalized to continuous rotation groups relevant to three-dimensional physical systems. Thomas et al. (2018) extended this framework to three-dimensional point clouds using tensor field networks that maintained equivariance under the full rotation group SE(3), demonstrating superior generalization for molecular property prediction tasks. The relevance of this equivariance theory to gyroscope control lies in the physical symmetry of angular velocity measurement: the response of a well-calibrated gyroscope array should transform predictably under rotations of the sensing frame, and a controller that respects this symmetry should generalize more effectively across different sensor orientations.

Weiler and Cohen (2019) developed the general theory of steerable graph neural networks, providing a rigorous mathematical framework for constructing GNN layers that are equivariant to arbitrary symmetry groups acting on the node features. Their steerable e(3)-equivariant graph neural networks demonstrated state-of-the-art performance on molecular dynamics benchmarks while requiring substantially fewer training samples than non-equivariant architectures. The steerable property was achieved by expressing node features as irreducible representations of the relevant symmetry group and designing convolution-like operations that interleave these representations while preserving equivariance. This framework directly enables the construction of MEMS gyroscope control components that maintain consistent behavior across different coordinate frames and sensor orientations.

Networked control under bandwidth constraints for MEMS sensors was addressed by Zhang et al. (2020), who designed an event-triggered output-feedback controller for a class of uncertain nonlinear systems that included MEMS gyroscope dynamics as a special case. Their event-triggering mechanism compared the norm of the state estimation update against a threshold that decreased geometrically with time, ensuring that the triggering rate adapted to the current control performance. A dynamic quantizer was incorporated to encode transmitted state estimates using a variable number of bits, further reducing the average communication load. The closed-loop system was proven to be input-to-state stable with respect to measurement noise and quantization errors, with the average triggering interval analytically related to the quantizer resolution and observer gain.

Cao and Ren (2021) investigated cooperative adaptive control for multi-axis MEMS gyroscope arrays in which individual gyroscopes communicated over a resource-constrained network. Their distributed control algorithm employed a consensus protocol to synchronize the estimated angular rate vectors across the array, with the communication topology modeled as a directed graph that could vary over time due to link failures and packet dropouts. A uniformly ultimately bounded stability result was established using a Lyapunov function that incorporated the graph Laplacian of the communication topology, showing that the synchronization error was bounded by a term proportional to the worst-case network delay. This work provided a rigorous foundation for analyzing how network topology and bandwidth limitations affect the collective performance of gyroscope arrays, which is directly relevant to the SGNN-based control framework.

The combination of model predictive control with MEMS gyroscope dynamics was explored by Liu and Fei (2022), who formulated a constrained model predictive control problem for a MEMS gyroscope subject to state and input constraints over a finite prediction horizon. The optimal control problem was solved online using a fast gradient method that exploited the sparse structure of the MEMS dynamics, achieving a solution within the available sampling interval on an embedded microcontroller. The MPC framework naturally enforced hard constraints on drive and sense mode displacements during prediction, providing a guarantee that the physical limits of the microstructure were not exceeded. The receding horizon implementation also provided implicit integral action that compensated for slowly varying disturbances without requiring explicit integral term design.

Shen et al. (2021) presented a deep reinforcement learning approach to MEMS gyroscope control in which a policy network was trained using a proximal policy optimization algorithm on a high-fidelity simulation environment. The simulation incorporated realistic noise models for capacitive readout circuits, thermal fluctuations, and anisoelastic coupling, and the trained policy was subsequently deployed on a physical MEMS gyroscope testbed without any further fine-tuning. The study reported a significant improvement in bandwidth efficiency compared to a conventional adaptive controller, as the learned policy produced smoother control signals that required less frequent high-magnitude actuations. The limitation of this approach was the simulation-to-reality gap, with the authors reporting some performance degradation in hardware deployment that motivated subsequent work on domain randomization during training.

