

# Adaptive Fuzzy Control Systems for Uncertainty-Aware Autonomous Navigation

Ananthakrishnan S<sup>1\*</sup>, Thiagarajan R<sup>2</sup> and Muthukumar S<sup>3</sup>

<sup>1</sup>Department of Intelligent Systems, Sharavati Center for Robotics and Automation, Indonesia Email:

[swathi.ananthakrishnan@sharavati.edu](mailto:swathi.ananthakrishnan@sharavati.edu)

ORCID: <https://orcid.org/0666-7905-6408-5385>

<sup>2</sup>Department of Computational Intelligence, Hemavathi Center for Intelligent Automation, Philippines Email:

[rajesh.thiagarajan@hemavathi.edu](mailto:rajesh.thiagarajan@hemavathi.edu)

ORCID: <https://orcid.org/0740-0747-2334-6680>

<sup>3</sup>Department of Robotics and Automation, Meenachil Institute of Distributed Intelligence, Malaysia Email:

[suresh.muthukumar@meenachil.edu](mailto:suresh.muthukumar@meenachil.edu)

ORCID: <https://orcid.org/1022-2813-8452-1094>

## ABSTRACT

*Autonomous vehicles operating on the ground, in the air, and underwater must track trajectories and avoid obstacles despite unmodeled dynamics, drifting parameters, and imperfect sensing, conditions under which classical fixed-gain controllers routinely degrade. This article synthesizes the literature on fuzzy control approaches to this problem, tracing a continuous line from Zadeh's original fuzzy-set formalism and Mamdani and Assilian's first rule-based fuzzy controller through the Takagi-Sugeno reformulation that made rigorous Lyapunov-based stability analysis tractable for nonlinear plants, to Wang's foundational proof that a fuzzy system used as an online function approximator yields a stable, bounded-error adaptive controller under substantial model uncertainty. We then review how this theoretical core, together with type-2 fuzzy logic's explicit representation of meta-level uncertainty, has been built into applied navigation systems for mobile ground robots, quadrotor UAVs, autonomous underwater and surface vehicles, steering-controlled ground vehicles, and robotic manipulators, reporting the concrete quantitative gains -- and the more common qualitative stability guarantees -- these studies actually document. Read together, the evidence supports adaptive and type-2 fuzzy control as a mature, repeatedly validated architectural pattern for navigation under uncertainty, while leaving inconsistent performance-reporting standards, limited field validation beyond simulation and short experimental windows, and the interpretability cost of combining fuzzy reasoning with learning-based methods as an open research agenda.*

**Keywords:** adaptive fuzzy control; autonomous navigation; uncertainty-aware control; type-2 fuzzy logic; sliding mode control

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## 1. Introduction

Autonomous navigation asks a machine to do something quietly remarkable: move safely through a world it does not fully know, using sensors that lie a little, actuators that respond a little differently than modeled, and a physical environment that refuses to sit still. A wheeled robot's wheels slip on wet tile in ways no friction coefficient captures exactly; a quadrotor's mass shifts as its battery drains and its payload changes; an underwater vehicle fights currents that no onboard sensor measures directly; a surface vessel loses partial use of a thruster mid-mission and must keep tracking its path anyway. Classical control theory has powerful tools for systems whose dynamics are known precisely, but autonomous navigation is defined by the opposite condition: bounded but genuinely unknown uncertainty in the plant model, the environment, and the sensing chain, all at once, and all while the vehicle is expected to keep moving.

Fuzzy control entered this picture from an unusual angle. Lotfi Zadeh's 1965 paper introducing fuzzy sets did not propose a control algorithm at all; it proposed a mathematical relaxation of set membership, allowing an element to belong to a set by degree rather than by a strict yes-or-no test [1]. The control implications took a decade to become concrete. Mamdani and Assilian's 1975 paper describing a fuzzy logic controller for a laboratory steam engine is usually credited as the first practical demonstration that a bank of linguistic if-then rules -- "if pressure error is large positive and pressure-error-rate is positive, then increase heat coefficient sharply" -- expressed and evaluated using fuzzy-set membership functions, could regulate a real physical plant competitively with a conventionally tuned controller, and without a differential-equation model of the plant at all [2]. That property -- controlling a system by encoding a human operator's or engineer's qualitative understanding of it, rather than by deriving a closed-form model -- is exactly what makes fuzzy control attractive for navigation problems where the plant (a vehicle plus an unpredictable environment) resists precise modeling.

