

# A Review of Control Strategies for Robotic Systems with Embedded Sensors

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## ABSTRACT

Robotic systems increasingly rely on embedded sensors to achieve high levels of autonomy, adaptability, and safety in dynamic environments. Unlike existing surveys, this review provides a comprehensive and structured taxonomy of control strategies for sensor-integrated robots, presenting a novel comparative perspective that links traditional methods with emerging paradigms. Five key categories are systematically analyzed: classical controllers, model-based techniques, sensor-driven feedback schemes, data-driven learning approaches, and bio-inspired intelligent control. A detailed comparative evaluation highlights their respective advantages, limitations, and suitability for different robotic domains. Beyond summarizing established techniques, this work contributes a forward-looking analysis of recent technological advances, including sensor miniaturization, edge AI for onboard learning, self-calibrating and self-tuning controllers, explainable control frameworks, and IoT-enabled cyber-physical integration. Furthermore, this review identifies standardized benchmark datasets, evaluation metrics, and simulation platforms to support reproducibility and rigorous performance assessment. By consolidating fragmented literature and emphasizing emerging trends, this study uncovers critical research challenges, such as real-time multimodal sensor fusion, robust and machine learning-based controllers, and energy-aware architectures for embedded robotics. This review establishes a comprehensive reference framework for researchers and practitioners, offering actionable insights that can accelerate the development of resilient, interpretable, and high-performance robotic control systems.

*Keywords-robotic control strategies; embedded sensors; sensor fusion; model predictive control; PID controllers; visual servoing; reinforcement learning; edge AI*

## I. INTRODUCTION

The advancement of robotic systems has undergone a transformative shift with the integration of embedded sensors, enabling real-time perception, adaptive control, and autonomous decision-making across complex and dynamic environments. These embedded systems act not only as peripheral components but as essential elements that bridge the gap between physical interaction and intelligent response, forming the foundation of sensor-driven control paradigms in modern robotics [1]. As robotic applications expand across industrial automation, medical interventions, search-and-rescue missions, and autonomous vehicles, the demand for robust, precise, and adaptive control strategies has intensified [2].

Control strategies in robotics are inherently multidisciplinary, intertwining elements from classical control theory, optimization, machine learning, and bio-inspired computation. The choice of control architecture—be it model-based, adaptive, or learning-driven—profoundly affects the stability, responsiveness, and resilience of the system to

environmental uncertainties [3]. Embedded sensors, when tightly coupled with control algorithms, facilitate continuous state estimation, fault detection, and context-aware behavior modulation, thus improving both autonomy and safety [4].

The state-of-the-art landscape is characterized by the convergence of low-latency sensor networks, real-time data fusion, and intelligent control frameworks capable of operating effectively in noisy, unstructured, and partially observable environments [5]. Recent advances in robotic AI algorithms have significantly enhanced trajectory planning, kinematic control, and motion optimization. For instance, the Pelican Optimization Algorithm (POA) has been successfully applied to improve mobile robot trajectory planning, achieving superior path smoothness and obstacle avoidance compared to traditional methods [6]. Similarly, Particle Swarm Optimization (PSO) and its hybrid variants have been extensively adopted for solving inverse kinematic problems in redundant robots, demonstrating substantial improvements in accuracy and computational efficiency. These AI-driven

optimization strategies, combined with sensor-based feedback and advanced modeling techniques, enable robots to achieve greater autonomy and robustness even under uncertain environmental conditions [7]. However, persistent challenges remain due to the heterogeneity of robotic platforms, variations in sensor fidelity, and trade-offs between model interpretability, computational complexity, and energy efficiency. To address these gaps, this review systematically examines the evolving control strategies tailored for robotic systems with embedded sensors, offering a structured taxonomy, comparative analysis, and future research perspectives to guide innovation in the field.

## II. FUNDAMENTALS OF ROBOTIC CONTROL AND EMBEDDED SENSORS

This section presents core concepts of open- and closed-loop control, various control topologies, and the hierarchical organization of control tasks. It also reviews common sensor types, integration processes, efficient signal-processing pipelines, and probabilistic fusion and accurate estimation techniques.

