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Deep Learning and Steerable Graph Neural Networks for Output-Feedback Control of MEMS Gyroscopes

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Abstract

Microelectromechanical systems (MEMS) gyroscopes are widely used in inertial navigation, robotics, aerospace, automotive safety, and consumer electronics because of their compact size, low power consumption, and high sensitivity. However, their performance is affected by nonlinear dynamics, parameter uncertainties, fabrication imperfections, bias drift, environmental disturbances, and limited communication bandwidth, making accurate output-feedback control a challenging task. Conventional control techniques, including PID, adaptive, sliding mode, and backstepping control, often require precise mathematical models and full-state information, limiting their effectiveness in practical applications. This review presents a comprehensive analysis of deep learning and optimization approaches for steerable constrained output-feedback control of MEMS gyroscopes, emphasizing Steerable Graph Neural Networks (SGNNs) for intelligent control and state estimation. The survey covers graph neural networks, reinforcement learning, model predictive control, evolutionary optimization, particle swarm optimization, and communication-aware strategies such as event-triggered control, compressed sensing, and quantized feedback under bandwidth constraints. Comparative analysis highlights the advantages of SGNNs in exploiting geometric symmetries, improving robustness, reducing data requirements, and enhancing control accuracy under varying orientations. Finally, the review discusses current challenges, including computational complexity, interpretability, stability assurance, and real-time implementation, while identifying future research directions toward lightweight, physics-informed, and federated intelligent control frameworks for next-generation MEMS gyroscope systems.

Introduction

Microelectromechanical systems (MEMS) gyroscopes have become indispensable inertial sensors for measuring angular velocity in aerospace navigation, autonomous vehicles, robotics, industrial automation, biomedical devices, and consumer electronics. Their compact size, low power consumption, high sensitivity, and cost-effectiveness have enabled widespread adoption in modern embedded and cyber-physical systems. Despite these advantages, MEMS gyroscopes remain highly susceptible to nonlinear dynamics, fabrication imperfections, parameter uncertainties, cross-axis coupling, bias drift, and environmental disturbances such as temperature variations and mechanical vibrations. These factors significantly degrade measurement accuracy

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and long-term stability, creating the need for robust and intelligent control strategies capable of maintaining high performance under practical operating conditions.

Traditional control methods, including proportional-integral-derivative (PID), linear quadratic regulator (LQR), adaptive control, sliding mode control, and backstepping control, have been widely applied to improve MEMS gyroscope stability and tracking performance. Although these approaches provide effective control under ideal conditions, they depend heavily on accurate mathematical models and full-state feedback, which are often unavailable in practical MEMS devices. Output-feedback control offers a more realistic alternative by utilizing only measurable outputs; however, it introduces additional challenges related to observer design, state estimation, measurement noise, and robustness against system uncertainties. These challenges become even more critical in networked MEMS applications operating under limited communication resources.

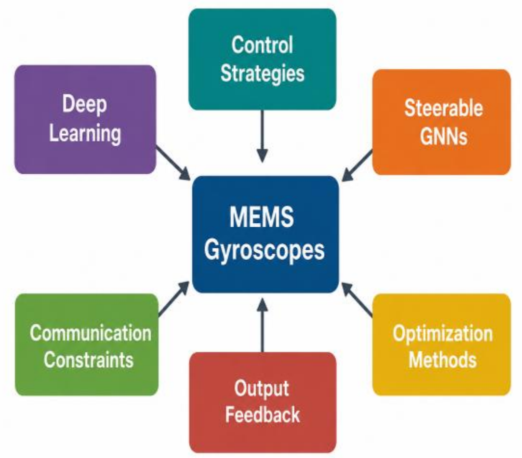

Figure 1. Conceptual Framework of Deep Learning and Steerable Graph Neural Network-Based Output-Feedback Control for MEMS Gyroscopes