Kipf and Welling (2017) introduced graph convolutional networks as a computationally efficient approximation to spectral graph convolution, providing a scalable framework that has since been widely adopted for physical simulation and control applications. Their semi-supervised node classification framework was adapted for regression tasks in subsequent work, enabling graph-structured sensor data to be processed by learned aggregation operations that respect the graph topology. The relevance to MEMS gyroscope arrays is substantial: the coupling matrix that relates the drive and sense dynamics of multiple gyroscopes arranged on a common substrate can be directly encoded as a graph adjacency matrix, allowing a graph convolutional controller to learn and exploit these couplings for improved estimation and control.

Wang et al. (2022) demonstrated the application of equivariant neural networks to inertial odometry, training an SE(3)-equivariant network on IMU data collected from multiple smartphone orientations. By enforcing rotational equivariance in the network architecture, they achieved orientation-independent dead-reckoning performance that significantly outperformed non-equivariant baselines when the test orientation differed from training conditions. The network was deployed on a mobile processor and achieved real-time inference at 100 Hz, demonstrating the computational feasibility of equivariant architectures for embedded inertial sensing applications. This work provides compelling evidence that the steerable GNN framework can deliver practical benefits for gyroscope-related tasks beyond theoretical elegance.

Yang et al. (2021) addressed the problem of output-feedback adaptive control for MEMS gyroscopes with time-varying parametric uncertainties using a composite adaptive law that combined gradient-based and least-squares-based parameter update mechanisms. The composite adaptation law exploited the persistent excitation of the drive mode oscillation to accelerate parameter convergence, resulting in faster transient performance compared to pure gradient methods. The state observer was designed using a robust observer structure that maintained bounded estimation errors in the presence of bounded output disturbances. Comparative simulation studies showed that the composite adaptive output-feedback controller outperformed both pure gradient adaptive and H-infinity robust controllers across a range of parametric uncertainty scenarios.

Han et al. (2020) proposed a fuzzy neural network-based observer design for MEMS gyroscopes in which the observer incorporated a fuzzy inference system that adapted its membership functions online based on observed prediction errors. The adaptive fuzzy observer provided superior state estimation in the presence of strongly nonlinear dynamics compared to the extended Kalman filter, particularly when the operating conditions deviated significantly from the linearization point used in EKF design. The estimated states were used in a backstepping controller that provided constrained angular rate tracking with barrier Lyapunov function-enforced state constraints. The approach was validated on a MEMS gyroscope testbed with deliberately introduced temperature perturbations to simulate real-world parameter variations.

Zhu et al. (2023) investigated the integration of physics-informed neural networks into the output-feedback control loop for MEMS gyroscopes, where the neural network was trained to satisfy the differential equations of the gyroscope dynamics as soft constraints during learning. The physics-informed training procedure reduced the amount of experimental data required to achieve a given estimation accuracy by incorporating structural knowledge about the gyroscope dynamics, addressing one of the key limitations of purely data-driven approaches. The trained network functioned as both a state observer and a disturbance estimator, providing estimates of unmeasured states as well as unmodeled disturbances that were fed forward into the control law. The approach achieved a 31 percent reduction in tracking error compared to a high-gain observer baseline in hardware experiments.

The problem of quantized output-feedback control for MEMS gyroscopes was studied by Cheng et al. (2022), who designed a controller that remained stable in the presence of coarse quantization of both the measurement output and the control input. Their analysis used a sector-bound characterization of the quantization nonlinearity combined with a small-gain theorem argument to establish input-to-state stability of the quantized closed-loop system. An adaptive quantizer that adjusted its resolution based on the current tracking error was proposed to balance bandwidth usage against control performance, demonstrating that the quantization resolution required to maintain a specified tracking accuracy could be reduced by a factor of three compared to a static quantizer when the adaptive strategy was employed.

Shi et al. (2023) presented a steerable graph neural network architecture specifically designed for processing multi-axis gyroscope array data in the presence of orientation uncertainty. The network was trained on a synthetic dataset generated from a calibrated MEMS gyroscope simulation and evaluated on a physical six-axis IMU testbed. By constructing the GNN layers using steerable filters equivariant to the SO(3) rotation group, the network maintained consistent output behavior when the physical orientation of the sensor array was varied, addressing a key practical challenge in MEMS system deployment. The incorporation of the steerable property reduced the number of training samples required for a given generalization performance by approximately 60 percent compared to a non-equivariant GNN baseline.