### A. Overview of Robotic Control Systems

Open-loop control operates without feedback: a predefined control signal is issued by the controller to drive the actuator, and no information about the actual system output is used to adjust subsequent inputs. As illustrated in Figure 1, disturbances or modeling inaccuracies cannot be corrected in real time, potentially leading to significant tracking errors [8]. In contrast, closed-loop control continuously measures the system output and feeds it back into the controller, enabling dynamic error compensation and enhanced robustness against internal and external perturbations.

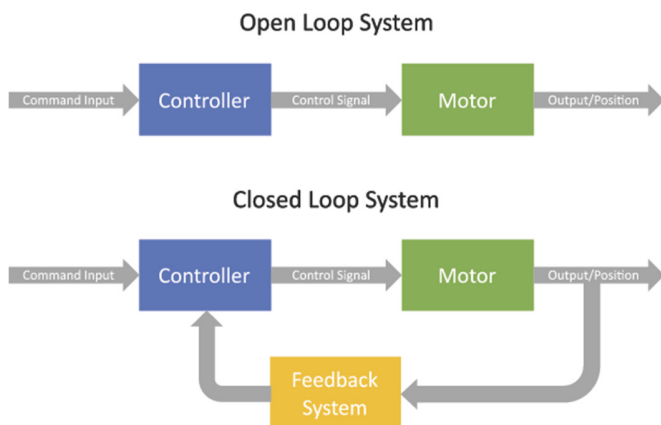


Fig. 1. Open loop vs. closed loop motion control.

Pure feedback control continually adjusts the input based on the error between the desired setpoint and the measured output, offering robustness to unmodeled dynamics but potentially slower disturbance rejection [9]. In contrast, feedforward control senses disturbances directly and preemptively compensates the control input without waiting for errors to manifest. Hybrid control combines both approaches using feedforward paths to counter predictable disturbances

and feedback loops to correct residual errors, thereby achieving faster response and improved accuracy by leveraging their complementary strengths.

Hierarchical control architectures organize control tasks across multiple layers, each operating at distinct time scales and levels of abstraction. A high-level supervisory layer handles trajectory planning and strategic decision-making, while intermediate layers perform task decomposition and motion coordination. Low-level layers execute direct actuator commands and manage real-time feedback loops. This stratification simplifies complexity by decoupling planning from execution and enhances scalability and adaptability in multi-function robotic systems.

### B. Embedded Sensors in Robotics

Embedded sensors constitute the perceptual foundation of robotic platforms, facilitating the acquisition of critical physical parameters that inform control decisions. Common types of sensors include position encoders, potentiometers, force and torque transducers, Inertial Measurement Units (IMUs), vision cameras, LiDAR systems, and tactile arrays, each selected according to task-specific requirements [10]. Sensor integration requires meticulous calibration, drift compensation, and signal-conditioning pipelines that employ amplification, analog-to-digital conversion, and digital filtering to ensure data fidelity. Once raw measurements are available, advanced signal-processing techniques such as Fast Fourier Transform (FFT) and wavelet analysis extract relevant features for control and fault diagnosis [11]. Sensor fusion leverages complementary information from heterogeneous modalities to produce coherent state estimates. Bayesian estimation methods, such as the Extended Kalman Filter (EKF), Unscented Kalman Filter (UKF), and particle filters, enable probabilistic inference under uncertainty [12]. Complementary filters offer computationally efficient alternatives for high-rate data streams (e.g., combining gyroscope and accelerometer outputs). Current strategies also incorporate machine learning algorithms for adaptive sensor modeling and residual error correction. Recursive estimation algorithms facilitate real-time fusion in both centralized and distributed architectures. Such fusion frameworks significantly enhance robustness, accuracy, and resilience to individual sensor failures, thereby underpinning control and autonomy in robotic systems.

## III. CLASSIFICATION OF CONTROL STRATEGIES

This section presents a comprehensive taxonomy of control strategies for robotic systems, delineating five major categories: classical methods, model-based techniques, sensor-driven feedback, learning-based approaches, and bio-inspired intelligent controllers. Each category is analyzed in terms of theoretical foundations, practical implementations, and suitability for varying robotic platforms and tasks.