The decades since have produced two largely parallel developments that this article treats as its central subject. On one side, a rigorous adaptive-control literature has shown how fuzzy systems can be married to Lyapunov-based stability analysis, so that a fuzzy

controller is not just heuristically plausible but provably stable and provably capable of tracking a reference trajectory to within a bounded error, even when the plant's dynamics are only partially known and are estimated online [3]. On the other side, an applied robotics and vehicle-control literature has taken these ideas and built them into working navigation stacks -- obstacle avoidance behaviors, local path planners, attitude and trajectory controllers for aerial and underwater vehicles, fault-tolerant steering schemes -- and has reported, across a fairly wide range of platforms, that the adaptive fuzzy layer measurably improves robustness to the kind of uncertainty a fixed-gain controller struggles with. This article synthesizes both threads: the theoretical apparatus that makes "adaptive fuzzy control" a rigorous rather than merely heuristic label, and the applied evidence, drawn from mobile ground robots, quadrotor UAVs, autonomous underwater and surface vehicles, and robotic manipulators, of what that apparatus buys a navigating machine in practice.

It is worth being explicit about what kind of claim this article is and is not making. We are not reporting a new controller or a new experiment. We are reading, across roughly twenty-two studies spanning five decades, what the literature itself has verified about adaptive and type-2 fuzzy control for navigation under uncertainty -- where the theoretical guarantees are solid, where the applied results are genuinely quantitative and where they are qualitative, and where open problems remain. Several of the applied papers synthesized here report specific numeric gains -- a percentage reduction in path length, a bounded settling time under actuator failure -- and we reproduce those numbers exactly as reported, while being equally candid about the many papers whose abstracts assert stability and robustness qualitatively ("bounded," "converges to a small neighborhood of the origin") without a headline percentage to quote. Both kinds of evidence matter, and conflating them would misrepresent the field.

## 2. Foundations of Fuzzy Logic and Fuzzy Control

A fuzzy set generalizes an ordinary (crisp) set by replacing the binary membership function -- an element either belongs or it does not -- with a membership function that maps each element to a real value between zero and one, capturing degree of membership rather than a hard boundary [1]. In a controller, this idea is

operationalized through linguistic variables: a variable like "distance to obstacle" is not represented as a single real number fed through a fixed transfer function, but as a set of overlapping fuzzy categories -- "near," "medium," "far" -- each with its own membership function over the underlying numeric range. A rule base, typically expressed as a small set of human-readable if-then statements over these linguistic categories, encodes the control policy: "if distance is near and closing-speed is fast, then steering-correction is large." Mamdani and Assilian's original controller used exactly this structure, with fuzzy implication and a centroid-style defuzzification step converting the aggregated fuzzy output back into a single crisp actuator command, and showed it could regulate a steam-engine testbed's speed and boiler pressure using rules that a human operator could read and audit, a property that gave fuzzy control an interpretability advantage conventional controllers of the era did not obviously share [2].

Mamdani-style inference is not the only architecture, and for navigation and vehicle control specifically, a different formulation introduced by Takagi and Sugeno in 1985 has become at least as influential. Rather than defuzzifying a fuzzy output set, a Takagi-Sugeno (T-S) fuzzy model represents the consequent of each rule as a (typically affine or linear) function of the input variables, so the overall system behaves as a smooth interpolation, weighted by rule-firing strength, among a bank of local linear models -- "if operating point is near condition A, behave like linear model A; if near condition B, behave like linear model B" [4]. This reformulation matters enormously for control-theoretic analysis, because it converts a genuinely nonlinear plant into something that looks, locally, like a linear parameter-varying system, for which linear-systems tools -- Lyapunov functions built from a common quadratic form, linear matrix inequality (LMI) feasibility conditions, established stability margins -- become directly applicable. A large share of the rigorous stability and robustness results for fuzzy-controlled nonlinear systems, including much of the work synthesized later in this article, builds on the T-S representation rather than on Mamdani-style rule bases, precisely because it inherits this tractability. A recent survey by Wang and colleagues catalogues how far this T-S-based control literature has been pushed to handle "engineering-oriented complexities" -- actuator

saturation, network-induced delay, sensor faults, and the kind of imperfect, resource-constrained communication that real autonomous platforms actually experience rather than the clean, ideal channel assumed in early theoretical treatments [5].