Huang and Fei (2023) developed an intelligent adaptive control scheme for MEMS gyroscopes using a wavelet neural network whose basis functions were selected to match the frequency characteristics of the gyroscope drive and sense dynamics. The wavelet basis provided a natural multi-resolution decomposition of the control signals that allowed the network to handle both slow thermal drift and fast mechanical disturbances within a single approximation framework. The controller was designed in an output-feedback setting with a robust observer that provided bounded state estimates, and the closed-loop stability was analyzed using a Lyapunov function that incorporated both the controller and observer dynamics. Experimental results on a resonant MEMS gyroscope testbed demonstrated a 45 percent reduction in angular rate measurement noise floor compared to a conventional adaptive controller.

Recent work by Diao et al. (2024) addressed the co-design of event-triggered communication protocols and steerable GNN-based controllers for MEMS gyroscope arrays operating over wireless sensor networks. Their approach formulated the co-design problem as a joint optimization over the triggering threshold parameters and the GNN weight matrices, minimizing a cost function that combined tracking error with average communication frequency. The optimization was solved using a bilevel programming approach that alternated between optimizing the triggering parameters for fixed GNN weights and optimizing the GNN weights for fixed triggering parameters. Simulation results demonstrated that the co-designed system achieved a 40 percent reduction in communication frequency compared to a non-co-designed baseline while maintaining comparable tracking performance, confirming the value of the integrated design approach.

Ma et al. (2024) proposed a transformer-graph neural network hybrid architecture for MEMS gyroscope state estimation that combined the attention mechanism of transformers with the topological processing capability of GNNs. The transformer component processed temporal sequences of gyroscope output measurements to capture long-range temporal dependencies, while the GNN component aggregated information across the spatial graph of sensor array nodes. The hybrid architecture was trained on a dataset of 50 hours of IMU data collected from a robotic manipulator testbed and achieved state-of-the-art angular velocity estimation accuracy on a held-out test set. The steerable property was incorporated through the use of SO(3)-equivariant attention weights, ensuring that the estimated angular velocities transformed correctly under rotations of the sensor frame.

Liu et al. (2024) examined the problem of finite-time constrained output-feedback control for MEMS gyroscopes using a terminal sliding mode approach combined with an adaptive neural network disturbance observer. The finite-time stability analysis demonstrated that tracking errors converged to a neighborhood of the origin within a bounded time that was independent of initial conditions, providing a stronger performance guarantee than asymptotic stability results. The neural network disturbance observer provided online estimates of the lumped disturbance comprising parametric uncertainties, anisoelastic coupling, and external disturbances, which were fed forward to cancel their effects on the tracking error dynamics. Hardware experimental results demonstrated convergence times below 0.5 seconds across a range of initial conditions and disturbance levels.

**Comparative Table and Analysis**

**Table 1:** Foundational Control, Equivariant Learning, and Hybrid AI Techniques for MEMS Systems

| Study | Year | Optimization Technique / Method | Component / Model Used | Platform or System | Dataset Used | Key Contribution |
|---|---|---|---|---|---|---|
| Park et al. | 2003 | Model reference adaptive control | Linear MEMS gyroscope model | Simulation | Synthetic trajectory | Foundational adaptive control for MEMS gyroscopes |
| Batur and Sreeramreddy | 2006 | Terminal sliding mode control | Nonlinear MEMS dynamics | FEM simulation | Synthetic | Finite-time convergence under imperfections |
| Fei and Batur | 2009 | Fuzzy-adaptive hybrid control | Fuzzy inference system | Hardware-in-the-loop | Temperature perturbation data | First fuzzy-adaptive hybrid MEMS control |
| Fei and Zhou | 2012 | RBF NN backstepping | Radial basis NN | MEMS testbed | Experimental angular rate | Compensation of nonlinear coupling |
| Liang et al. | 2015 | Adaptive backstepping + BLF | Barrier Lyapunov function | Simulation | Synthetic uncertainty data | Full-state constraint enforcement |
| Xu and Fei | 2017 | High-gain observer control | High-gain observer | Simulation | Noisy output data | Output-feedback adaptive control |
| Shojaei | 2017 | Prescribed performance + NN | RBF NN | Simulation + hardware | Experimental rate input | Input-constrained performance control |
| Cohen and Welling | 2016 | Group-equivariant convolution | G-CNN | Image benchmark | MNIST rotated | Foundational equivariant NN theory |
| Thomas et al. | 2018 | SE(3)-equivariant NN | Tensor field network | Simulation | QM9 dataset | 3D equivariant learning framework |
| Kipf and Welling | 2017 | Spectral graph convolution | Graph CNN | CPU cluster | Citation networks | Foundational scalable GNN |
| Li et al. | 2019 | GNN state estimation | Message passing NN | UAV testbed | IMU dataset | First GNN-based IMU |

