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Guidance, Navigation, and Control: A Survey, Taxonomy, and Challenges (2020–2025)

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ABSTRACT

Guidance, Navigation, and Control (GNC) underpin autonomous systems across aerial, terrestrial, surface, and underwater domains. Over the last five years, progress has accelerated with stronger onboard compute, maturing sensors, and the rise of learning-assisted methods. This paper offers a structured review of recent GNC advances (2020–2025), organized around three pillars: (i) guidance and trajectory planning, covering real-time optimal control and modern motion planners; (ii) navigation and state estimation, including multi-sensor fusion, INS/GNSS integration, visual/lidar-inertial odometry, and information-aiding for GNSS-denied operation; and (iii) control strategies, spanning linear/nonlinear, robust and model-predictive control, adaptive and learning-based designs. Beyond summarizing contributions, we identify converging trends—most notably the integration of physics-based models with data-driven components—and map open challenges in scalability, verification, energy efficiency, benchmark comparability, and robustness under distribution shift. We propose a concise taxonomy to harmonize terminology, relate methods across domains and levels of autonomy, and enable fair comparison. By consolidating key results and highlighting research opportunities, this review aims to guide researchers in selecting and combining GNC methods that meet real-time, safety, and deployment constraints across the full GNC stack and all four operating domains.

Keywords: Guidance, Navigation, Control, State Estimation, Autonomous Systems

Nomenclature

BA	=	Bundle adjustment	DL	=	Deep learning
FBL	=	Feedback linearization	GNSS	=	Global navigation satellite system
IA	=	Information-aided	IMU	=	Inertial measurement unit
INS	=	Inertial navigation system	KF	=	Kalman filter
LC/TC	=	Loosely/tightly-coupled	MEMS	=	Micro-electromechanical systems
MHE	=	Moving-horizon estimation	ML	=	Machine learning
NN	=	Neural network	PI	=	Physics-informed
RL	=	Reinforcement learning	SLAM	=	Simultaneous localization and mapping
SWaP	=	Size, weight, and power	UAV	=	Unmanned aerial vehicles
VIO	=	Visual–inertial odometry	ZUPT	=	Zero-velocity update

1 Introduction

Guidance, Navigation, and Control (GNC) constitute the core of modern autonomous systems, enabling platforms to plan, localize, and act safely and efficiently. Over the past five years, progress has been propelled by three converging trends: rapidly increasing onboard computing; the maturation and cost reduction of sensing (MEMS IMUs, GNSS, vision); and the widespread adoption of machine-learning methods. In parallel, operational demands have intensified—requiring robust performance in contested or GNSS-degraded environments, shorter development cycles, and real-time, deployment-ready solutions [1, 2]. These pressures span all operating domains and levels of autonomy, from human-in-the-loop to fully autonomous systems. Across this spectrum, GNC must deliver consistent state estimation, constraint-aware motion planning, and stabilizing feedback control at the temporal and accuracy scales the mission dictates.

In the aerial domain, platforms range from UAVs and multirotors to fixed-wing and vertical takeoff and landing (VTOL) aircraft, including cooperative swarms. Key challenges include agile trajectory generation, energy-aware path planning, and precise attitude stabilization [3].

Land systems encompass automated guided vehicles (AGVs); unmanned ground vehicles (UGVs) with wheeled, tracked, or legged mobility; humanoid robots; unmanned ground combat vehicles (UGCVs); planetary rovers; and multi-vehicle convoys. Dominant concerns include terrain–vehicle interaction, slip estimation, real-time obstacle avoidance, and coordinated multi-agent motion [4]. The surface (maritime) domain includes autonomous/uncrewed surface vessels (ASVs/USVs), small autonomous ferries, and cooperative fleets for harbor and offshore operations. Here, GNC must reject environmental disturbances from wind, waves, and currents while ensuring waypoint tracking and collision avoidance [5].

Underwater platforms include autonomous underwater vehicles (AUVs), remotely operated underwater vehicles (ROVs), hybrid ROV/AUV systems, and buoyancy-driven gliders. Severe communication constraints, complete GNSS unavailability, and strongly nonlinear hydrodynamics motivate drift-bounded navigation, terrain-relative localization, and fault-tolerant control [3, 6].

Fig. 1 summarizes these four operating domains and highlights representative platforms, underscoring that each domain imposes distinct sensing, actuation, and algorithmic constraints on GNC design.

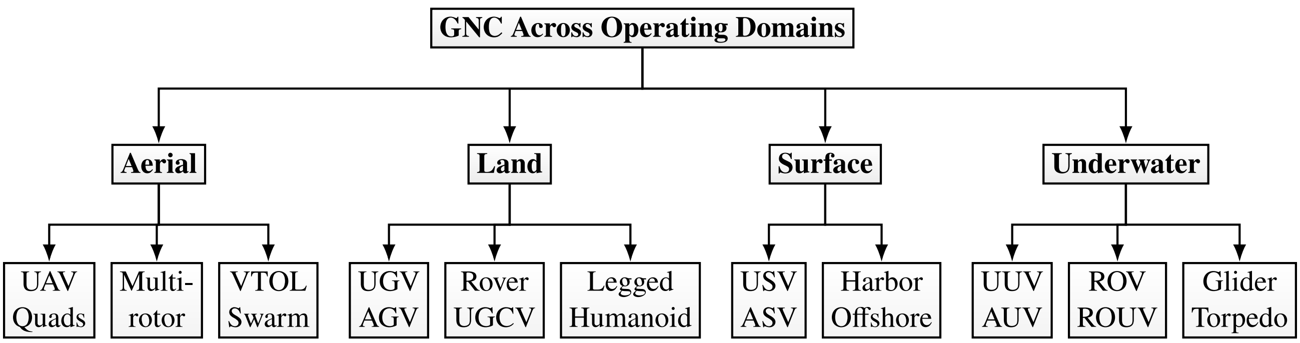

Fig. 1 Taxonomy of GNC across four operating domains, each with representative paltforms.