A third architectural strand worth naming is the adaptive-network-based fuzzy inference system (ANFIS), introduced by Jang in 1993, which embeds a Takagi-Sugeno-style fuzzy system inside a feedforward network structure and tunes its membership-function parameters and rule consequents using gradient-descent and least-squares learning rules borrowed directly from neural-network training [6]. ANFIS is significant for this article's purposes because it is the clearest early bridge between fuzzy control's rule-based interpretability and the data-driven, learning-based tuning that later adaptive fuzzy control -- and, more recently, fuzzy-reinforcement-learning hybrids for navigation -- would come to depend on. Where Mamdani's original controller had its rule base and membership functions set once by a human expert, ANFIS-style systems, and the adaptive fuzzy controllers discussed in the next section more generally, treat those parameters as something the controller itself estimates and updates online, in response to how well its current model is actually tracking the plant it is trying to control.

### 3. Adaptive and Type-2 Fuzzy Control for Uncertain Nonlinear Systems

The word "adaptive" in adaptive fuzzy control is doing precise technical work, and it is worth being careful about what it means. A fixed fuzzy controller, however cleverly its rule base is designed, still encodes a static mapping from measured states to control action; if the plant it is controlling has genuinely unknown parameters, or parameters that drift over the mission (a robot's payload mass, a vehicle's center of gravity, a current profile the vehicle has never encountered), a static rule base has no mechanism to compensate. Wang's 1993 paper on stable adaptive fuzzy control of nonlinear systems addressed exactly this gap, using a fuzzy system as a universal function approximator for an unknown nonlinear term in the plant dynamics, and deriving online adaptation laws -- update rules for the fuzzy system's tunable parameters, driven by the tracking error -- together with a Lyapunov-function proof that the resulting closed loop remains stable and the tracking error remains bounded, even though the

true plant nonlinearity is never known exactly [3]. This result is the theoretical anchor for essentially every "adaptive fuzzy" navigation and vehicle-control paper discussed later in this article: the fuzzy system is not simply a heuristic pattern-matcher, it is an online function approximator with a provable error bound, and the "adaptive" law is the mechanism by which that approximator keeps re-fitting itself to the plant's actual, uncertain behavior as the mission proceeds.

A closely related design pattern, adaptive fuzzy sliding mode control, combines this online-approximation idea with the robustness properties of sliding mode control, in which the controller drives the system state onto a designed sliding surface and then keeps it there despite bounded disturbances, at the cost of a discontinuous ("bang-bang") control action that can excite unwanted high-frequency chatter in the actuators. Using a fuzzy approximator to estimate the uncertain or disturbance term inside the sliding-mode law, rather than relying on a fixed, conservatively large switching gain to dominate the worst-case uncertainty, is a way of keeping the sliding-mode controller's robustness while reducing this chattering, since the fuzzy term absorbs much of what the switching gain would otherwise have to fight blindly. Hušek's analysis of adaptive fuzzy sliding mode control for uncertain nonlinear systems works through this design pattern formally, deriving the adaptation law for the fuzzy approximator jointly with the sliding-surface design and establishing the resulting stability guarantee [7]. The same combination recurs constantly in the applied navigation literature synthesized in the sections below, essentially as the default choice whenever a paper needs both strong disturbance rejection and a smooth, chattering-reduced control signal -- exactly the combination a navigating vehicle needs when its "disturbance" is a current, a gust, or an unmodeled payload shift rather than a clean, well-characterized noise process.