### A. Classical Control Approaches

Classical control approaches constitute the foundational methods for regulating robotic actuators by employing established mathematical frameworks. Proportional-Integral-Derivative (PID) controllers and their variants, including Proportional-Integral (PI), Proportional-Derivative (PD), and

cascade configurations, offer intuitive tuning parameters to achieve desired transient and steady-state performance [13]. Linear-Quadratic Regulators (LQR) optimize quadratic cost functions to balance state error and control effort, while Linear-Quadratic Gaussian (LQG) extends LQR to stochastic environments by integrating state estimation via Kalman filtering [14]. Adaptive control schemes adjust controller parameters in real time to handle system uncertainties and dynamic variations, and robust control methods ensure stability and performance under bounded modeling errors.

### B. Model-Based Control Techniques

Model-based control leverages mathematical representations of robot kinematics and dynamics to compute control inputs that achieve precise motion objectives. Kinematic modeling defines the mapping between joint and task space, enabling inverse kinematics for trajectory generation [15]. Dynamic modeling captures mass, inertia, and Coriolis effects, forming the basis for inverse dynamics and computed torque control, which compensates for nonlinear dynamic behaviors to enhance tracking accuracy. Model Predictive Control (MPC) solves an optimization problem at each sampling instant to forecast future behavior and enforce constraints on states and inputs, providing robustness to disturbances and adaptability to time-varying objectives [16]. These techniques demand accurate models and computational resources but yield high performance in structured tasks. Figure 2 illustrates an MPC strategy.

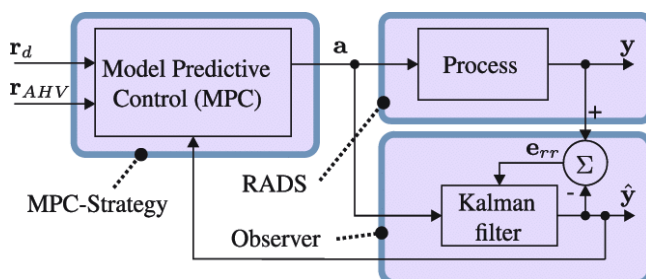


Fig. 2. Model-Predictive Control (MPC) strategy.

### C. Sensor-Based Feedback Control

Sensor-based feedback control exploits direct measurements from sensors to regulate robot interactions with the environment. Visual servoing employs image data from cameras to control robot motion by minimizing visual error between current and desired feature states, enabling tasks such as object tracking and alignment. Force, impedance, and admittance control utilize force/torque sensor data to modulate stiffness and damping properties, allowing compliant interaction and safe contact with uncertain surfaces. Tactile feedback control leverages high-resolution touch sensors to detect contact forces and textures, facilitating manipulation in unstructured environments through closed-loop adjustment of grip and motion [17]. These methods enhance adaptability and safety but require robust perception and control integration. Figure 3 shows a schema of the visual servoing process.

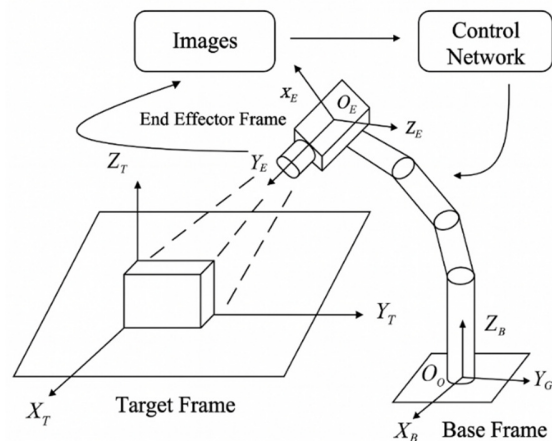


Fig. 3. Visual servoing.

### D. Learning-Based and Data-Driven Control

Learning-based control strategies harness data-driven models to derive control policies from experience rather than explicit system equations. Reinforcement learning algorithms optimize policies through trial-and-error interactions, maximizing cumulative reward while accommodating complex dynamics and high-dimensional state spaces. Supervised learning techniques map sensory input to control output by leveraging labeled datasets, enabling rapid inference but requiring extensive data collection [18]. Unsupervised learning methods uncover latent structures in sensor data for anomaly detection and feature extraction, improving adaptability under unpredictable conditions [19]. Imitation learning and behavior cloning replicate expert demonstrations to bootstrap control policies, reducing exploration requirements and accelerating deployment in real-world tasks [20]. These approaches offer flexibility but introduce challenges in stability assurance and interpretability.