Classical GNC solutions—grounded in model-based optimal control, Kalman filtering, and trajectory optimization—remain widely used and well understood. A mission-level planner issues high-level objectives that the guidance module decomposes into dynamically feasible trajectories and waypoints under platform and environmental constraints (e.g., actuation limits, no-fly zones, collision margins). The control module then generates low-level ("atomic") actuator commands—often combining feedforward terms with stabilizing feedback and reference—governor logic—to track these references while rejecting disturbances and handling input saturation [2].

These commands drive the plant (vehicle plus environment), but the true state is latent and only indirectly observed through noisy, biased, and sometimes delayed sensors. A navigation/state-estimation module—typically a Kalman-filter variant—fuses measurements with model-based predictions in a prediction–update loop to recover best-estimate states with bounded error [5].

Practical implementations augment the state with nuisance parameters and account for timing across sensors (inertial sensors, GNSS, vision, lidar). The resulting estimates, with associated covariances, feed back to guidance and control to enable consistent re-planning, health monitoring, and gain scheduling across operating regimes. Fig. 2 illustrates this closed-loop perception–action architecture, emphasizing that the cycle continues until the mission objectives are satisfied and termination criteria are met.

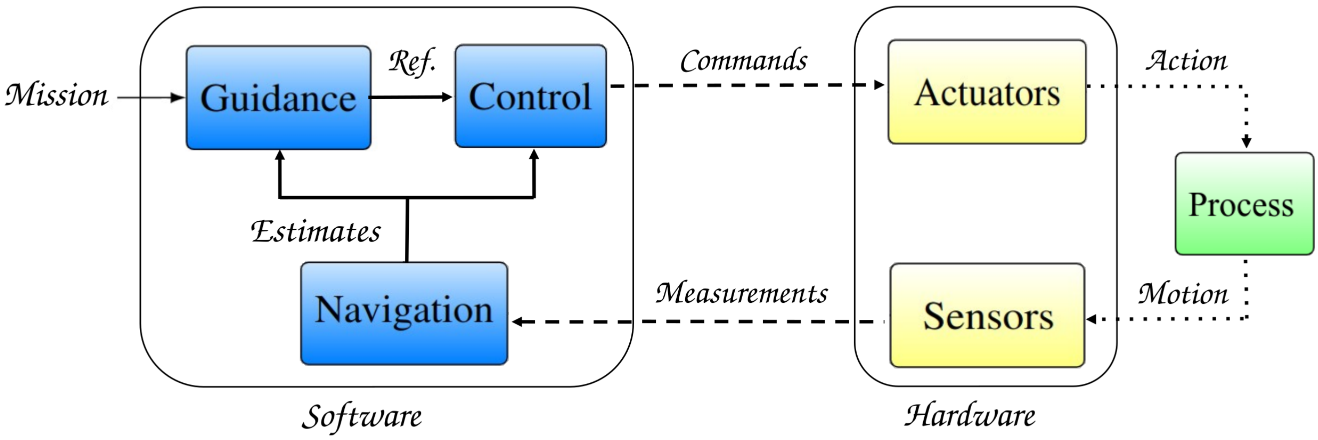

Fig. 2 Functional interconnects among Guidance, Navigation, and Control modules.

In recent years, however, the field has pivoted toward hybrid methods that fuse first-principles models with data-driven components, seeking to combine physics-based generalization and safety with the adaptivity and expressiveness of learning. Representative directions include:-augmented estimators for unmodeled effects, RL/learning-to-plan for near-optimal real-time trajectories, and adaptive/robust controllers with learned residuals that maintain stability under structural changes or actuator faults. This trend raises open questions in scalability, interpretability, and verification/certification [5, 6].
Fig. 3 delineates the scope of this review, organizing principal advances from 2020–2025 across the three GNC pillars, with line styles encode the algorithmic paradigm: solid for model-based, dashed for data-driven, and dash-dotted for hybrid approaches, enabling quick visual comparison across domains and methods.

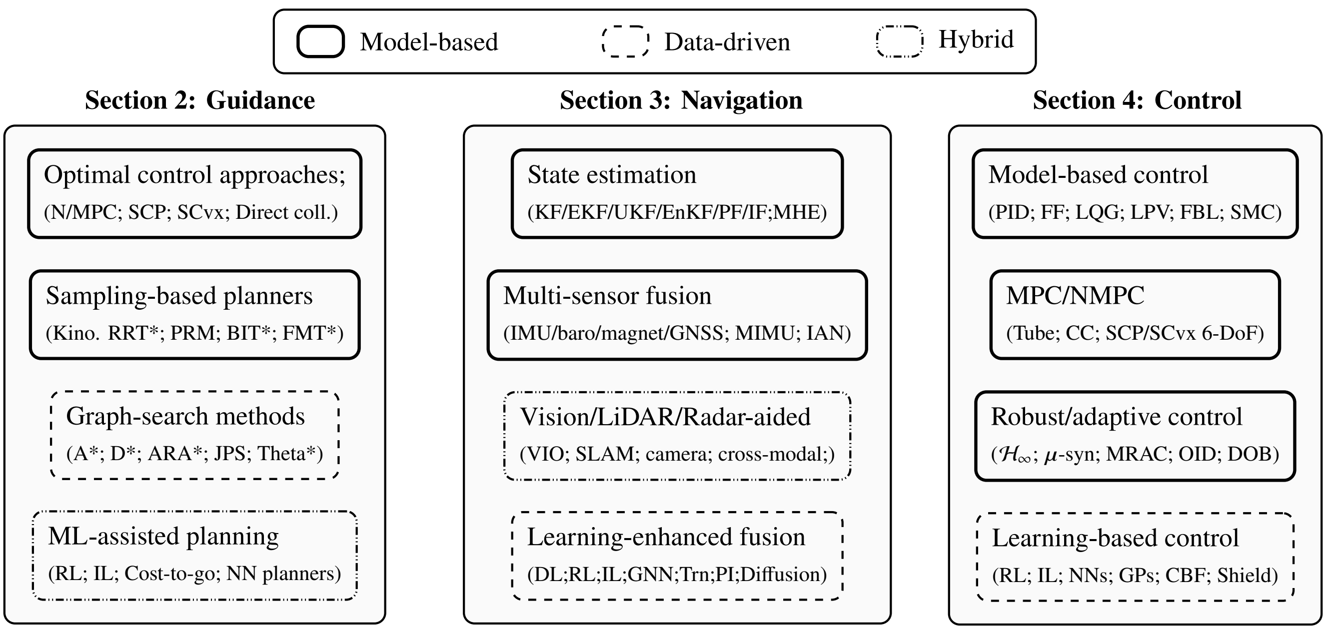

Fig. 3 Survey taxonomy: key trends in Guidance, Navigation, and Control (2020–2025).

