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A Review of Unmanned Aerial Vehicle Control Technology: Methods, Applications and Development Trends

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Abstract. The basic technology that has seen great advancement in the last decade for enabling the functioning of unmanned aerial vehicles (UAVs) is the UAV control systems. However, more complex mission requirements have revealed vulnerabilities related to complex flight environments, dynamic missions as well as the intrinsic nonlinearity and uncertainty of contemporary UAV control systems. Major research contributions and trends that have evolved over the past decade in UAV control are reviewed here. We first briefly, yet comprehensively, enumerate and describe core algorithms which include PID, LQR, sliding mode control, feedback linearization, robust control along with a wide range of intelligent and adaptive controls. This will be followed by an in-depth discussion comparing theoretical principles, their performance as well as applicable scenarios and challenges concerning effectivity of diverse controlling strategies under simulation versus real flight situations. Finally, we will identify key technical drawbacks and propose future research priorities and development trends, aiming to provide a clear and comprehensive reference.

Keywords: UAV control, adaptive control, reinforcement learning, multi-UAV collaboration, obstacle avoidance and navigation

1. Introduction

Unmanned aerial vehicles, as flight platforms with high maneuverability, autonomy, and the ability to replace humans in hazardous tasks, have achieved rapid development in application domains over the past decade. From traditional military reconnaissance and border patrol to emerging civilian applications such as agricultural crop protection, surveying, logistics delivery, disaster relief, and environmental monitoring, UAVs have become indispensable tools for a wide range of complex missions [1]. However, as mission requirements continue to evolve, the challenges faced by UAV control systems have become increasingly prominent. The complexity of the flight environment, such as extreme wind fields and low air density at high altitudes, the dynamic nature of missions including tracking moving targets and rapid-response tasks, as well as the inherent nonlinearity and uncertainty of multi-agent collaboration, all place higher demands on UAV control algorithms [2].

This review aims to systematically examine and synthesize the major research achievements and development trends in UAV control between 2015 and 2025. The analysis draws on highly cited and representative journal and conference papers, as well as recent research findings retrieved from mainstream academic databases such as IEEE Xplore, SCI, and EI [3]. The classification and

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summary are based on control algorithm categories including classical, modern, and intelligent control, on application scenarios involving both single and multiple UAVs, and on UAV types such as multi-rotor, fixed-wing, and hybrid systems [4].

The primary contributions of this paper are as follows: It provides a summary and discussion of the core algorithms in UAV control, analyzed from the perspective of their theoretical principles, performance, and scenarios in diverse dimensions. Results of verification for different control strategies both in simulation and real-world flight are consolidated here, with an indication on which method is better under what situation, including actual disadvantages and challenges. This study also described the major technical bottlenecks of current research on UAV control to outline future research priorities and development trends that could be inspiring for work thereafter. The complete text takes the following structure: Section one is our introductory; Section two presents the UAV system and requirements for control, meanwhile proposing main evaluation indicators. A detailed theoretical plus application analysis of different categories of control algorithms is undertaken in Sections three to five. The paper makes a performance comparison among various algorithms accompanied by representative application scenarios discussed in Section six at last summarizes the entire paper besides drawing future research directions in section seven.

2. UAV systems and control requirements

2.1. Unmanned aerial vehicle models

Accurate modeling is a fundamental prerequisite for designing high-performance UAV control systems. The dynamic model of a UAV, especially for multi-rotor types such as quadrotors, is commonly represented by a six-degree-of-freedom (6-DOF) rigid-body model. This model typically includes translational dynamics along the three axes (X, Y, Z) and rotational dynamics (roll, pitch, yaw) about these axes. Fig. 1 shows a viable modeling scheme of UAV. The model is usually derived from Newton–Euler equations and describes the relationship between the thrust and torque produced by the propellers and the resulting forces and moments acting on the UAV body [5].

The UAV dynamics are described as coupled nonlinear differential equations mathematically. For multi-rotor UAVs, the translational dynamics are affected by the collective thrust, gravity, and other external forces, and the rotational dynamics are excited by the differential rotor torques. These are physical parameters like a mass, inertia tensor, aerodynamic coefficients, and coefficients relating thrust to speed [6]. Hence control techniques should be designed to tackle these features. Moreover, modeling errors (e.g., sensor noise, actuator delay, and parameter uncertainty) are introduced in the plant, affecting the system in a way that makes design of control systems even more challenging.