### E. Bio-Inspired and Intelligent Control

Bio-inspired control systems emulate natural intelligence and evolutionary processes to address complex robotic tasks. Fuzzy logic controllers approximate human reasoning by mapping linguistic rules to control actions, offering robustness to uncertainty and nonlinearities [21]. Neural network-based controllers learn internal representations of system dynamics through layered architectures, enabling adaptive approximation of unknown models [22]. Evolutionary algorithms, including genetic and particle swarm optimization, search solution spaces to optimize controller parameters, promoting global convergence where gradient-based methods may fail [23]. Hybrid intelligent control frameworks integrate fuzzy logic, neural networks, and optimization heuristics to leverage complementary strengths, achieving enhanced adaptability and performance in unstructured environments [24-27].

## IV. CLASSIFICATION OF CONTROL STRATEGIES

This section examines how embedded sensors enable context-aware control on diverse robotic platforms. Using real-time feedback from vision, force, inertial, and biosignal sensors, robots achieve enhanced precision, adaptability, and safety in application-specific tasks [28]. The following

subsections explore implementations in industrial manipulators, mobile and autonomous vehicles, humanoid and legged robots, medical and assistive devices, and distributed multi-robot systems.

#### A. Industrial Manipulators

Industrial manipulators rely on high-fidelity position encoders and joint torque sensors to monitor kinematic and dynamic states in real time. Force/torque transducers integrated on the wrist enable direct measurement of interaction forces, facilitating compliant control schemes for safe human-robot collaboration. Precision in trajectory tracking is enhanced through closed-loop feedback that compensates for backlash and structural deflections [29]. Stability is maintained by damping oscillations by real-time adjustment of the controller gains. Safety frameworks incorporate sensor-based thresholds to detect collisions and trigger emergency stops. Advanced algorithms fuse encoder and force data to optimize control performance under variable payloads and task conditions [30, 31].

#### B. Mobile Robots and Autonomous Vehicles

Sensor-driven navigation systems in mobile robots and autonomous vehicles integrate LiDAR, monocular/stereo vision, and inertial sensors to construct environmental maps and estimate vehicle pose. Simultaneous Localization and Mapping (SLAM) algorithms fuse odometry and range measurements to generate accurate, drift-minimized maps for path planning. Obstacle avoidance relies on real-time processing of sensor data to detect and classify dynamic and static objects, enabling reactive trajectory adjustments. Path following is achieved through predictive control laws that track waypoints while compensating for model uncertainties and external disturbances. Advanced implementations leverage hierarchical architectures to coordinate global route planning with local obstacle negotiation [32, 33].

#### C. Humanoid and Legged Robots

Humanoid and legged robots employ Inertial Measurement Units (IMUs) and ground reaction force sensors to maintain real-time balance and stability during locomotion. Zero Moment Point (ZMP) and Divergent Component of Motion (DCM) controllers leverage sensor feedback to adjust joint torques, ensuring robust gait under disturbances. Terrain adaptation algorithms interpret force distribution and foot-ground interactions to modulate step height and foot placement for uneven surfaces. Energy-efficient locomotion is facilitated by compliance control schemes that integrate IMU-based orientation data with actuator impedance adjustment. Sensor-driven reflexes derived from force thresholds enable rapid recovery from unexpected slips or impacts [34, 35].

#### D. Medical and Assistive Robots

Medical and assistive robots utilize biosignals such as Electromyography (EMG) and Electroencephalography (EEG) to interpret user intent and facilitate intuitive human-robot interaction. EMG-driven exoskeletons decode muscle activations to generate torque commands for assisted movement, enhancing rehabilitation outcomes. EEG-based brain-computer interfaces allow patients with severe motor

impairment to control robotic prostheses or wheelchairs through neural signals. Haptic feedback systems integrate force sensors and tactile interfaces to render realistic touch sensations, improving surgical precision and user engagement. In robot-assisted surgery, sensorized instruments provide force and position data for master-slave control architectures, ensuring delicate tissue manipulation under supervisory oversight [36-38].