1.1 Contextualization and Objectives

This review synthesizes principal GNC advances from 2020–2025 across leading journals and conferences and timely preprints with convincing empirical evidence. Rather than compiling an exhaustive bibliography, we extract signal from volume: we curate representative contributions, introduce a taxonomy aligned with operational constraints, and compare reported performance where common baselines exist.
We cover model-based, data-driven, and hybrid methods, prioritizing studies with high-fidelity simulation or hardware validation, explicit metrics (accuracy, robustness, latency, energy/trajectory cost), and reproducibility artifacts (code/data/benchmarks). We exclude speculative work, domain-specific applications unrelated to motion guidance, state estimation, or feedback control, and pre-2020 papers unless foundational. To situate our contribution, Table 2 contrasts influential state-of-the-art reviews, analyzing their scope and emphases to contextualize and position this work within the literature.

Table 2 Synthesis and comparison of major GNC review papers (2020-2025).

Ref.	Title	Recency	Papers	G	N	C	Limitation
[7]	Control Strategies and Novel Techniques for Autonomous Rotorcraft Unmanned Aerial Vehicles: A review	2020	212	✗	✗	✓	A control-centric review misses guidance-navigation couplings, overlooking trajectory feasibility, estimator-induced constraints, and system-level SWaP/safety trade-offs that a full GNC survey addresses.
[8]	A Survey of Guidance, Navigation, and Control Systems for Autonomous Multirotor Small Unmanned Aerial Systems	2021	272	✗	✗	✓	While thorough for multirotor UAS, it omits GNC applications beyond rotorcraft—space, ground, surface, and underwater—and gives limited coverage of hybrid/learning-based methods, and safety assurance.
[9]	On the Guidance, Navigation and Control of In-Orbit Space Robotic Missions: A Survey and Prospective Vision	2021	427	✗	✓	✓	Comprehensive yet domain-narrow, the survey centers on control for space robotics and on-orbit tasks while largely overlooking navigation (estimation, fusion, integrity) and its interplay with guidance and control.
[10]	State-of-the-Art Integrated Guidance and Control Systems in Unmanned Vehicles: A Review	2022	98	✓	✗	✓	Offers a smaller corpus than peer surveys-covering fewer cross-domain works and providing less depth on navigation, platform coverage, and case studies.
[11]	Information-Aided Inertial Navigation: A Review	2023	288	✗	✓	✗	Focused on GNSS-contested navigation via nonholonomic constraints and ZUPT variants; offers limited coverage of guidance and control aspects and deployment concerns.
[12]	A Review of Small UAV Navigation System Based on Multisource Sensor Fusion	2023	170	✗	✓	✗	Focused on small-UAV multisensor fusion, it offers limited cross-domain coverage (land, surface, underwater) and only cursory treatment of guidance and closed-loop performance.
[13]	Inertial Navigation Meets Deep Learning: A Survey of Current Trends and Future Directions	2024	162	✗	✓	✗	Authoritative for DL-for-INS, yet learning-centric rather than system-level GNC, with little on guidance/control integration, verification/safety filters, and cross-domain evidence.
Ours	Guidance, Navigation, and Control: A Survey, Taxonomy, and Challenges (2020–2025)	**2026**	**241**	✓	✓	✓	While mid-sized and light on visualizations and head-to-head benchmarks, it emphasizes breadth and currency—covering the full GNC stack across aerial, land, and surface domains, including the latest hybrid/learning approaches.

Evidently, prior surveys offer rigorous treatments of classical, model-based GNC—covering optimal control and trajectory optimization, Kalman-family estimation and sensor fusion, and canonical guidance architectures. However, the surge of learning-based and hybrid methods since 2020 (especially after 2022) lies largely beyond their scope, limiting their relevance to current deployment settings.

Our review explicitly addresses this gap by (i) extending the scope to energy-aware, SWaP-constrained design and realistic onboard compute budgets; (ii) broadening the coverage to include fault-tolerant control, safety filters/shields, and online adaptation; and (iii) ensuring currency by synthesizing hybrid and learning-assisted techniques across the full GNC stack. These gaps motivate the present review, which synthesizes advances from 2020–2025 across the full GNC stack and operating domains, with particular emphasis on hybrid and learning-assisted methods.

The remainder of the paper is organized as follows: Section 2 introduces guidance and trajectory planning; Section 3 covers navigation and state estimation; Section 4 presents control; and Section 5 offers concluding remarks. To aid orientation, the table of contents below summarizes the three GNC pillars and the topics covered within each.

Contents

2 Guidance and Trajectory Planning

Guidance and trajectory planning form the decision-making layer of GNC, converting mission objectives into dynamically feasible reference trajectories. Between 2020 and 2025, this area has advanced significantly, driven by demands for autonomy in cluttered and dynamic environments, the need for energy-optimal and safe maneuvers, and the increasing availability of onboard computational resources. Standard approaches such as optimal control formulations, graph-based search, and sampling-based planners remain widely used but are now complemented by real-time convexification techniques, receding-horizon strategies, and machine-learning-assisted planners that enable faster reaction and adaptation. This section reviews key contributions from this period, categorizing them into model-based optimal control, sampling and search methods, and learning-enabled decision making.
Particular attention is given to works that address real-time feasibility, robustness under uncertainty, and integration with navigation and control loops, as these factors are critical for deployment in time-critical missions [3, 6]. Building on the literature analyses in [9] and [10], Fig. 4 depicts a taxonomy of recent state-of-the-art guidance methods, ranging from model-based to machine learning (ML) approaches.