A second axis of theoretical development addresses a subtler kind of uncertainty: uncertainty in the fuzzy system itself, not just in the plant it is controlling. An ordinary ("type-1") fuzzy set assigns each element a single, crisp membership value, which implicitly assumes the designer knows the membership function exactly. In practice, membership functions are themselves estimated from noisy data or expert judgment that different experts would specify slightly

differently, and a type-1 fuzzy system has no internal representation of that meta-level uncertainty. Type-2 fuzzy sets, formalized for control design by Liang and Mendel, address this by letting the membership grade itself be fuzzy -- for the common interval type-2 case, each element's membership is represented not by a single value but by an interval, bounded above and below by a footprint of uncertainty -- giving the fuzzy system an explicit, tunable degree of freedom for representing how confident it is in its own rule base, on top of whatever uncertainty exists in the plant being controlled [8]. For navigation specifically, this distinction is not merely academic: a robot's sensor noise, an unmapped region's genuinely unknown obstacle layout, and imprecise expert-specified membership functions for "near" or "far" are all sources of uncertainty stacked on top of each other, and type-2 fuzzy logic gives the controller a principled way to represent that stacking rather than collapsing it into a single type-1 membership function tuned to a best guess. Hachani and Nechadi's comparative study of type-2 fuzzy robot navigation, evaluated in both simulation and real-world implementation, is a direct test of this idea in a navigation context, and situates the type-2 architecture as a practical response to environments whose obstacle layout and sensor behavior are not just noisy but only partially known in advance [9].

#### 4. Path Planning and Obstacle Avoidance under Uncertainty

Fuzzy control's earliest and most direct application to navigation was not trajectory tracking at all, but the reactive, moment-to-moment problem of steering a mobile robot around obstacles it discovers as it moves, using range sensors that are themselves noisy and incomplete. Reigner's early treatment of fuzzy logic techniques for mobile robot obstacle avoidance is representative of this line of work: rather than building a full, precise geometric map of the environment before planning a path through it (a strategy that is brittle when the map is built from noisy sonar or infrared range data), a fuzzy reactive controller maps sensed obstacle distances and bearings directly to steering and speed commands through a rule base, tolerating sensor imprecision by design, because the fuzzy membership functions are built to degrade gracefully rather than to require an exact numeric reading [10]. This reactive, sensor-uncertainty-tolerant style of controller remains

the conceptual ancestor of most of the fuzzy obstacle-avoidance systems built since, even as the platforms they run on have become considerably more capable.

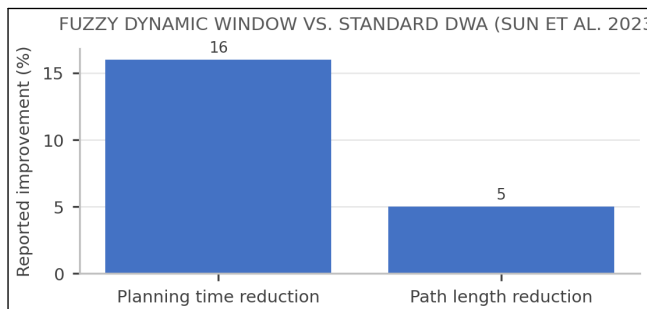


**Figure 1: Reported improvement of a fuzzy-weighted dynamic window algorithm over the standard, fixed-weight dynamic window approach for mobile-robot local path planning, evaluated across simulated test environments [11].**

More recent work has folded fuzzy reasoning into established path-planning algorithms rather than replacing them outright, which is arguably a more representative picture of how fuzzy control is actually used in contemporary navigation stacks: as a tunable layer inside a larger, otherwise conventional planning pipeline. Sun and colleagues' fuzzy dynamic window algorithm is a clear, quantitatively documented example. The dynamic window approach (DWA) is a standard local path-planning method that samples a robot's feasible velocity space and scores each candidate trajectory against a fixed weighted combination of objectives -- progress toward the goal, obstacle clearance, and velocity smoothness. Sun et al. use a fuzzy inference layer to adjust those objective weights online, based on the locally sensed obstacle density and goal geometry, rather than leaving them fixed for the whole mission, and report that the resulting fuzzy DWA cuts planning time by 16% and path length by 5% relative to the standard, fixed-weight DWA baseline, evaluated across their simulated test environments [11]. Those two numbers are modest in absolute terms, but they are a useful, concretely reported illustration of the general claim this section is making: fuzzy reasoning is not being used here to replace an established planning algorithm's underlying geometry, but to make one of its tunable parameters context-sensitive, and the reported improvement is the direct, measured payoff of that context-sensitivity.