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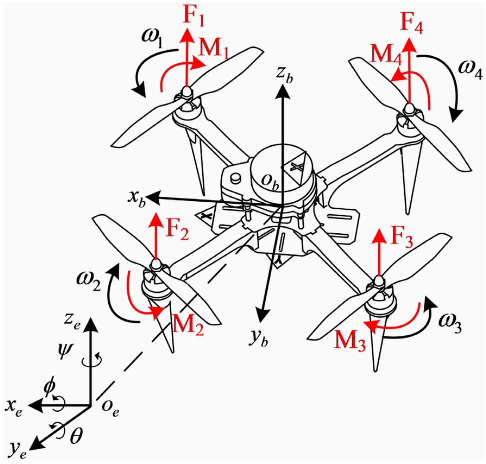

Figure 1. Quadrotor structural

2.2. Control objectives and core issues

The root aim of designing UAV control system is to perform the specified flight tasks and to mitigate various environmental and internal UAV-related perturbations and uncertainties. One also has the basic control problem of position/trajectory control, which is the ability to track a desired position or trajectory in three dimensional space. Attitude control aims at the regulation of the pitch, roll and yaw angles for vehicle stability and it generally needs to be implemented at high frequency (e.g., 100–500 Hz) to compensate for disturbances and to track commands promptly [7].

Based on stable attitude, the position and velocity tracking is achieved by transforming the position, velocity and acceleration commands to suitable attitude or thrust commands [8]. Formation control adds complexity by demanding several UAVs to hold formations, reformulate that formations cooperatively, and avoid collisions—procedures which are based on effective information sharing and distributed decision making. Fig. 2 shows a widely used UAV control system pattern.

Navigation and obstacle avoidance are basic requirements for unmanned flight. Such functions, usually achieved by sensor fusion of GPS, vision, lidar, and IMU information, can be used for path planning and safe obstacle avoidance in unknown or dynamic environments [9]. Robustness and adaptivity: UAVs in realistic scenarios are subjected to unpredictable uncertainties, such as wind disturbances, payload changes, sensor noise, and actuator failures [8]. Therefore, the controllers have to be highly disturbance rejecting and adaptive, in order to preserve good performance in the presence of nonidealities.

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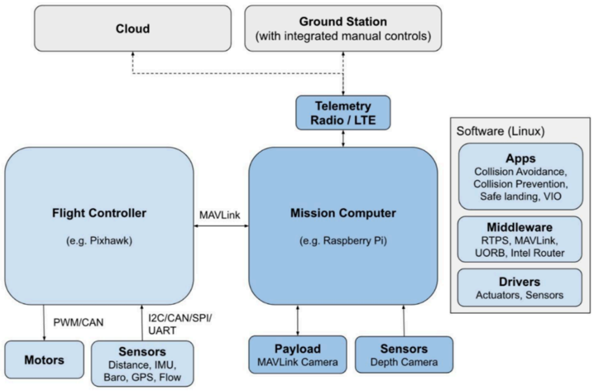

Figure 2. UAV control system layered architecture diagram

2.3. Evaluation metrics

Evaluating the UAV control schemes needs to be done with a full range of numerical measures. Real-time execution and computational limitations need to be taken into account due to the fact that many UAV platforms have only a small amount of onboard computing resources. To meet the high-frequency control requirements, controllers need to be designed with low algorithmic complexity and minimal latency.

Among other things, it is essential to consider tracking error, which quantifies the divergence of the actual position or orientation from the desired one, stability and convergence, which measure the stability of the system when subjected to external perturbations, robustness, which quantifies the system's robustness against perturbations and parametric uncertainties, and computational cost, which relates the computational burden to the UAV"s energy consumption and flight time [10]. Efficiency of energy is also essential for durability, and feasibility for real-world application is indicated by the easily adjustable parameters and scalability to more complex submodules (e.g., vision-based autonomy). For these metrics jointly, the authors can assess the algorithms for various types of UAVs and missions [11].