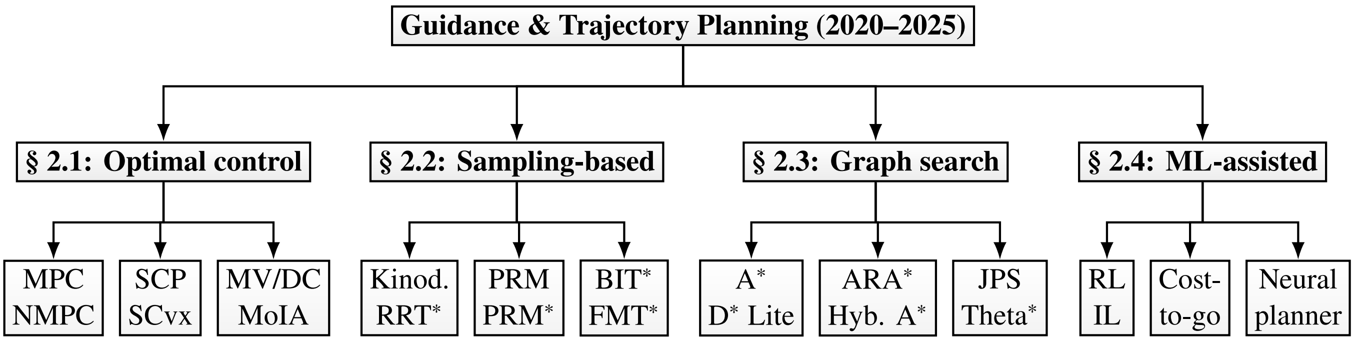

Fig. 4 Guidance paradigms (2020–2025): taxonomy with representative methods.

2.1 Optimal Control Approaches

Recent advances in optimal-control-based guidance are anchored in (nonlinear) model predictive control (MPC/NMPC). Developments include Lyapunov-based NMPC and backstepping-informed designs [14]; consensus-based MPC for multi-agent coordination [15]; event-triggered MPC that reduces computation/communication while maintaining stability and recursive feasibility [16]; and receding-horizon formulations tailored for real-time deployment [17]. Obstacle avoidance and goal-directed trajectory generation have advanced rapidly in autonomous driving and planetary landing [18]. Convexification-based solvers—successive convex programming (SCP) [19], lossless convexification (SCvx) [20], and dual/bi-convex decompositions [21]—recast nonconvex dynamics and constraints into tractable convex subproblems, yielding fast convergence and reliable feasibility in real time. Complementary work explores minimum-variance formulations (MV) to trade disturbance sensitivity against control effort [22], while multi-objective incremental allocation (MoIA) [23] and direct collocation (DC) strategies [24] enforce actuator limits with low latency—advancing hardware-in-the-loop and field performance.

2.2 Sampling-Based Planners

Sampling-based planners offer probabilistic completeness in high dimensions and, in asterisk-marked variants (‘*’), asymptotic optimality under mild assumptions. They handle differential/kinodynamic constraints via steering functions and motion primitives. Rapidly-exploring random trees (RRT) grow by sampling states and connecting to suitable existing nodes, expanding toward unexplored regions. Recent advances include informed sampling for faster convergence [25], bi-directional RRT* [26], planning under stringent constraints [27], geometric heat flow [28], and kinodynamic extensions using pose-based steering [29] and vector-field primitives [30]. Related graph-search work—e.g., Iterative discontinuity bounded A*—provides complementary guarantees for discontinuity-bounded dynamics and cost maps, and serves as a heuristic/warm start [31]. Another family suited to real-time planning in complex environments is probabilistic roadmaps (PRM/PRM*), designed for multi-query settings. Recent variants improve sampling and edge selection—e.g., pseudo-random (smart) sampling [32], hybrid potential–based schemes [33], physics-informed sampling [34]—with paths extracted via graph search (A*/bidirectional A*) over the roadmap [35]. From 2020–2025, batch-informed methods (BIT*) [36, 37] and fast marching trees (FMT)* [38] further reduced compute by biasing samples toward promising regions and exploiting ordered, lazy collision checking. These planners are widely used in cluttered urban scenes and exploration tasks where deterministic grid search is computationally prohibitive.

2.3 Graph-Search Methods

Graph-search planners—A*, D*, and derivatives—remain strong baselines for grid/graph representations, offering completeness and (with admissible, consistent heuristics) optimality. Recent work refines A* with lightweight improvements [39], fixed-wing obstacle avoidance [40], and dynamics/kinematics-aware costs for AGVs [41, 42]. Incremental methods (D*, D* Lite) improve replanning under map changes [43, 44], with applications in route construction [45] and hybrid graph–continuous planning [46]. Anytime variants such as ARA* provide bounded suboptimal solutions that converge as time allows [47], while constraint-repairing schemes support on-the-fly feasibility for multisatellite inspection [48]. Hybrid A* embeds kinematic constraints directly in the search and remains effective for non-holonomic vehicles [49]. Jump point search (JPS) accelerates uniform-cost grid search via symmetry breaking [50, 51], and Theta* relaxes grid headings for any-angle paths and smoother trajectories, including minimum-snap post-processing [52, 53]. These methods exploit known obstacle maps and structured environments, making them attractive for ground and indoor robotics, and they integrate naturally with higher-level guidance and local optimization.