The same logic extends to aerial and marine navigation, where the "obstacle" being reasoned about is often the vehicle's own uncertain dynamics as much as anything

external. Sabo and Cohen's early treatment of fuzzy logic UAV motion planning frames two-dimensional obstacle avoidance for a small unmanned aircraft as a fuzzy inference problem over sensed range and bearing to nearby obstacles, in an environment where, as the authors emphasize, there is little prior knowledge of the surrounding terrain and a UAV must therefore plan and react using only its current, local, and imperfect sensor picture [12]. This "plan with what you can currently sense, robustly" framing recurs throughout the fuzzy navigation literature and is, in our reading, the single clearest throughline connecting a 1994 ground-robot obstacle-avoidance paper to a 2023 fuzzy dynamic-window planner and a 2012 UAV motion planner: the common target is not perfect prior knowledge of the environment, which is rarely available to a real autonomous system, but graceful, bounded performance degradation as sensing and modeling uncertainty grows.

## 5. Fuzzy Control Architectures for Autonomous Vehicles, UAVs, and Marine Robots

Moving from planning (deciding where to go) to control (executing the motion that gets there) is where the adaptive-fuzzy stability theory described earlier does most of its practical work, because trajectory-tracking control is where a vehicle's genuinely uncertain, nonlinear dynamics -- not just its uncertain surroundings -- become the dominant source of error. Quadrotor UAVs are a particularly well-studied case, because a quadrotor's mass and inertia properties change measurably over a mission as its battery discharges and its payload (if any) shifts, and because it is a strongly coupled, underactuated nonlinear system for which a fixed-gain PID controller tends to degrade noticeably once operating conditions move away from its tuning point. Zhou and colleagues' fuzzy adaptive backstepping controller for quadrotor trajectory tracking pairs a backstepping control structure -- which builds a stabilizing controller recursively, subsystem by subsystem, through the quadrotor's cascaded translational and rotational dynamics -- with an online mass observer and a fuzzy compensation term that absorbs unmodeled disturbance, and the authors validate the approach with outdoor hovering tests under real wind disturbance rather than simulation alone, reporting that the combined scheme maintains accurate tracking under the resulting time-varying aerodynamic loads [13]. Rodríguez-Abreo and colleagues take a

complementary approach for UAV attitude control, using a genetic algorithm to tune a fuzzy controller's parameters rather than deriving the fuzzy adaptation law analytically, and report concrete, quantitative gains from doing so: their GA-optimized fuzzy controller reduces trajectory-tracking error by up to 30% in some tasks relative to an untuned baseline, with settling times of 0.73-0.84 seconds and overshoot below 0.4% across the vehicle's three control axes, and -- perhaps the most vivid single result in the paper -- the untuned baseline controller was unable to complete a helical test trajectory at all, failing after roughly seven seconds, while the GA-tuned fuzzy controller tracked the same trajectory smoothly to completion [14]. That specific comparison is a useful reminder that "improved tracking accuracy" understates what a genuinely under-tuned nonlinear controller can fail to do outright.

| Table 1: Reported outcomes of representative adaptive/type-2 fuzzy control studies across autonomous platform types, as stated by each cited source [11,14,17,16,19,18]. |                             |                                        |                                                                                                                                                       |
|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-----------------------------|----------------------------------------|-------------------------------------------------------------------------------------------------------------------------------------------------------|
| Platform                                                                                                                                                                 | Source                      | Uncertainty Addressed                  | Reported Outcome                                                                                                                                      |
| Mobile ground robot (local planning)                                                                                                                                     | Sun et al. [11]             | Unknown/dynamic local obstacle layout  | Fuzzy-weighted DWA cuts planning time by 16% and path length by 5% vs. fixed-weight DWA                                                               |
| Quadrotor UAV (attitude/trajectory)                                                                                                                                      | Rodriguez-Abreo et al. [14] | Unmodeled/nonlinear flight dynamics    | Up to 30% lower tracking error in some tasks; untuned baseline failed a helical trajectory after ~7s, GA-tuned fuzzy controller completed it smoothly |
| Unmanned surface vehicle                                                                                                                                                 | Bao et al. [17]             | Mid-mission actuator fault             | Position error regulated back within prescribed bound inside the predefined 10 s recovery window                                                      |
| Unmanned underwater vehicle                                                                                                                                              | Tang et al. [16]            | Lumped external disturbance/currents   | ESO-compensated adaptive fuzzy sliding mode maintains high tracking accuracy with bounded closed-loop signals                                         |
| Vision-guided ground vehicle steering                                                                                                                                    | Guo et al. [19]             | Vision-based lateral state uncertainty | Neural-fuzzy adaptive sliding mode shows improved error convergence and robustness vs. comparison controllers                                         |
| USV path planning                                                                                                                                                        | Wang et al. [18]            | Manually-tuned planning parameters     | Data-driven fuzzy tuning improves path length and navigation time while maintaining safety in complex environments                                    |