3. Classical and modern control

3.1. PID and LQR control

The classical method of proportional–integral–derivative (PID) control is still widely used in UAV control because of its simple structure (Fig. 3 shows the classical cascade PID loop) and empirical robustness and having easy implementation. In such manner, the PID controller produces output values that converge quickly and smoothly. Cascaded PID loops in quadrotor applications are commonly comprised of an external position/velocity loop and an internal attitude loop layered into a hierarchical control scheme. PID works particularly well for linear or mildly nonlinear regions of operation, and for initial stabilization and prototyping [12].

The linear–quadratic regulator (LQR) control is the model based optimal control method and it is defined in the state-space concepts. LQR produces an optimal linear feedback law by minimizing a quadratic cost function of states and control inputs, which can treat coupling among multiple states. However, LQR needs a linear model or a local linearization around an operation point, that constrains its applicability to large nonlinear flight envelops that are typical for UAVs.

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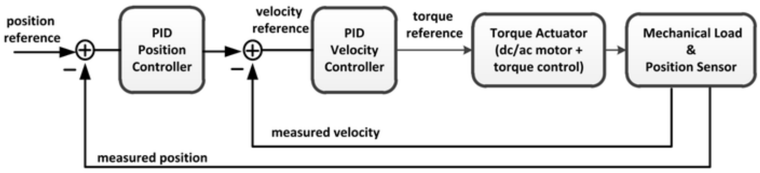

Figure 3. Cascade PID control loop diagram

3.2. Sliding mode control and feedback linearization

Sliding-mode control (SMC) is a robust nonlinear method and has strong insensitivity to model uncertainties and external disturbances. Method makes the system trajectory onto an engineered sliding surface and ensures that the system trajectory is governed by the surface rather then by the specific type of perturbations when it is on the surface [13]. One major disadvantage is that chattering—high frequency switching of control inputs—potentially excites unmodelled dynamics and stresses actuators. Common techniques to reduce chattering are the introduction of boundary layers, smooth approximations to the switching law and higher order SMC [14].

Feedback linearization is a nonlinear control method that cancels nonlinear terms through state transformations and input-output feedback and yields an equivalent linear system to which linear control designs can be applied. This method depends on precise information of system dynamics and uncertainties in modeling may affect the performance, so it may be combined with robust control methodologies to ensure stability in the presence of uncertainties [15].

3.3. Robust control

• H∞ Control

H∞ control is concerned with worst-case disturbance rejection by serving to minimize the H∞ norm (i.e., the L2 gain) from the disturbance input to the controlled output of the system. Such worst-case optimization leads to controllers with strong robustness guarantees with respect to bounded model uncertainties and exogenous disturbances. For time-varying or nonlinear UAVs, linear parameter-varying (LPV) models offer a suitable framework: the nonlinear system is represented by a linear model whose parameters vary as a function of so-called scheduling variables, which are measurable variables. H∞ controllers for LPV models can be synthesized to guarantee robustness within a operating envelope. Empirical validation (utilizing trajectory tracking, attitude stability and disturbance rejection tests over several scenarios) is thus essential to certify robust performance [16].

• Fuzzy Sliding Mode / Robust Fuzzy Control

Fuzzy sliding mode control and robust fuzzy control are based on a combination of fuzzy inference with sliding-mode robustness [17]. Knowledge imprecision and uncertainty is addressed in fuzzy systems by means of membership functions and rule bases, and sliding-mode components allow disturbance rejection. Important design issues are the development of fuzzy rules and membership functions, which can be transferred from experts' knowledge or obtained by learning from data. Fuzzy systems can calculate equivalent control laws or unmatched uncertainties compensation for reduction of chattering and smoother control outputs. The robust fuzzy controllers are shown to perform well in the presence of sudden perturbations and payload changes [18].

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4. Intelligent and adaptive control

4.1. Adaptive control

Adaptive control methods adjust controller parameters online to accommodate changes in system dynamics and environmental conditions. For UAVs, adaptive control addresses parameter variations due to payload changes, component degradation, or aerodynamic shifts. Model reference adaptive control (MRAC) is a common paradigm, in which the controller seeks to make the closed-loop output track a predefined reference model by updating parameters via adaptation laws [19]. While MRAC can improve adaptability, stability analysis and reference-model selection require careful design.