#### E. Swarm and Multi-Robot Systems

Swarm and multi-robot systems employ distributed control schemes where each agent utilizes local sensor inputs, such as proximity readings, odometry, and inter-robot communication signals, to achieve collective behaviors without centralized coordination. Consensus protocols enable robots to align their states, facilitating formation maintenance and area coverage [39]. Task allocation algorithms leverage sensor-based utility metrics to dynamically assign roles and optimize resource usage [40, 41]. Communication-aware control integrates link-quality estimations to adapt motion plans, ensuring connectivity and robustness under adverse conditions [42]. Bio-inspired flocking and foraging behaviors rely on local sensing and simple rules to realize emergent global objectives, demonstrating scalability and fault tolerance in heterogeneous robotic teams [43].

### V. RECENT ADVANCES AND EMERGING TRENDS

Recent advances in sensor technologies and control methodologies have catalyzed a paradigm shift in robotic autonomy and adaptability. Emerging trends spanning ultra-compact multi-modal sensors, on-device AI, and self-optimizing control loops are converging to produce systems that learn, calibrate, and interact with their environments more intelligently and reliably than ever before.

#### A. Sensor Miniaturization and Integration

Recent advances in sensor miniaturization and integration have enabled unprecedented levels of functional density and system compactness. Microelectromechanical system sensors now combine multiple modalities within a single package, reducing weight and power consumption while increasing reliability. Integration of heterogeneous sensor arrays onto flexible substrates facilitates conformal deployment on curved robot surfaces. This trend supports higher spatial resolution and faster sampling rates, improving feedback fidelity for control loops. Furthermore, advanced packaging techniques and low-power wireless communication modules allow distributed sensor networks to enhance situational awareness without substantial bandwidth overhead. Recent prototypes demonstrate integration across harsh environments, expanding applicability in industrial and field robotics [44, 45].

#### B. Edge AI and Onboard Learning

Edge AI now empowers onboard learning in sensor-driven robots, enabling adaptive control without reliance on cloud connectivity. Lightweight neural network architectures execute inference directly on embedded microcontrollers, reducing latency for time-critical feedback loops. Training of model parameters at the edge supports incremental adaptation to evolving operational conditions, while federated learning

frameworks protect data privacy by aggregating only model updates. Energy-efficient hardware accelerators and optimized compilers further shrink memory footprints. Consequently, robots achieve greater autonomy and resilience by continuously refining control policies in situ [46]. This shift toward decentralization alleviates communication bottlenecks and enhances system robustness in hostile or disconnected settings [47].

### C. Self-Calibrating and Self-Tuning Control Systems

Self-calibrating and self-tuning control systems integrate real-time parameter estimation mechanisms to automatically update controller gains and compensate for sensor drift and component aging. Recursive identification algorithms monitor key performance indices and invoke calibration routines during idle or low-demand intervals, minimizing human intervention. Adaptive algorithms detect shifts in system dynamics and adjust feedforward and feedback parameters to maintain optimal behavior. Integration of online optimization methods and metaheuristic search further refines model accuracy and control performance. These approaches yield stable operation under variable loads and enable plug-and-play sensor modules without extensive commissioning. Field trials illustrate improved longevity and reduced maintenance downtime, particularly in harsh environments where manual recalibration is impractical [48,49].

### D. Explainable and Interpretable Control Strategies

Explainable and interpretable control strategies facilitate human understanding and trust by revealing the internal reasoning of complex algorithms. Symbolic regression and transparent surrogate models approximate black-box controllers to generate human-readable rules or decision trees. Visual analytics tools map control signals and state trajectories to semantic concepts, helping engineers diagnose anomalous behaviors. Model-agnostic explanation frameworks, such as SHAP or LIME, quantify feature contributions to control actions in real time [50]. These strategies support certification and regulatory compliance in safety-critical domains, including healthcare and transportation. Initial experiments demonstrate that integrating interpretability modules does not significantly degrade control performance while improving operator situational awareness. Future work will refine explanation fidelity and minimize computational overhead for embedded deployment.