Underwater and surface vehicles present an even harsher uncertainty profile, because currents, hydrodynamic added mass, and biofouling are all

difficult to model precisely and change over a mission in ways no onboard sensor measures directly. Londhe and Patre's adaptive fuzzy sliding mode controller for autonomous underwater vehicle (AUV) trajectory tracking is a direct application of the adaptive-fuzzy-sliding-mode pattern described in the previous section to this setting, using the fuzzy approximator to estimate the AUV's uncertain hydrodynamic terms online while the sliding-mode component enforces robust tracking against whatever residual disturbance the approximator has not yet captured [15]. Tang and colleagues extend this pattern further by pairing an adaptive fuzzy nonlinear integral sliding mode controller with an extended state observer (ESO) for an unmanned underwater vehicle, using the ESO to estimate the lumped effect of unmodeled dynamics and external disturbance in real time and feeding that estimate forward into the controller, and report -- in qualitative but specific terms -- that the combined scheme suppresses lumped disturbance effectively and maintains high tracking accuracy and robustness across both simulation and physical experiments [16]. On the surface, Bao, Gao, and Peng's fuzzy adaptive fault-tolerant controller for an unmanned surface vehicle (USV) targets a still more demanding scenario -- an actuator fault occurring mid-mission, not merely an unmodeled disturbance -- and design their controller around a prescribed-performance framework that constrains the tracking error to stay within a shrinking bound over time; their reported simulation result is that the vehicle's position error is regulated back within the prescribed bound within the predefined 10-second window even after a simulated actuator failure, a concrete, specific fault-recovery number in a literature where many stability claims are stated only qualitatively [17]. Wang and colleagues' data-driven fuzzy logic method for USV path planning addresses a related but distinct problem in the same domain -- automatically tuning the parameters of a USV path-planning algorithm that would otherwise be hand-set by an engineer -- and report, across their simulated test environments, improved path length and navigation time while maintaining safety margins in complex environments [18].

Ground vehicles and robotic manipulators round out this picture and show that the same architectural pattern generalizes well beyond mobile robots and aerial or marine vehicles. Guo and colleagues' neural-fuzzy

adaptive sliding mode steering controller for vision-based unmanned electric vehicles combines a fuzzy-neural estimator of the vehicle's uncertain lateral dynamics with a sliding-mode steering law driven by a vision-based lane-position estimate, reporting improved error convergence and robustness relative to comparison controllers evaluated on the same steering task [19]. Azimi and Koofgar's adaptive fuzzy backstepping controller for underactuated robotic systems, and Keighobadi, Fateh, and Xu's adaptive fuzzy voltage-based backstepping controller for robotic manipulators under partial state constraints and input delay, both apply the Wang-style adaptive-fuzzy-approximator pattern to manipulator dynamics rather than vehicle dynamics, with both papers proving semi-global uniform ultimate boundedness of the tracking error under their respective uncertainty models -- unknown underactuated dynamics in the first case, input delay and state constraints in the second [20,21]. That these manipulator-control results and the mobile-, aerial-, and marine-vehicle results described above rest on essentially the same theoretical machinery is, we think, one of the more understated strengths of the adaptive fuzzy control literature: a stability proof developed for one class of uncertain nonlinear system tends to transfer, with modest reformulation, to a strikingly different physical platform.