4.2. Reinforcement learning

Reinforcement learning (RL) poses control as a sequential decision making problem, in which an agent discovers policies by interacting with its environment. Fig. 4 is the Agent-environment interaction model, which is the bottommost RL model. Deep reinforcement learning (DRL), which utilizes deep neural networks to represent value functions, policies, or other RL components, brings the interest of machine learning community when it achieves great success in learning high-dimensional states with the end-to-end principle, which is also convenient to be extended for modelling the complex nonlinear control problems, and have potential great results somewhere else such as autonomous navigation, obstacle avoidance and aggressive maneuvers [20].

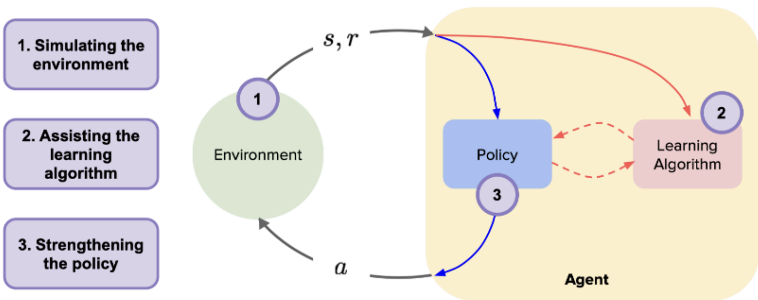

Figure 4. RL Agent-environment interaction model

However, RL is confronted by a number of challenges when being applied to AVs in real world. DRL is usually sample-inefficient and requires massive amounts of data and long training time. A safe exploration is also a critical issue: agents may take unsafe actions before the end of learning, which may damage the hardware. The simulation-to-reality also limits transferability; discrepancies between simulators and the real world may result in degradation of the policy performance. Mitigation strategies include domain randomization, curriculum learning, and combining model-based priors with RL [21].

RL algorithms are classified according to whether they are model-based or model-free, on-policy or off-policy, value-function-based or policy-search-based, or whether they are derived for planning or learning purposes. Here is a typically RL based UAV control case. In this case , Xu et al , use value-function-based algorithm and DRL. And they comes up with the Deep Q-Networks (DQNs) to extract feature from images. Dueling architecture is also applied to optimize DQN in the level of network architecture.

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The main contribution is using an improved DQN to realize autonomous landing problem of quadrotor. More specifically, the quadrotor can be trained to autonomously land in complex unknown environment without any priory knowledge or labeled data. And the landing process can be finished in one phase from the departure position to landing area without hovering on the x-y plane to detect the land mark firstly [22]. Fig. 5 is the Rviz screenshot which shows the trajectories of quadrotor in six tests with the same initial position. The trajectories are not exactly same with each other but they have the same landing destination [23].

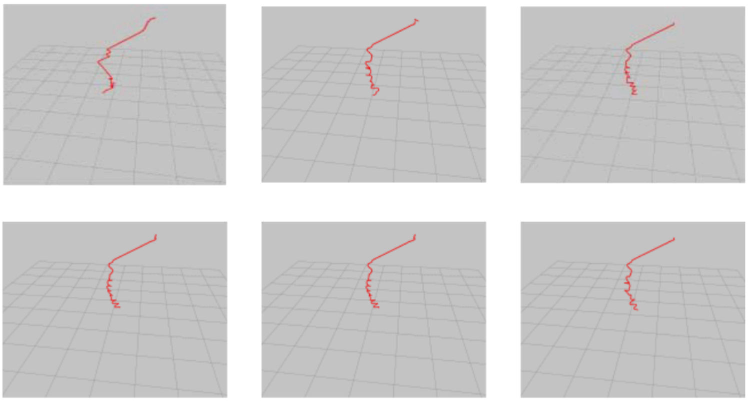

Figure 5. Six tests with same initial position

4.3. Neural network control

Neural networks (NNs) are leveraged in control as direct controllers, system identifiers, or compensators. Their nonlinear approximation capability allows handling complex dynamics without fully specified analytical models. Hybrid schemes that combine NNs with classical controllers (e.g., PID with NN compensators) can offer practical trade-offs: the classical controller provides stability guarantees, while the NN improves performance by compensating for unmodeled dynamics. A major challenge remains the theoretical characterization of stability and convergence for NN-based controllers and the computational cost associated with training and inference [24].