2.4 ML-Assisted Planning

Learning augments trajectory generation by providing priors, heuristics, and policies that enhance classical planners. Value/cost-to-go networks guide A*/RRT*/BIT* toward promising regions and prune expansions, typically trained from demonstrations [54]. Neural samplers—e.g., stepwise goal-driven networks [55], GCNs guided by human attention [56], and uncertainty-aware models [57]—yield collision-aware proposals and implicit distance fields that sharpen search. Reinforcement learning (RL) delivers end-to-end or waypoint policies under dynamics and constraints [58], increasingly coupled with model-based rollouts [59] and risk-aware objectives [60]. Imitation learning (IL) extends to adversarial formulations for missile guidance [61] and to imperfect demonstrations for AUV tracking/avoidance [62]. Hybrid schemes fuse learning with trajectory optimization, e.g., DiffTORI—a differentiable RL–IL pipeline for optimization-in-the-loop planning [63]. Practical trends include decentralized multi-robot coordination [64], sim-to-real transfer via latent dynamics adaptation [65], and embedded deployment on SWaP-limited platforms using code generation or lightweight inference [66].

2.5 Trends and Challenges

Guidance is trending toward hybrid pipelines that combine optimal control, graph- and sampling-based search, and learning-assisted components to reduce solve time, improve feasibility, and handle uncertainty. Current practice emphasizes better initialization (warm starts), learned model residuals, risk-aware constraints, and tight integration with dense maps. Looking ahead, priorities include scalable guarantees under distribution shift, verifiable safety, and fair cross-domain benchmarks. Further needs are robust kinodynamic planning under tight actuation limits and explicitly energy-aware objectives. Progress will hinge on standardized tasks and metrics, calibrated uncertainty, runtime safety filtering/shielding, and tighter estimator–planner–controller coupling with provable closed-loop performance.

3 Navigation and State Estimation

Navigation and state estimation are the perceptual backbone of GNC, delivering best-estimate pose, velocity, and attitude to downstream guidance and control. From 2020–2025, advances were driven by low-cost MEMS sensors, increased GNSS-denied operation, vision-aided navigation/SLAM, pedestrian dead reckoning, and stronger onboard compute [67, 68]. Classical Kalman filters and variants remain the real-time standard, strengthened by error-state/robocentric formulations and adaptive noise/bias modeling, while multi-sensor fusion now couples inertial, GNSS, barometer, magnetometer, vision, radar, and LiDAR in filter or factor-graph frameworks [69]. In parallel, learning-enhanced navigation lets deep networks estimate biases, tune covariances, and provide learned residuals or direct pose estimates—typically wrapped by filters for consistency and integrity monitoring [13]. Fig. 5 summarizes this landscape.

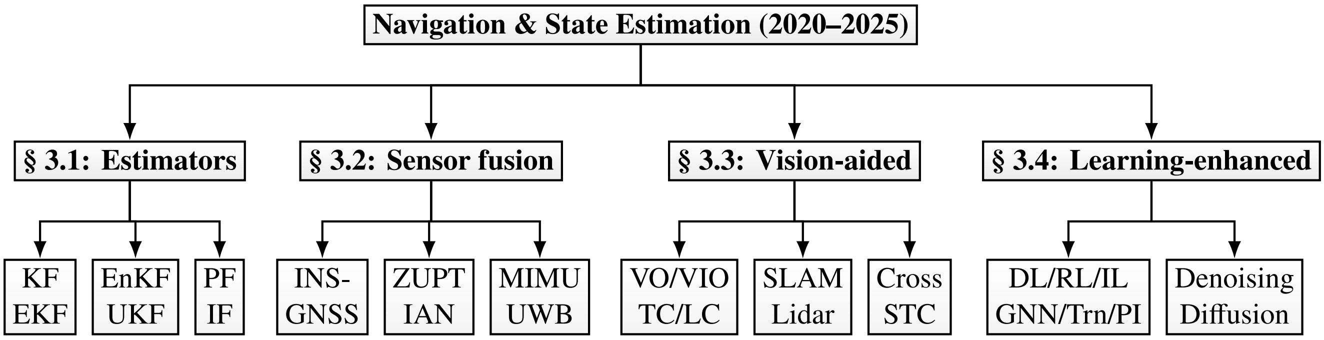

Fig. 5 Navigation paradigms (2020–2025): taxonomy with representative methods.

3.1 Estimators

Recent progress in state estimation coalesces around three families—(i) classical and extended (KF/EKF), (ii) unscented and ensemble (UKF/EnKF), and (iii) particle and invariant (PF/IF)-with optional augmentations that reduce cross-coupling and improve prediction. For KF/EKF, key trends include error-state and robocentric formulations [70], invariant EKF [71, 72], adaptive variants (e.g., $\mathcal{H}_\infty$ [73], kernel [74], transformer-based [75, 76]), as well as asynchronous filter [77, 78], delay-aware fusion (camera/IMU/GNSS/LiDAR) with robust costs [79, 80] and outlier rejection [81, 82].
UKF/EnKF address stronger nonlinearities and higher dimensions via square-root forms [83], sigma-point design augmentation [84, 85], augmented virtual filters [86], and adaptive neural UKF [87]. Lastly, PF advancements include informed proposals [88], variational Bayesian schemes [89], Rao–Blackwellization [90], and implicit/regularized resampling [91]. Moving Horizon Estimation (MHE) pushes optimization-based smoothing toward real time using surfel mapping [92], learned/NN surrogates [93], multivariate Laplace noise models [94], and hard constraints with warm starts from KF/VIO [95].

3.2 Sensor Fusion

Multi-sensor fusion leverages complementary modalities to reduce individual error sources and improve overall navigation accuracy [12]. From 2020–2025, INS/GNSS integration tightened via selectively blended loosely, tightly, and deeply coupled architectures [96–98]. Additional aids—barometers, magnetometers, ultra-wideband (UWB), and radar—are increasingly incorporated using cubature-based filters [99], quaternion-based formulations [100], or factor-graph methods [101].
Falling manufacturing costs and improved MEMS performance have made multi-IMU (MIMU) fusion common, with averaging of residuals to enhance observability and fault detection [102–104]. Extensions include pseudo-measurements (e.g., ZUPT and nonholonomic constraints) that exploit platform priors [11, 105], UAV dead-reckoning for GNSS-denied operation [106], and ML-based heading estimation [107, 108]. Recent implementations also report EKF-centric fault detection [109], variational-Bayesian adaptive fusion [110], and adaptive IMU/UWB fusion for indoor positioning [111].