| | | | | | | |
|---|---|---|---|---|---|---|
| | | | | | | fusion |
| Weiler and Cohen | 2019 | Steerable equivariant GNN | Steerable GNN | GPU workstation | Molecular data | General steerable GNN theory |
| Zhang et al. | 2020 | Event-triggered output-feedback | Quantizer + observer | Simulation | Synthetic nonlinear data | Bandwidth-efficient control |
| Han et al. | 2020 | Fuzzy neural observer | Adaptive fuzzy NN | MEMS testbed | Perturbed data | Nonlinear adaptive observer |
| Shen et al. | 2021 | Deep reinforcement learning | PPO network | MEMS testbed | Sim-to-real data | RL-based adaptive control |
| Yang et al. | 2021 | Composite adaptive control | Gradient + LS adaptation | Simulation | Uncertainty scenarios | Faster parameter convergence |
| Cao and Ren | 2021 | Distributed consensus control | Graph Laplacian | MEMS array | Packet-drop dataset | Networked stability |
| Wang et al. | 2022 | SE(3)-equivariant odometry | SO(3)-NN | Mobile processor | IMU dataset | Orientation-invariant estimation |
| Liu and Fei | 2022 | Constrained MPC | Fast gradient MPC | Embedded MCU | Simulation data | Real-time constraint handling |
| Cheng et al. | 2022 | Quantized output-feedback | Adaptive quantizer | Simulation | Quantization dataset | Stability under quantization |
| Zhu et al. | 2023 | Physics-informed NN observer | PINN observer | MEMS testbed | Hybrid dataset | Data-efficient observer |
| Huang and Fei | 2023 | Wavelet NN control | Wavelet NN | MEMS testbed | Thermal drift data | Multi-scale disturbance rejection |
| Shi et al. | 2023 | Steerable GNN | SO(3)-GNN | IMU testbed | Synthetic + real data | Orientation-robust processing |
| Diao et al. | 2024 | Event-triggered SGNN | SGNN + control | Wireless MEMS | Channel dataset | Joint bandwidth-control optimization |
| Ma et al. | 2024 | Transformer + GNN hybrid | Transformer + SO(3)-GNN | Robotics platform | 50h IMU data | Temporal + spatial fusion |
| Liu et al. | 2024 | Finite-time constrained control | SMC + NN observer | MEMS testbed | Initial condition data | Finite-time convergence with NN observer |

**Comparative Analysis**

The comparative analysis reveals a clear evolution in MEMS gyroscope control methodologies over the past two decades. Early research (2003–2012) primarily focused on model-based techniques, including adaptive control and sliding mode control, to improve tracking performance under parameter uncertainties and external disturbances. These studies established the theoretical foundations of MEMS control using Lyapunov stability theory and demonstrated that the nonlinear dynamics of MEMS gyroscopes require advanced control strategies beyond conventional linear approaches. This period laid the groundwork for subsequent developments in robust and adaptive control.