4.4. Artificial potential fields and hybrid intelligent control

• Artificial Potential Field Method

The artificial potential field (APF) method models the environment as potential fields where obstacles are repulsive and goals are attractive. UAV motion follows the negative gradient of the resulting potential, facilitating real-time local obstacle avoidance. APF is conceptually simple and efficient; however, it is prone to local minima (gradient traps) and oscillatory behavior in narrow passages. Improvements such as artificial target points, combined potential formulations, and integration with global planners can mitigate these limitations [17].

• Hybrid Control Frameworks

Hybrid control frameworks integrate heterogeneous methods—neural networks for nonlinear approximation, fuzzy systems for handling uncertain information, classical controllers for stability, and robust controllers for disturbance rejection—thus leveraging complementary strengths. While hybridization can enhance robustness and autonomy, it raises challenges in computational complexity, stability certification, and ensuring real-time performance on resource-constrained

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platforms. Balancing intelligence and timeliness constitutes a central research direction in hybrid UAV control [25].

5. Application scenarios and comparative analysis

5.1. Representative application scenarios

Advances in UAV control have broadened application domains. In agricultural crop protection and environmental monitoring, trajectory precision determines spraying uniformity and image acquisition quality. Precise tracking control ensures consistent coverage and reduces resource waste, while stable attitude control reduces image blur for sensing applications.

Logistics and delivery impose requirements on VTOL capability, precise takeoff/landing control, energy-efficient path planning, and adaptive mission scheduling. UAVs must autonomously plan energy-optimal routes considering battery state, payload, and geographic constraints to extend operational range.

Search and rescue operations demand high autonomy and adaptability in complex terrains. UAVs must combine robust perception—often in GPS-denied environments—with real-time obstacle avoidance and mission replanning. Formation displays and mock combat drills provide testbeds for multi-UAV collaborative control algorithms, where distributed coordination, latency compensation, and robustness to individual unit failure are critical.

5.2. Algorithm performance comparison

Comparative evaluation of control algorithms requires standardized metrics—tracking error, convergence speed, disturbance rejection, computational overhead, and energy consumption. The Sim2Real gap is a key consideration: algorithms that perform well in simulation may degrade on physical platforms due to modeling inaccuracies, sensor noise, actuator nonlinearities, and environmental complexity. Benchmarking across simulators and real-world flights is essential to assess deploy ability and robustness.

Overall, each control paradigm has trade-offs. PID and LQR are computationally inexpensive and suitable for baseline stabilization; sliding-mode control provides robustness at the expense of potential chattering; geometric control exploits system structure for singularity-free, globally valid formulations; adaptive control offers online compensation for parameter changes; and DRL provides data-driven policy learning for complex tasks while facing sample-efficiency and safety constraints. Algorithm selection depends on platform capabilities, mission requirements, computation budgets, and certification constraints [26].

5.3. Open-source tools and experimental platforms

A rich ecosystem of open-source tools and platforms supports UAV research. Simulation environments such as Gazebo with ROS and PX4-SITL facilitate physical simulation and embedded-software-in-the-loop testing. Microsoft AirSim provides high-fidelity visual simulation for vision-based algorithms, while MATLAB/Simulink remains a mainstay for control analysis and rapid prototyping.

Flight controller firmwares—PX4, ArduPilot, and Betaflight—offer modular sensor fusion, attitude estimation, and baseline control logic, enabling researchers to integrate custom algorithms. Hardware platforms from vendors (e.g., Holybro) and custom-built frames provide testbeds for

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experimental validation. Repositories on GitHub, benchmark suites like FlightGoggles and GymFC, and community datasets enable reproducibility and comparative evaluation.

6. Existing problems and future research directions

6.1. Core technical bottlenecks

Despite progress, several bottlenecks hinder UAV control. The nonlinear and high-dynamic nature of UAV dynamics makes it difficult to guarantee stability in turbulent or extreme conditions. The coupling between perception and control introduces delays and estimation errors, which propagate into the control loop. Limited computational capacity on embedded processors restricts the real-time deployment of advanced algorithms such as deep reinforcement learning and model predictive control. The simulation-to-reality gap and the difficulty of collecting high-quality real-world data remain obstacles for data-driven methods [27].