3.3 Vision-Aided Navigation

Vision complements INS with drift-correcting exteroceptive cues—especially in GNSS-denied or contested settings [112]. Building on monocular/stereo VO and SLAM, recent systems favor tightly coupled VIO: keyframe BA or factor-graph smoothing maintains consistency, while robust costs, loop closure, and relocalization bound drift [113]. For reliability in the wild, pipelines estimate camera–IMU time/extrinsics (often with online/unsupervised calibration), use position-aware optical flow, and learn process-noise models for calibrated uncertainty [114–116]. Rolling-shutter and full spatiotemporal calibration (STC) reduce modeling error [117, 118], while radar–camera fusion with temporal priors and event-camera front ends extend operation to high speed and low light [119–121].

A parallel trend exploits LiDAR's geometric fidelity: scan matching and geometric/semantic features feed LiDAR–inertial odometry (LIO) in filters or factor graphs, with degeneracy detection and motion compensation improving reliability during sparse structure or aggressive motion; metric–semantic mapping tightens the link to downstream planning [122–126]. Cross-modal fusion (camera–LiDAR–radar) then hedges complementary failure modes—texture-poor, geometry-poor, or weather-degraded scenes—while voxel/ESDF maps provide planner-ready representations [127–129]. Finally, learning augments these stacks by supplying depth/flow priors, scalable place recognition, and calibrated uncertainty for integrity monitoring, yielding navigation that is both drift-bounded and robust to distribution shift [130–132].

3.4 Learning-Enhanced Navigation

Machine learning increasingly augments classical navigation stacks by modeling components that are hard to capture analytically—both within estimators and at the sensor interface [133]. Deep networks estimate sensor biases, adaptively tune process/measurement covariances, and fuse high-dimensional inputs (images, point clouds) end-to-end [13]. These gains are especially valuable in GNSS-contested, underwater, and subterranean settings where external positioning is unreliable [134–136].

Current work targets principled ML–estimator integration that preserves interpretability and safety, with validation under distribution shift still open [137]. On the theory side, uncertainty-aware, data-driven Kalman filtering formalizes learned components within covariance updates [138], and system-level studies report experimentally validated hybrids [139, 140]. At the signal/model layer, learned residuals and denoisers improve—neural inertial regression, diffusion denoising, rapid calibration, and MEMS-gyro denoising [141–144]. Hybrid filters adapt online via model–learning couplings (adaptive attitude, hybrid adaptive filters) [145–149], while pure-inertial DL frameworks extend operating envelopes [150–155]. Physics-informed (PI) networks and learned navigation/tracking/mapping integrate dynamical priors for better generalization [156–159].

Applications illustrate breadth: pedestrian inertial navigation and smartphone heading [68, 160]; wheel-mounted IMU with DL for ground vehicles and GNSS-loss compensation [161, 162]; gyrocompassing (north-finding) with mid-tier sensors [163, 164]; and AUV navigation where Transformers (Trn) and data-driven DVL enhancement/imputation frameworks handle sparse or missing beams [165–167]. Finally, learning-informed planning—via sequence models or reinforcement learning (RL)—points toward estimator–planner co-design that is robust, certifiable, and resource-aware [168–170].

3.5 Trends and Challenges

Navigation is trending toward tighter, continuous sensor fusion, with learning used as an assistive layer rather than a replacement. Near term, robust GNSS-denied operation will hinge on combining vision, LiDAR, and opportunistic aids to bound drift over long missions. Looking ahead, priorities include dependable performance under distribution shift, resilience to outages and spoofing, and simpler, self-calibrating systems that transfer across platforms with minimal tuning. Persistent challenges remain: drift accumulation without absolute references, loop-closure fragility under perceptual aliasing or large viewpoint change, and hardened robustness to sensor failures and adversarial interference.

4 Control Strategies

Control sits at the core of the GNC stack: it closes the loop by turning guidance commands and state estimates into actuator inputs that stabilize and maneuver the vehicle. From 2020 to 2025, the field advanced on two fronts—the continued refinement of classical designs and the maturation of optimization-based schemes enabled by faster solvers and embedded computing [9, 10].
Linear–quadratic Gaussian (LQG) and nonlinear dynamic inversion (NDI) remain staples for their analytical tractability and guaranteed stability margins, while nonlinear methods—feedback linearization (FBL), sliding-mode control (SMC), and gain scheduling (GS)—have been sharpened for robustness to modeling error and disturbances [4]. Model predictive control (and its nonlinear variants) has moved closer to real-time deployment via tailored convexification and code-generated solvers, delivering constraint-aware performance on agile aerial and ground platforms [7]. In parallel, learning-based controllers have emerged, using Gaussian-process residuals and safe reinforcement learning to adapt online and compensate unmodeled dynamics, raising new questions about guarantees and certification [2, 5].
This section reviews these developments with emphasis on stability assurances, real-time feasibility, and certifiability for safety-critical missions. Drawing on [171], Fig. 6 organizes contemporary control methods across model-based, data-driven, and learning-assisted paradigms.

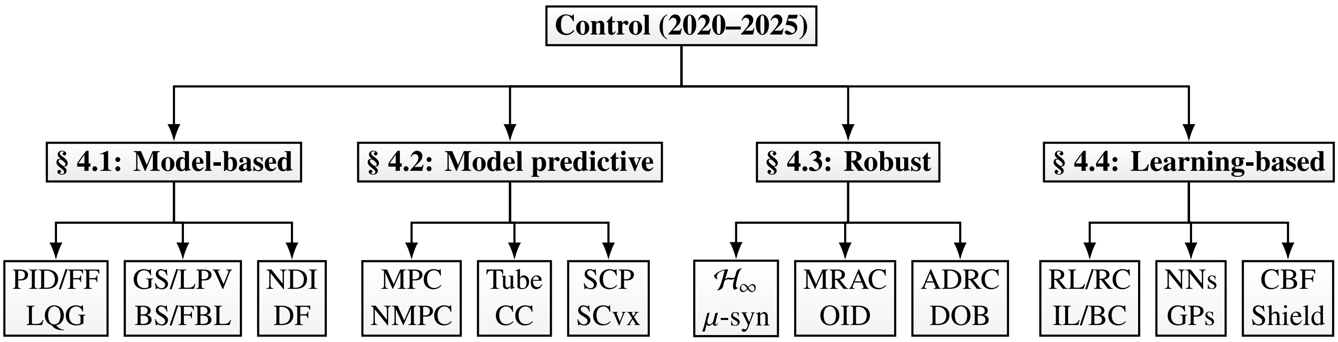

Fig. 6 Control paradigms (2020–2025): taxonomy with representative methods.