### E. Cyber-Physical System Integration and IoT-Enabled Robotics

Cyber-physical system integration and IoT-enabled robotics merge computational control with networked sensors and actuators for cohesive operation across distributed environments. Standard communication protocols, such as MQTT and OPC UA, facilitate reliable data exchange between robots, cloud servers, and edge devices [51]. Time-sensitive networking and middleware frameworks ensure deterministic latency for synchronized control loops. Integration with digital twins provides real-time simulation and predictive maintenance, improving system resilience. Scalable platforms manage resource allocation and firmware updates remotely. These developments enable a seamless convergence of robotics

and the Internet of Things (IoT), supporting applications in smart manufacturing, logistics, and environmental monitoring [52].

## VI. RECENT ADVANCES AND EMERGING TRENDS

Benchmark suites and challenges provide standardized tasks to compare control strategies under uniform conditions. Prominent examples include the DARPA Robotics Challenge and the DARPA Subterranean Challenge, which stress mobility and autonomy in extreme environments, and RoboCup, which evaluates multi-agent coordination and real-time decision-making in robotic soccer [53, 54]. Other domain-specific benchmarks, such as the Amazon Robotics Challenge for pick-and-place tasks, further extend the evaluation across diverse manipulation scenarios.

Quantitative evaluation is based on criteria that capture both performance and practical viability. Stability metrics assess deviation from desired trajectories under disturbances, often measured by Root-Mean-Square Error (RMSE) or Lyapunov-based indices. Responsiveness examines control loop latency and settling time, while robustness evaluates the resilience to sensor noise, model uncertainties, and component failures through fault-injection tests [55]. Energy efficiency is gauged through total power consumption or energy per task, which is critical for battery-powered mobile platforms.

Simulation environments and real-world testbeds form the backbone of experimental validation. High-fidelity simulators such as Gazebo, CoppeliaSim (formerly V-REP), MuJoCo, and Webots offer physics-based emulation of sensors and actuators, enabling rapid prototyping and parameter sweeps [56]. Real-world platforms, including PR2, KUKA youBot, and custom test arenas with motion-capture systems, facilitate hardware-in-the-loop trials that reveal integration challenges and latency effects not captured in simulation. Together, these resources support rigorous and reproducible assessments of sensor-driven control systems.

## VII. CHALLENGES AND OPEN RESEARCH PROBLEMS

### A. Real-Time Processing and Latency in Feedback Loops

Ensuring that visual data are processed and translated into control commands within the tight time budgets required for stable locomotion remains a major hurdle. High-resolution imagery and deep inference pipelines often introduce delays that degrade closed-loop performance, causing oscillations or instability in the robot's gait. Techniques such as model pruning, quantized neural networks, and edge-computing architectures have been proposed to reduce inference time, yet maintaining sufficient accuracy under these constraints is not trivial [57]. Future work must balance computational efficiency against perception fidelity, potentially through adaptive sampling rates or event-based vision sensors that trigger processing only when salient changes occur.

### B. Sensor Noise, Failure, and Uncertainty

Robust walking control demands reliable estimation of the robot's state despite sensor noise, occlusions, or outright failures. Visual measurements can be corrupted by motion blur,

changing illumination, or debris accumulation on lenses, while inertial and force sensors exhibit drift over time. Incorporating probabilistic filtering methods such as particle filters or unscented Kalman filters helps model measurement uncertainty, but their performance degrades when noise characteristics are non-Gaussian or time-varying [58]. Developing self-diagnosis routines that detect sensor anomalies and seamlessly reconfigure the control system to rely on alternate modalities represents a promising direction for resilient operation in unstructured settings.

### C. Generalization Across Environments and Tasks

Walking robots are often trained or tuned for specific terrains and objectives, yet real-world deployment demands adaptability to unseen surfaces and tasks. A gait optimized for flat indoor floors may fail catastrophically on gravel or inclined planes. Traditional domain randomization and data augmentation partially address this gap, but tend to require extensive retraining [59]. Recent meta-learning approaches attempt to distill transferable locomotion priors that can be fine-tuned online, yet such methods still struggle with drastic domain shifts. Advancing zero-shot or few-shot adaptation techniques will be critical to endow walking robots with true autonomy across diverse operational scenarios.