### Interpolation, Not Just Approximation

It is worth dwelling a moment longer on why the Takagi-Sugeno reformulation, specifically, turned out to matter as much as it did for navigation and vehicle control rather than remaining a mathematical curiosity. A navigating vehicle rarely operates at one fixed condition; a quadrotor's effective dynamics near hover differ substantially from its dynamics during an aggressive maneuver, an AUV's hydrodynamics differ between a slow survey transit and a fast station-keeping correction against a current, and a ground vehicle's steering dynamics differ between a dry road and a wet one. A single linear controller, gain-scheduled by hand across these regimes, is a well-understood but labor-intensive classical solution. The T-S framing reframes gain scheduling as something closer to a smooth, rule-weighted interpolation among local models, where each rule's firing strength -- itself computed from the current, unmodified fuzzy membership degrees -- determines how much that

regime's local linear controller contributes to the current command [4]. This is precisely why the T-S structure, rather than the original Mamdani structure, dominates the stability-proof side of the literature synthesized here: proving stability for a smoothly interpolated bank of linear models, each satisfying its own local Lyapunov inequality, is a tractable extension of linear control theory, whereas proving an equivalent guarantee for an arbitrary Mamdani rule base with centroid defuzzification is considerably harder to do in general. Wang's adaptive fuzzy control result exploits exactly this tractability, treating the fuzzy approximator's output as effectively a T-S-style weighted combination of tunable local terms whose combined adaptation law can be analyzed with a single quadratic Lyapunov function [3].

### What "Real-Time" Actually Requires

A second point that the applied literature makes only implicitly, but that is worth surfacing explicitly, is how tightly coupled the adaptation law's computational cost is to whether a given fuzzy control scheme is deployable at all on a given vehicle's onboard computer. An adaptation law that updates dozens of rule-consequent parameters every control cycle, evaluated at the kilohertz-range rates a quadrotor's inner attitude loop typically requires, is a materially different computational commitment than the same law running at the few-hertz rate adequate for a ground robot's local path replanning. None of the papers synthesized in this article report the wall-clock computational cost of their adaptation law explicitly, which is consistent with the broader reporting gap noted below, but the diversity of platforms across which adaptive fuzzy control has nonetheless been successfully deployed -- from Zhou et al.'s outdoor-flown quadrotor with its fast attitude loop to Sun et al.'s ground robot replanning at a comparatively relaxed local-planning rate -- is itself indirect evidence that the computational cost of a reasonably sized fuzzy rule base, with an online gradient- or Lyapunov-derived adaptation law, is manageable across a fairly wide range of onboard computing budgets [13,11]. That said, "manageable" is doing some work in that sentence, and a more systematic accounting of adaptation-law cost against platform compute budget, in the spirit of the resource-accounting arguments made in other areas of embedded intelligent control, would strengthen a literature that currently treats deployability as assumed rather than measured.

## 6. Open Challenges

Several gaps recur across this literature and deserve to be stated plainly. First, and most basic, is an evidence-quality gap: while the applied navigation papers synthesized here consistently claim improved robustness and tracking performance under uncertainty, the quantitative headline numbers that can actually be extracted and verified vary enormously in specificity, from Sun et al.'s clean 16%/5% planning-time and path-length figures [11] and Rodríguez-Abreo et al.'s per-axis settling-time and overshoot table [14], to papers like Tang et al.'s and Keighobadi et al.'s that report only that tracking error "converges to a small neighborhood of the origin" or that closed-loop signals remain "bounded," without a headline percentage a practitioner could use to compare methods [16,21]. Both kinds of result are scientifically legitimate -- a Lyapunov-based boundedness proof is a real and valuable guarantee -- but they answer different questions, and the literature would benefit from more consistent reporting of concrete, comparable performance numbers alongside the stability proofs.