4.1 Model-Based Control

Classical, model-based linear controllers remain workhorses for flight and ground vehicles due to simplicity, analyzable stability margins, and straightforward tuning. Recent developments in proportional–integral–derivative (PID) include intelligent [172], self-adaptive [173], and fuzzy [174] PIDs, with feedforward (FF) augmentations for improved tracking under known references and disturbances [175]. Lately, linear–quadratic–Gaussian (LQG) designs have also been used for hover stabilization and disturbance rejection in quadrotors [176, 177]. To handle strong nonlinearities and couplings, backstepping (BS) employs cascaded controls with Lyapunov-based guarantees [178, 179], while sliding-mode control (SMC) reshapes the dynamics via a discontinuous signal law that drives trajectories to a sliding surface [180–182]. Complementary advances include GS designs [183, 184], and linear parameter-varying (LPV) control, which updates controller gains online using estimated scheduling variables [185, 186]. Nonlinear dynamic inversion (NDI) [187–189] and its incremental extension (INDI) [190–193] cancel nominal dynamics through virtual-input tracking, with INDI reducing model dependence via incremental dynamics and sensor feedback to improve robustness. Other nonlinear methods—feedback linearization (FBL) [194–196] and differential flatness (DF) for reference generation and trajectory tracking [197–200]—provide precise tracking when model structure is exploitable.

4.2 Model Predictive Control

Model predictive control (MPC) is approaching real-time operation through faster solvers, warm starts, and code generation [201–203], while NMPC extends these benefits to systems with pronounced dynamics and hard constraints [204, 205]. Practical implementations on embedded hardware combine proximal/first-order methods with move-blocking or adaptive horizons to meet cycle-time budgets [206]. Robust formulations include Tube MPC—constraint tightening around a nominal trajectory with ancillary feedback—and Chance-Constrained (CC) MPC, which enforces bounded risk under stochastic disturbances [207, 208]. Successive programming/convexification (SCP/SCvx) formulations improve feasibility for aggressive 6-DoF maneuvers [209, 210]. Recent advances in terminal ingredients (sets/-costs) [211], online constraint-tightening [212], and barrier-function augmentations [213] further enhance stability, constraint satisfaction, and endurance.

4.3 Robust and Adaptive Control

Robust and adaptive designs address uncertainty, disturbances, and slow time variation beyond nominal models. $\mathcal{H}_\infty$ and μ-synthesis shape closed-loop sensitivity and enforce performance under bounded and model-structured uncertainty via weighting design and structured singular-value analysis; recent work advances mixed-$\mathcal{H}_2/\mathcal{H}_\infty$ trade-offs and scalable synthesis for high-order plants [214–217].
Model-reference adaptive control (MRAC) with online identification (OID) adapts gains to track a reference model under parametric drift, employing projection/normalization and robust (e.g., $\mathcal{L}_1$-style) modifications to guarantee bounded signals and predictable transients [218, 219]. Disturbance-observer–based (DOB) and active disturbance-rejection controllers (ADRC) estimate lumped uncertainties with extended-state or disturbance observers and cancel them through inner-loop compensation [220–222]. Emerging trends integrate event-triggered updates [223], robust adaptive learning schemes [224], and compute-aware scheduling [225] to maintain guarantees and meet real-time constraints on embedded platforms.

4.4 Learning-Based Control

Learning-based control augments model-driven designs with data-driven components to improve adaptation, performance, and robustness. Recent reinforcement learning (RL) work delivers state–action policies optimized for long-horizon objectives under dynamics and constraints [226–228]. Since 2022, imitation learning (IL), behavior cloning (BC) and DAgger, have provided sample-efficient initialization from expert demonstrations, commonly refined by RL or online adaptation [229–231]. Gaussian processes (GPs) contribute learned residual models and calibrated uncertainty for prediction and gain scheduling, enabling risk-aware decisions and stronger disturbance rejection [232–234].
On the neural networks (NNs) side, Koopman operators, neural state-space models, NN-assisted NMPC, and NN-based risk analysis expand modeling and planning capability [235–239]. Emerging practice couples learning with MPC/NMPC, calibrates uncertainty for out-of-distribution detection, and uses event-triggered/compute-aware execution on embedded platforms—while control barrier functions (CBFs) and shielding layers enforce real-time safety and closed-loop guarantees [240, 241].

4.5 Trends and Challenges

From 2020–2025, control research trends toward tighter integration and real-time feasibility. Classical linear and nonlinear controllers are increasingly embedded in hierarchical architectures and paired with high-fidelity observers for resilience to model error and sensor imperfections. MPC continues to gain traction as tailored, faster solvers make constraint-aware control practical even on agile, resource-limited platforms. Hybrid approaches—combining predictive control, robust/adaptive layers, and learning-based residuals or warm starts—are moving from proofs of concept to deployment.
Key challenges remain: (i) certifiable guarantees with learning in the loop; (ii) robustness to distribution shift and time variation; (iii) standardized cross-domain benchmarks; (iv) energy- and SWaP-aware control trading agility for endurance; (v) estimator–controller coupling with latency/uncertainty; (vi) compute-aware implementations sustaining high update rates.