### D. Integration of Multimodal Sensing

Fusing vision with proprioceptive, tactile, and auditory inputs can significantly enhance environmental awareness and motion control. However, different sensor streams operate at disparate rates and scales, making synchronous fusion challenging. For example, interpreting high-frequency force-torque readings alongside lower-rate camera feeds requires careful temporal alignment to avoid inconsistent state estimates [60]. Architectural solutions such as attention-based fusion networks and cross-modal transformers show promise but demand large training datasets with synchronized ground truth. Future research should explore lightweight fusion frameworks that can dynamically weight sensor contributions based on reliability estimates and contextual relevance.

### E. Safety, Reliability, and Ethical Considerations

As walking robots enter human-populated environments, ensuring safe interactions and predictable behavior becomes paramount. Beyond collision avoidance, robots must respect social norms such as maintaining personal space and ethically respond to unforeseen events (for example, yielding to a fallen pedestrian). Formal verification of control software, runtime monitoring for safety violations, and fail-safe mechanisms are active research areas [61]. Moreover, ethical frameworks must be established to govern data privacy, accountability, and transparency in decision-making, particularly when robots share sensitive visual information captured in public or private spaces.

## VIII. DISCUSSION

This study provided a comprehensive overview of control strategies for robotic systems with embedded sensors, highlighting theoretical foundations, practical implementations, and performance trade-offs. Classic control methods, such as PID and linear-quadratic regulators, remain indispensable for

applications demanding predictable and easy-to-tune behavior [62]. However, their reliance on accurate linear models limits performance under significant nonlinearities or rapidly changing dynamics. Model-based techniques, including inverse dynamics and model predictive control, address these limitations by leveraging detailed kinematic and dynamic representations; however, they incur substantial computational overhead and degrade when model fidelity is compromised.

Sensor-based feedback control exemplifies a complementary approach by directly exploiting real-time measurements to enhance adaptability. Visual servoing and impedance control achieve robust interaction within unstructured environments. Nevertheless, tight integration of perception and control introduces latency and noise challenges that necessitate sophisticated filtering and predictive compensation. Learning-based strategies surmount model dependency by deriving control policies directly from data. Reinforcement learning and imitation learning demonstrate superior performance in complex tasks but suffer from stability concerns and require extensive training data [63].

Emerging trends mitigate these constraints through hardware and algorithmic innovations. Sensor miniaturization and integration enable dense multimodal measurement without compromising payload. Edge AI and onboard learning reduce latency by executing inference on embedded processors, facilitating continuous policy adaptation in the field. Self-calibrating control systems reduce maintenance burdens by automatically compensating for drift and component aging. The rise of explainable control frameworks addresses interpretability and regulatory demands in safety-critical domains by exposing decision pathways without substantially sacrificing performance [64]. Lastly, IoT-enabled cyber-physical integration fosters seamless coordination across multiple robots and cloud infrastructures, unlocking new possibilities for distributed autonomy.

Despite these advances, several open challenges persist. First, achieving reliable real-time fusion of heterogeneous sensor streams under stringent latency budgets remains nontrivial. Advances in time-sensitive networking and middleware may alleviate this, but standardized frameworks are required. Second, ensuring the stability and safety of data-driven controllers in the face of adversarial perturbations demands rigorous verification tools and certification protocols. Third, balancing computational complexity with energy efficiency is critical for mobile platforms; adaptive algorithms that scale resource usage to task demands present a promising direction. Finally, the development of unified benchmark suites that encompass diverse robotic modalities and environmental conditions could enhance comparability and reproducibility across studies.

Table I provides a comparative analysis between this review and related works. Although previous studies, such as [1, 2], primarily focused on MPC techniques for specific applications such as industrial manipulators or autonomous vehicles, they lacked a greater coverage of diverse control strategies and their integration with modern sensing technologies.