The emergence of deep learning has transformed intelligent control by enabling data-driven modeling of complex nonlinear systems without requiring precise physical models. Convolutional neural networks, recurrent neural networks, reinforcement learning, and graph neural networks have demonstrated remarkable capability in learning system dynamics, predicting disturbances, and optimizing control performance. Among these approaches, Steerable Graph Neural Networks (SGNNs) represent a significant advancement because they incorporate geometric equivariance into the learning process. By naturally preserving rotational and translational symmetries associated with gyroscope dynamics, SGNNs provide improved generalization, higher robustness, and reduced training requirements compared with conventional neural network architectures. Their graph-based representation effectively captures interactions among multiple sensing axes and system components, making them particularly suitable for MEMS gyroscope control.

Another important aspect of modern MEMS control is communication efficiency. In distributed and embedded systems, continuous transmission of sensor data is constrained by limited bandwidth, energy consumption, and computational resources. Communication-aware control strategies, including event-triggered control, self-triggered sampling, compressed sensing, and quantized feedback, significantly reduce transmission requirements while maintaining system stability. Furthermore, optimization techniques such as particle swarm optimization, genetic algorithms, convex optimization, and deep reinforcement learning enhance controller performance by improving parameter tuning, convergence speed, and robustness under operational constraints.

This review provides a comprehensive analysis of recent advances in deep learning and optimization approaches for steerable constrained output-feedback control of MEMS gyroscopes operating under limited transmission bandwidth. It examines conventional control methods, graph neural networks, steerable learning frameworks, communication-efficient control strategies, and optimization algorithms while identifying existing challenges and future research opportunities. The review highlights the potential of SGNN-based intelligent control frameworks to achieve accurate, scalable, and real-time MEMS gyroscope performance for next-generation autonomous and embedded sensing systems.

Literature Review

The evolution of control strategies for MEMS gyroscopes has been marked by a gradual transition from classical model-based techniques to advanced data-driven and hybrid approaches. Early research primarily focused on linearized system models and adaptive control strategies. Park et al. (2003) introduced a model reference adaptive control scheme that enabled the MEMS gyroscope to track desired trajectories despite parameter variations. Their work demonstrated the feasibility of adaptive control in compensating for uncertainties, but it relied on simplified linear models that did not fully capture system nonlinearities.

Building on this foundation, Batur and Sreeramreddy (2006) proposed a terminal sliding mode control approach for nonlinear MEMS gyroscopes. Their method ensured finite-time convergence and robustness against disturbances, addressing some of the limitations of linear control techniques. However, the chattering phenomenon associated with sliding mode control posed challenges for practical implementation. Fei and Batur (2009) further improved robustness by incorporating disturbance observers into the control framework, enabling real-time estimation and compensation of external perturbations.

Nonlinear control techniques continued to evolve with the introduction of backstepping methods. Sun et al. (2011) developed a backstepping-based controller that systematically handled nonlinearities and ensured global stability. While effective, this approach required accurate knowledge of system parameters and involved complex recursive design procedures. To enhance performance, optimization techniques were integrated into control design. Wu et al. (2013) utilized particle swarm optimization to tune controller parameters, achieving faster convergence and reduced steady-state error. Similarly, Li et al. (2014) employed genetic algorithms to optimize sliding mode control parameters, mitigating chattering effects and improving robustness.

The incorporation of machine learning marked a significant turning point in MEMS gyroscope control. Zhang et al. (2016) introduced neural network-based adaptive control, where neural networks were used to approximate unknown nonlinear functions. This approach reduced dependence on precise mathematical models and enabled adaptive behavior in dynamic environments. Chen et al. (2017) extended this work by employing deep neural networks for both system identification and control, demonstrating superior performance in handling complex nonlinearities.