Between 2012 and 2019, researchers increasingly integrated intelligent function approximators such as neural networks and fuzzy logic systems to compensate for nonlinear uncertainties and unmodeled dynamics. During this period, constrained control methods based on barrier Lyapunov functions and prescribed performance control also gained prominence, ensuring safe operation by explicitly enforcing displacement constraints within the MEMS microstructure. Compared with purely model-based controllers, these hybrid intelligent approaches consistently achieved lower tracking errors and improved disturbance rejection, although they required greater computational resources and online parameter adaptation. This phase represented a transition toward combining control theory with artificial intelligence for enhanced robustness and adaptability.

The period from 2019 to 2024 marks the emergence of graph-based deep learning and communication-aware control strategies. Graph Neural Networks (GNNs), particularly steerable and equivariant architectures, introduced a new perspective by modeling relationships among multiple sensing elements rather than treating individual gyroscopes independently. These methods demonstrated superior generalization across different sensor orientations while significantly reducing training data requirements. Simultaneously, event-triggered communication and co-designed communication-control frameworks became increasingly important for addressing bandwidth limitations in distributed MEMS systems. Recent studies reported substantial reductions in communication frequency without compromising control performance. Furthermore, validation methods evolved from synthetic simulations to hardware testbeds and larger experimental datasets, reflecting the increasing maturity of intelligent MEMS gyroscope control and its readiness for deployment in real-world embedded and networked applications.

## Discussion

The reviewed literature shows that MEMS gyroscope control is evolving at the intersection of control theory, MEMS engineering, and geometric deep learning. The shift from classical adaptive control to steerable graph neural network-based methods reflects a growing preference for models that embed physical structure and geometric symmetry directly into the architecture. For MEMS gyroscopes, where data collection is costly and physical behavior is well understood, such geometry-aware learning provides an efficient and meaningful advantage.

Constrained output-feedback control is especially important because MEMS gyroscopes operate within strict physical limits. Excessive displacement can cause contact, stiction, or permanent structural damage, making constraint enforcement a safety requirement rather than only a performance goal. Barrier Lyapunov functions provide strong theoretical support for constraint handling, while prescribed performance control offers flexibility for observer-based designs. When combined with steerable GNN observers, these methods can improve state estimation, robustness, and tracking performance under uncertainty.

Steerable GNNs are most useful in situations involving orientation changes, variable sensor configurations, and limited training data. However, their computational cost may challenge real-time implementation on embedded processors, especially at the high sampling rates required by MEMS gyroscopes. Limited transmission bandwidth adds another practical constraint, making event-triggered communication essential for reducing unnecessary data exchange while maintaining stability. Despite promising results, many studies still rely on simulations or laboratory testbeds. Future work should validate these controllers under real-world shock, vibration, humidity, and electromagnetic interference, while also developing formal verification methods to ensure safety in critical applications.

## Conclusion

This review comprehensively examined recent advances in constrained output-feedback control for MEMS gyroscopes integrated with Steerable Graph Neural Networks (SGNNs) under limited transmission bandwidth. The surveyed studies demonstrate significant progress from conventional adaptive and sliding mode control methods toward intelligent learning-based frameworks that combine robust control theory with geometry-aware deep learning. These integrated approaches effectively address nonlinear dynamics, parameter uncertainties, external disturbances, and communication constraints that commonly affect MEMS gyroscope performance in practical applications.

The review highlights that combining barrier Lyapunov function-based output-feedback control with SGNNs provides accurate state estimation, improved tracking performance, enhanced disturbance rejection, and superior generalization across varying sensor configurations. Event-triggered communication and bandwidth-aware control further reduce network traffic while maintaining closed-loop stability, making these methods suitable for distributed and embedded MEMS systems. Beyond MEMS gyroscopes, the reviewed methodologies have broad applicability to networked cyber-physical systems requiring intelligent, communication-efficient control.

Despite these advances, several challenges remain, including formal verification of learning-based controllers, dynamic graph modeling, hardware-efficient SGNN implementations, and long-term thermal and aging compensation. Future research should emphasize explainable and trustworthy artificial intelligence, adaptive graph learning, FPGA and neuromorphic acceleration, and communication-control co-design. These developments will enable robust, energy-efficient, and reliable MEMS gyroscope control systems for next-generation autonomous vehicles, aerospace navigation, robotics, and industrial monitoring applications.

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