5 Closing Remarks

This review synthesized key advances in GNC from 2020–2025, illustrating how the field is being reshaped by two forces: increasingly demanding missions and rapidly improving onboard computation. Framing the literature around the three canonical pillars, we introduced a coherent taxonomy that reflects both the maturity of classical methods and the ascent of data-driven, learning-augmented approaches. Across aerial, land, surface, and underwater domains, we observe a decisive shift toward real-time feasibility, learning-assisted capability, robustness in GNSS-denied and adversarial settings, and energy/safety-aware designs suitable for SWaP-constrained deployment. These trends point to tighter integration across the stack, with uncertainty propagated from perception through planning to control. Although learning-based approaches now play a central role in GNC, model-based methods remain the dependable backbone thanks to their reliability, transparent reasoning, formal guarantees, and inherent fault tolerance; in practice, the strongest systems are hybrid, leveraging the strengths of both.
Table 3 integrates the survey across all three pillars, enumerating key subtopics, representative methods, advantages, and limitations, and concluding with cross-cutting themes that span the pipeline—providing a compact roadmap for researchers and practitioners.

Table 3 Representative 2020–2025 GNC methods with key advantages and limitations.

Category	Representative works / methods	Key advantages	Limitations / open issues
Guidance	MPC/NMPC (tube, CC); SCP/SCvx, direct collocation; RRT*/PRM*, BIT*/FMT*; A*/D* Lite/Hybrid A*; learning-assisted (RL/IL, value nets, neural samplers)	Constraint-aware, near–real-time planning; asymptotic optimality (star variants); handles kinodynamics; learning provides warm starts/heuristics	Compute burden in high dimension; certification of learning components; limited field validation and long-duration trials; simplified environment models
Navigation	Kalman filter variants; linear, extended, unscented, particle, and adaptive; INS/GNSS coupling; VIO and LiDAR–inertial SLAM; pseudo-measurements (ZUPT/IAN); learning-enhanced bias / covariance / residuals	Drift-bounded estimates in GNSS-denied settings; robust multi-sensor fusion; maturity of MEMS instrumentation for high-precision tasks; online calibration/sync feasible	Estimating non-gaussian, non-white, non-stationary noise; degeneracy under poor excitation; timing/asynchrony handling is fragile; SWaP constraints limit map/graph size;
Control	PID/FF; LQR/LQG; SMC, FBL, GS/NDI; MPC/NMPC (SCP/SCvx, tube, CC); H_∞/μ-syn; MRAC/ID; learning-assisted (GP/NN residuals, Safe RL/IL, CBF-QP shields)	Stability/robustness margins; explicit constraint handling; disturbance rejection; learning residuals improve modeling while shields enforce safety	Model dependence and tuning effort; real-time NMPC still tight on fast platforms; formal guarantees with learning in the loop remain limited
Cross-cutting	Hybrid model–data pipelines; uncertainty calibration; safety filters/shielding; GNSS-denied operation (VIO+LIO+opportunistic aids); energy/SWaP-aware design; estimator–planner–controller coupling	Bridges physics and learning; robust and safe; faster warm starts and solver convergence; better adaptation to sensor drift; enhanced resilience in GNSS-denied settings	Toolchain maturity and reproducibility; lack of unified cross-domain benchmarks; explainability/traceability of learned components; limited standardized energy metrics

Evidently, boundaries between all three operating domains are increasingly blurred: co-design of estimators, planners, and controllers—with explicit end-to-end uncertainty propagation—is becoming the norm. These joint formulations improve closed-loop performance but also raise computational and integration demands. Looking ahead, priorities include certifiable learning-in-the-loop, dependable performance under distribution shift, standardized cross-domain benchmarks, and tighter estimator–planner–controller coupling with explicit uncertainty carried through to decisions.
By situating recent advances alongside prior surveys and clarifying terminology, we aim to provide a timely guide to a rapidly expanding literature. We hope this survey serves as a practical map of methods and trade-offs for building high-performance, deployable GNC systems.

5.1 Research Gaps and Future Directions

Despite rapid progress, several gaps remain before GNC methods become broadly certifiable, scalable, and deployment-ready across domains.

1) Explainable AI (XAI) for GNC: generate actionable, auditable rationales for estimator–planner–controller decisions, with fidelity metrics and counterfactuals—enabling certification, human-on-the-loop oversight, and post-incident forensics under distribution shift.

2) Standardized, cross-domain benchmarks: Establish common tasks, metrics, and datasets—covering GNSS-denied, adverse weather, and long-duration missions—to enable fair comparison and reproducibility; include energy/SWaP metrics, latency budgets, and failure reporting.

3) End-to-end uncertainty propagation: Carry calibrated uncertainty from perception through planning to control, enabling risk-aware decisions and verifiable chance constraints; quantify integrity and detect distribution shift online.

4) Estimator–planner–controller co-design: Move beyond sequential pipelines to joint designs that account for sensing latency, actuation limits, and model mismatch; study closed-loop performance with tight coupling and feedback of information value.

5) Compute-and energy-aware GNC: Create algorithms that adapt to onboard compute, power, and thermal limits (anytime/interruptible solvers, policy warming, model reduction) with explicit energy–agility trade-offs.

6) Robust operation under degradation: Improve resilience to sensor outages, spoofing/jamming, calibration drift, and map uncertainty via redundancy, integrity monitoring, and graceful degradation/fallback modes.

7) Long-horizon autonomy: Address drift accumulation and map maintenance with lifelong mapping, selective memory, and periodic absolute updates (e.g., opportunistic beacons/terrain fixes) suitable for weeks-to-months deployment.

8) Human factors and oversight: Design interfaces, explanations, and intervention policies for human-on-the-loop operations, including accountability and post-incident analysis.

Addressing these directions should yield hybrid GNC architectures that pair formal guarantees with data-driven adaptability, enabling resilient, certifiable, and energy-efficient autonomy across aerial, land, surface, and underwater domains.

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Declaration of Use of Artificial Intelligence

AI tools were used only for language polishing (grammar, spelling, minor style edits). No AI was used to generate technical content, figures, tables, or literature summaries. The authors have carefully reviewed and verified the entire manuscript to ensure that the scientific ideas, analyses, and conclusions remain entirely their own.

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