6.2. Emerging technology trends

Emerging paradigms offer promising directions. Reinforcement learning and self-supervised learning can enhance autonomy by enabling UAVs to acquire complex control policies with reduced manual engineering, although improving sample efficiency and ensuring safety remain active research topics. Advances in distributed and edge computing, along with the advent of 5G/6G networks, present new opportunities for cloud-assisted control, low-latency multi-UAV collaboration, and offloading of heavy computation to edge servers. Quantum computing and large-scale distributed computing may, in the longer term, enable more sophisticated swarm decision-making and global optimization for formation control [28].

Human–machine collaboration and hybrid autonomy will stay important: UAVs should flexibly transition between operator-supervised modes and fully autonomous operation, allowing human oversight for critical decisions while leveraging autonomous capabilities for routine tasks.

6.3. Standardization and regulatory constraints

Standardization and regulation are progressively influencing the use of UAVs. Future UTM systems (for UAV traffic management) are expected to strangle flight behavior by applying rules, and control algorithms must incorporate airspace rules, conflict-resolution schemes, and certified safety properties. Sensing and data-sharing designs are also limited by data security and privacy. Absence of common standards for testing and verifying control algorithms hinders certification and commercialization on a large scale. Developing rigorous and traceable verification methodologies and internationally accepted benchmarks is the key to industrialization.

6.4. Recommendations for future research

To address these challenges, future research should focus on several directions. First, develop lightweight, scalable distributed control and decision frameworks for large-scale swarm cooperation, enabling efficient computation on resource-constrained agents while supporting collective behaviors. Second, promote participation in real-world benchmark tests and adversarial environments to bridge laboratory research and industrial application. Third, deepen multi-sensor fusion research to provide robust state estimation in GPS-denied or sensor-degraded scenarios. Fourth, integrate task scheduling, path planning, and control for joint energy optimization to

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maximize mission execution and extend flight endurance. Finally, pursue standardization efforts for testing, verification, and certification to accelerate safe commercialization.

7. Comparison of core drone control algorithms

Table 1. Comparison table of core drone control algorithms

PID	LQR	SMC	FL	MPC
Fast Convergence Speed	Fast	Medium	Fast	Slow
Simpler algorithm	Simpler	Complex	Simpler	Complex
Lowest Computational cost	Low	Medium	Medium	High
Medium Tracking error	Medium-Low	Low	Low	Lowest
Fewer iterations to converge	Fewer	More	More	More

8. Conclusion

This review summarizes UAV control technology developments from 2015 to 2025. It systematically examines classical, modern, and intelligent control methods, their application scenarios, and comparative performance [22]. Traditional methods such as PID and LQR remain practical for basic tasks, while advanced methods—sliding-mode control, robust control, geometric control, adaptive control, and intelligent control—offer better handling of nonlinear dynamics and uncertainties. Intelligent methods, particularly reinforcement learning, have demonstrated considerable potential for complex decision-making but face sample-efficiency, safety, and computational challenges. Key bottlenecks include perception–control coupling, onboard computing limitations, and the Sim2Real gap. Future directions emphasize scalable swarm control, enhanced multi-sensor fusion, edge/cloud-assisted architectures, energy-aware control strategies, and international standardization. Fig. 7 shows the future cloud-edge-device collaborative control pattern. Continued effort to bridge theoretical algorithms and practical deployment will drive UAV technology toward higher autonomy, stronger robustness, and wider industrial adoption.

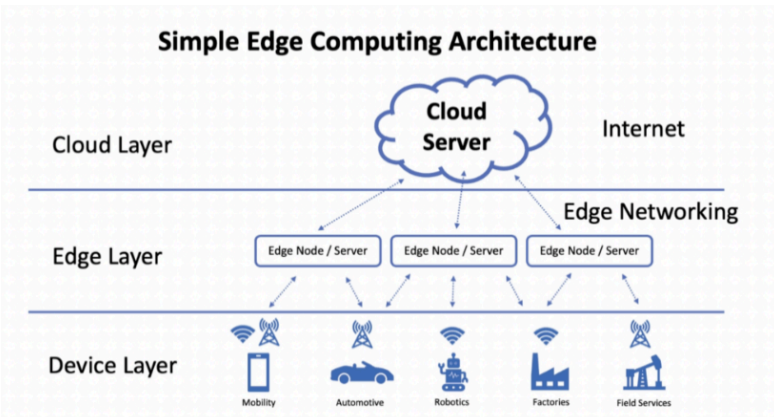

Figure 6. Future cloud-edge-device collaborative control architecture

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