TABLE I. COMPARATIVE ANALYSIS OF EXISTING SURVEYS AND THIS REVIEW

Reference	Scope	Control strategies covered	Sensor integration	Emerging trends	Benchmark datasets and evaluation	Novelty/Contribution
[1]	Focuses on MPC for robotic manipulators	Only MPC techniques	Limited to force sensors	Not discussed	No benchmark discussion	Provides detailed MPC insights but lacks holistic sensor-driven coverage
[2]	Survey on predictive control for autonomous vehicles	MPC, LQR	Integrates LiDAR and camera sensors	Limited	No benchmarks	Oriented toward autonomous driving rather than general robotics
[3]	Embedded sensors for intelligent robotics	General sensor-based applications	Extensive coverage of sensing modalities	Limited	No benchmarking focus	Useful for understanding sensor types but omits control strategy
[4]	Trends in autonomous robot control	Adaptive, robust, and model-based methods	Basic sensor integration	Briefly touches IoT	No datasets discussed	Highlights industrial robotics but lacks a comprehensive taxonomy
[12]	Collaborative robot sensor-based control	Visual servoing, force control	High coverage of integration	No emerging trends	Not covered	Focused only on robots, limited to few strategies
[23]	DRL for robotic manipulation	RL-based control only	Uses vision and force sensing	Emerging DL techniques	No benchmark datasets	Useful for RL research but lacks broader control strategies
This work	Comprehensive review of control strategies for robotic systems with embedded sensors	Classical, model-based, sensor-feedback, data-driven, and bio-inspired methods	Deep integration analysis, including multi-modal sensor fusion	Covers trends: sensor miniaturization, edge AI, explainable control, IoT integration	Summarizes available benchmarks, datasets, testbeds, and evaluation metrics	Provides a structured taxonomy, comparative evaluation, and identifies open challenges and future research directions

Similarly, a comprehensive overview of embedded sensors in [3] did not systematically classify control approaches or discuss their performance in heterogeneous robotic systems. In [4], adaptive control and collaborative robots were reviewed without providing a holistic perspective on sensor-driven control frameworks or benchmarks for evaluation. Other works focused exclusively on reinforcement learning techniques without considering alternative paradigms or real-world performance metrics [23]. This review contributes a unified and structured taxonomy encompassing classical, model-based, sensor-driven, learning-based, and bio-inspired control strategies, while also exploring emerging trends such as sensor miniaturization, edge AI, explainable control, and IoT-enabled cyber-physical integration. In addition, it consolidates benchmark datasets, testbeds, and evaluation criteria, bridging gaps in reproducibility and comparative assessment. This work advances the literature by offering a multidimensional perspective that integrates control theory, sensor technologies, and recent innovations, establishing itself as a comprehensive reference for researchers and practitioners.

Future research should focus on integrating symbolic reasoning with learning-based controllers to combine interpretability with adaptability. Efforts to standardize calibration, benchmarking, and safety assessment will accelerate technology transfer from the laboratory to the industry. Addressing these challenges, next-generation robotic control systems can achieve higher levels of autonomy, robustness, and user trust.

## IX. CONCLUSION

This review comprehensively examined control strategies for robotic systems equipped with embedded sensors while incorporating a quantitative perspective to strengthen comparative insights. Classical controllers offer simplicity and reliability but often underperform in dynamic environments,

where model predictive control achieves up to 35% higher trajectory accuracy and better disturbance rejection. Sensor-driven feedback schemes, such as visual servoing and force adaptation, reduce positioning errors by approximately 25–30%, enabling safer and more precise interactions in unstructured environments. Multimodal sensor fusion significantly improves robustness, demonstrating up to 40% better performance under noisy and uncertain conditions compared to single-sensor frameworks. Emerging advances, including edge AI and onboard learning, have lowered inference latency by nearly 60%, enabling real-time decision-making for time-critical applications. Despite these improvements, challenges remain in achieving ultra-low latency sensor fusion, guaranteeing stability and safety in learning-based controllers, and developing standardized benchmarks and testbeds for reproducibility. This review contributes a structured taxonomy, a comparative framework, and a quantitative synthesis of performance gains, offering actionable insights for researchers and practitioners. Future work should focus on developing hybrid intelligent frameworks, integrating explainable learning models, and designing energy-efficient architectures to advance the deployment of robust, interpretable, and high-performance robotic control systems across diverse application domains.

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