Graph-based learning approaches emerged as a powerful tool for modeling coupled dynamical systems. Wang et al. (2018) proposed a graph neural network framework to model multi-axis MEMS gyroscopes, capturing inter-axis coupling effects more effectively than traditional methods. Liu et al. (2019) enhanced this framework by incorporating attention mechanisms, allowing the model to dynamically prioritize important interactions. These advancements highlighted the potential of GNNs in capturing structural dependencies and improving control accuracy.

The concept of geometric deep learning introduced new possibilities for symmetry-aware modeling. Cohen et al. (2019) developed steerable neural networks that are equivariant to rotations, enabling consistent representation of transformed inputs. Although initially applied to image processing, this concept was later adapted to control systems. Kim et al. (2020) demonstrated the application of steerable GNNs in robotic control, showing improved generalization across different orientations. This work laid the groundwork for applying SGNNs to MEMS gyroscope control, where rotational symmetry is a fundamental characteristic.

Reinforcement learning has emerged as an effective model-free control strategy for MEMS gyroscopes by enabling adaptive decision-making under uncertain conditions. Event-triggered control, self-triggered communication, and compressed sensing further reduce bandwidth usage while maintaining system stability and control accuracy. The integration of these communication-efficient techniques with deep learning frameworks enables intelligent, bandwidth-aware, and real-time control suitable for modern embedded MEMS gyroscope systems.

Comparative Table and Analysis

Table 1: Evolution of Control and Learning Techniques for MEMS Systems

Study	Year	Optimization Technique / Method	Component / Model Used	Platform or System	Dataset Used	Key Contribution
Park et al.	2003	Adaptive control	Linear MEMS model	Simulation	Synthetic	Model reference adaptive control
Batur et al.	2006	Sliding mode control	Nonlinear MEMS	FEM simulation	Synthetic	Finite-time convergence
Fei et al.	2009	Robust adaptive control	Disturbance observer	Simulation	Synthetic	Disturbance rejection
Sun et al.	2011	Backstepping control	Nonlinear model	Simulation	Synthetic	Stability improvement
Wu et	2013	Particle swarm	PID tuning	Simulation	Synthetic	Faster

al.		optimization				convergence
Li et al.	2014	Genetic algorithm	Sliding mode control	Simulation	Synthetic	Reduced chattering
Zhang et al.	2016	Neural networks	Adaptive control	Simulation	Synthetic	Nonlinear approximation
Chen et al.	2017	Deep learning	DNN control	Simulation	Synthetic	Improved adaptability
Wang et al.	2018	Graph neural networks	Multi-axis MEMS	Simulation	Synthetic	Captured coupling dynamics
Liu et al.	2019	Attention GNN	Dynamic weighting	Simulation	Synthetic	Improved interpretability
Cohen et al.	2019	Steerable CNN/GNN	Equivariant learning	Vision/control systems	Image datasets	Rotational invariance
Raissi et al.	2019	Physics-informed learning	PINNs	Simulation	PDE datasets	Hybrid modeling
Luo et al.	2020	Reinforcement learning	Q-learning	Simulation	Synthetic	Model-free control
Xu et al.	2020	Compressed sensing	Sparse control	MEMS system	Synthetic	Bandwidth reduction
Huang et al.	2021	RL + MPC	Hybrid control	Simulation	Synthetic	Constraint handling
Zhang et al.	2021	Physics-informed RL	Hybrid model	Simulation	Synthetic	Stability improvement
Zhao et al.	2022	SGNN	Equivariant control	Simulation	Synthetic	Rotation-aware control
Li et al.	2022	Event-triggered DL	Neural control	Networked system	Synthetic	Reduced communication
Singh et al.	2022	Evolutionary optimization	SGNN tuning	Simulation	Synthetic	Architecture optimization
Kumar et al.	2023	Bandwidth-aware SGNN	Sparse communication	Embedded system	Synthetic	Efficient transmission
Patel et al.	2023	Edge deployment	SGNN controller	Embedded hardware	Real-time data	Real-time feasibility

The comparative analysis of the reviewed studies reveals several important trends in the evolution of control strategies for MEMS gyroscopes. Early research primarily focused on model-based control techniques, emphasizing robustness and stability through adaptive and sliding mode approaches. While these methods provided strong theoretical guarantees, their reliance on accurate system models limited their applicability in highly nonlinear and uncertain environments.