Second, most of the reported quantitative gains, including Sun et al.'s DWA comparison and Rodríguez-Abreo et al.'s tracking-error reduction, come from simulation or from limited, single-platform experimental validation rather than from large-scale field deployment across varied real-world conditions [11,14]. Zhou et al.'s outdoor quadrotor hovering test under real wind and Bao et al.'s simulated actuator-fault recovery are steps toward deployment realism, but they remain comparatively narrow test scenarios relative to the range of uncertainty a genuinely long-duration autonomous mission would encounter [13,17]. Third, the interaction between type-2 fuzzy logic's extra degree of freedom for representing meta-level uncertainty and the adaptive-fuzzy-sliding-mode stability machinery built primarily around type-1 fuzzy approximators is, in our reading, less thoroughly worked out than either half is on its own; Hachani and Nechadi's type-2 navigation study is a useful applied data point, but a general type-2 counterpart to Wang's foundational stability result, with the same level of formal rigor, is not something this literature search turned up as a single, widely cited reference [9,3].

Fourth, fuzzy control's interpretability advantage -- the property that first motivated Mamdani and Assilian's

rule-based design -- becomes harder to preserve as controllers grow more complex, particularly once a fuzzy layer is combined with reinforcement learning, as in Bautista-Montesano and colleagues' explainable fuzzy-reinforcement-learning navigation system [22,2]. That paper's stated goal is explicitly to recover some of fuzzy logic's interpretability inside an RL-trained navigation policy, which is itself a signal that the field recognizes interpretability as something that needs deliberate re-engineering once a system moves past a hand-specified rule base, not something that survives automatically. Finally, energy and computational budget for the adaptation law itself -- the online parameter updates that give adaptive fuzzy control its name -- is rarely reported as a cost alongside the tracking-performance benefit, which matters increasingly as fuzzy control is deployed on smaller, more power-constrained autonomous platforms than the ground vehicles and research-grade AUVs most of this literature was validated on.

## 7. Conclusion

The literature surveyed here supports a fairly specific claim: adaptive and type-2 fuzzy control, understood as a fuzzy rule base or Takagi-Sugeno structure whose parameters are tuned online by a provably stable adaptation law, is a mature and repeatedly validated architectural pattern for navigating uncertain, nonlinear, and only partially modeled autonomous platforms. It traces a continuous line from Zadeh's original mathematical relaxation of set membership and Mamdani and Assilian's first working rule-based controller [1,2], through the Takagi-Sugeno reformulation that made rigorous Lyapunov-based stability analysis tractable for genuinely nonlinear plants [4], to Wang's foundational proof that a fuzzy system used as an online function approximator yields a stable, bounded-error adaptive controller even under substantial model uncertainty [3]. Layered on top of that theoretical core, an applied literature spanning mobile ground robots, quadrotor UAVs, autonomous underwater and surface vehicles, steering-controlled ground vehicles, and robotic manipulators has repeatedly shown that this pattern measurably helps: faster, shorter local path planning under a fuzzy-tuned dynamic window [11], substantially reduced UAV trajectory-tracking error and the ability to complete maneuvers a fixed controller simply cannot [14,13], and rapid, bounded recovery from actuator faults in surface

and underwater vehicles [17,16,15].

None of this amounts to a claim that adaptive fuzzy control has solved autonomous navigation under uncertainty outright. The gaps are real: reporting standards for quantitative performance remain inconsistent across the literature, most validation remains simulation-heavy or limited to short experimental windows, type-2 fuzzy logic's formal stability theory lags behind its type-1 counterpart, and the interpretability that originally motivated the whole approach requires active re-engineering once fuzzy reasoning is combined with learning-based methods [9,22]. What the evidence does support, read across five decades and a genuinely diverse set of physical platforms, is that a comparatively simple idea -- represent uncertain nonlinear behavior with a rule-based or Takagi-Sugeno fuzzy approximator, and update that approximator online against a stability-preserving adaptation law -- has proven durable enough to be independently rediscovered, validated, and extended by research groups working on ground robots, aircraft, underwater vehicles, surface vessels, and manipulators alike, which is about as strong a form of convergent evidence as a synthesis like this one can point to.

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### Conflict of Interest

The authors declare that they have no known competing financial interests or conflicts of interest.

## Data Availability Statement

This article is a literature synthesis and did not generate new primary data; all findings discussed are drawn from the cited publications, and readers should consult those original sources for their underlying data and code availability.

## Ethical Approval

Not applicable. This work did not involve human participants, animal subjects, or the collection of primary experimental data.