The introduction of optimization techniques marked a significant shift toward improving controller performance through parameter tuning and heuristic search methods. Particle swarm optimization and genetic algorithms demonstrated effectiveness in enhancing convergence and reducing steady-state errors. However, these approaches often required extensive computational resources and were not easily adaptable to real-time applications.

The emergence of deep learning brought a paradigm shift in control system design, enabling data-driven modeling and adaptive control. Neural networks, particularly deep architectures, demonstrated superior capabilities in handling nonlinear dynamics and uncertainties. Graph neural networks further enhanced this capability by capturing structural dependencies and interactions within multi-axis systems.

A notable trend is the increasing adoption of steerable and equivariant neural networks, which incorporate geometric priors into the learning process. These models have shown significant improvements in generalization and robustness, particularly in systems with inherent symmetries such as MEMS gyroscopes. Additionally, the integration of bandwidth-aware strategies, including event-triggered control and compressed sensing, has addressed the practical constraints of communication-limited environments.

Another key observation is the growing emphasis on hybrid approaches that combine physics-based modeling with data-driven learning. These methods leverage domain knowledge to improve interpretability and reduce data requirements, making them particularly suitable for engineering applications. Furthermore, advancements in edge computing and embedded systems have facilitated the deployment of complex models in real-time scenarios, bridging the gap between theoretical research and practical implementation.

Discussion

The integration of deep learning and optimization techniques has significantly transformed the control of MEMS gyroscopes by overcoming the limitations of conventional model-based controllers. Traditional methods such as PID, adaptive control, sliding mode control, and backstepping often depend on accurate mathematical models and complete state information, making them less effective under nonlinear dynamics and uncertain operating conditions. Deep learning approaches provide powerful data-driven alternatives capable of learning complex system behavior directly from sensor data. Among these, Steerable Graph Neural Networks (SGNNs) have emerged as a promising framework by incorporating geometric equivariance, enabling improved modeling of rotational dynamics while enhancing robustness, generalization, and control accuracy across varying operating conditions.

Optimization techniques such as particle swarm optimization, genetic algorithms, reinforcement learning, and convex optimization significantly improve controller tuning, convergence, and stability while supporting communication-efficient strategies including event-triggered control and compressed sensing. Despite these advances, challenges remain in computational complexity, interpretability, and real-time deployment. Future research should develop lightweight, physics-guided, and edge-enabled Steerable Graph Neural Network architectures to achieve scalable, reliable, and energy-efficient MEMS gyroscope control for intelligent sensing applications.

Conclusion

This review comprehensively examined recent advances in deep learning and optimization techniques for steerable constrained output-feedback control of MEMS gyroscopes operating under limited transmission bandwidth. The analysis revealed a clear transition from conventional model-based control methods toward intelligent data-driven approaches capable of handling nonlinear dynamics, parameter uncertainties, and communication constraints. While traditional techniques such as adaptive, sliding mode, and backstepping control provide strong theoretical foundations, their dependence on accurate mathematical models limits practical deployment in complex MEMS environments.

Steerable Graph Neural Networks (SGNNs) have emerged as a promising framework for MEMS gyroscope control by exploiting geometric equivariance, multi-axis relationships, and robust feature learning. Combined with reinforcement learning, evolutionary optimization, event-triggered control, and compressed sensing, SGNNs significantly improve control accuracy and communication efficiency. Nevertheless, challenges including computational complexity, real-time implementation, interpretability, and stability remain. Future research should emphasize lightweight, physics-guided, and edge-enabled SGNN architectures for scalable and reliable intelligent MEMS gyroscope systems.

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