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Resilient Hybrid AI Navigation for Mobile Robots in Hazardous Cyber-Physical Environments: A Review

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ABSTRACT

In this work, we present a comprehensive review on how to tackle the challenging tasks of navigation of mobile robots in cyber-physical environments which are prone to failures. The main contribution of this paper is to present a system partitioning criterion, i.e. how to divide the control authority of the different subsystems in order to prevent a single failure from triggering a chain of system failures. To this end, we analyze the effects of three types of environmental degradation, i.e. environmental disturbances, structural instability and cyber-physical disturbances, on the different layers of a typical robot, i.e. perception, SLAM, planning and control. We then review all the existing methods for navigation, i.e. probabilistic methods for uncertainty estimation, learning methods and hybrid systems for various layers and provide a review of the ways to test them. We also provide a number of observations such as the high navigation performance of multi-layered hybrid learning systems which can reach up to 99% while single networks fail to reach even 48% and the high performance of embedded perception which reaches up to 93% when the onboard perception fails. We also present a modeling method for such systems by combining an adaptive learning representation with a model-based representation which can be used for recursive feasibility and safety verification. Finally, we present the open challenge of cross-layer verification for such complex systems.

Keywords: Mobile robot navigation, Hazardous environments, Hybrid AI systems, Cyber-physical resilience, Model-based control.

1. INTRODUCTION

There are various applications for unmanned robots in inaccessible areas such as in the case of a disaster, when the robot is required to close a nuclear power plant, when it is required to dig deep into the earth for mining, and when it is required to inspect important things such as roads and bridges etc. **(Contreras et al., 2025).** In these types of situations, it's not always easy to get the robots to operate autonomously in a manner that's trustworthy, as there are many things that are not guaranteed and the environment can be very

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unpredictable. For the robot to do its job, it has to be able to keep working when things are not perfect, so that the mission can be a success **(Seward et al., 2007; Obosu and Frimpong, 2025)**. There are a lot of problems that exist in challenging environments. In such environments, robots face challenges: Radiation and particles can damage their sensors, extreme temperatures can affect their ability to operate, and low visibility can render the robot navigation difficult, making it less predictable to navigate. The robot may not be able to rely solely on GPS signals. This makes things more uncertain for robots, in hazardous environments **(Wong et al., 2017; Alghamdi et al., 2025)**. The robot must see and feel the things; it is called perception. Next the robot needs to figure out where it is and what is around it. This is known as localization and mapping. Once that is done, the robot decides on what to do, which is called planning. Lastly, the robot adheres to its plan, known as control **(Garrett et al., 2021; Zhang et al., 2024**). In such situations, robots must learn the map of the environment and locate themselves, which is known as Simultaneous Localization and Mapping (SLAM): the robot constructs a map of the environment as it moves through it. It can be challenging when the sensors in the robot are not functioning properly, or when objects move around the robot quickly, such as when people move or objects are shifted **(Beghdadi and Mallem, 2022; Raj and Kos, 2024a).** The disturbance in the sense level may travel step-by-step throughout the system. Estimates of the robot's position get less accurate as the accuracy of the sensor data diminishes, the robot grows less confident about its location and small errors accumulate to corrupt the map. This degrades the reliability in the robot plan generation, and its control actions may make these errors worse instead of solving them **(Cadena et al., 2017; Tian et al., 2022).** Thus, if something goes wrong in one part, it can propagate through multiple layers and ultimately become a mission failure. Main types of failures and their impact on system level are listed in **Table 1** and **Fig. 1** demonstrate how failures propagate and grow through the various layers of autonomy in the robot leading to a catastrophic failure of the system.

Table 1. Representative failure modes and system-level impacts in hazardous navigation. Sources: compiled by the authors from **(Cadena et al., 2016; Momtaz et al., 2018; Wan et al., 2022)**

Failure Mode	Primary Layer	System-Level Impact
Sensor degradation	Perception	Increased estimation uncertainty
Localization drift / GNSS denial	SLAM	Map inconsistency and trajectory deviation
Planning infeasibility	Planning	Constraint violation or unsafe paths
Control instability	Control	Tracking failure and safety risk
Cyber-physical interference	Multi-layer / System-level	Cascading system degradation

Robots are employed in areas where they may be damaged by computer criminals or other issues. In these situations, the robot is part of a system that combines real things and computer things, like things that feel and see, talking to each other, thinking and doing things and being in charge. All these parts are closely connected, and threats can come from many different directions at the same time, such as fake sensor readings, corrupted maps, disrupted communication, or unauthorized control commands **(Yang et al., 2019; Aremu et al., 2026)**. The effects of purposeful attacks on systems are quite different to random environmental disturbances. These attacks are carefully. They are able to switch their ways to escape detection. They tend to blow their own horns. They frequently sound like background noise. This makes the attacks difficult to be detected with the detection methods **(Iñigo-Blasco et al., 2012; Valme et al., 2025).** Add the damage done to the environment and the intentional attacks, and it makes for a larger problem. The bad input can be exacerbated by natural stress. Keep them hidden, which makes it difficult to determine the underlying issues that are causing the issues **(Garrett et al., 2020; Rui et al., 2026).** A person in such circumstances has to be able to withstand the stress of being attacked in both the cyber worlds. It needs to be capable of reducing the errors it commits while keeping running and prevent any action which may endanger people **(Samarakoon et al., 2024; Anand et al., 2026).** There has been a lot of work on specific components, like aggregating data from different sensors, employing learning techniques for localization, and planning safely, but much of this work is limited to individual components, with assumptions that may not be valid in all contexts **(Beghdadi and Mallem, 2022; Patil and Farzan, 2026)**.

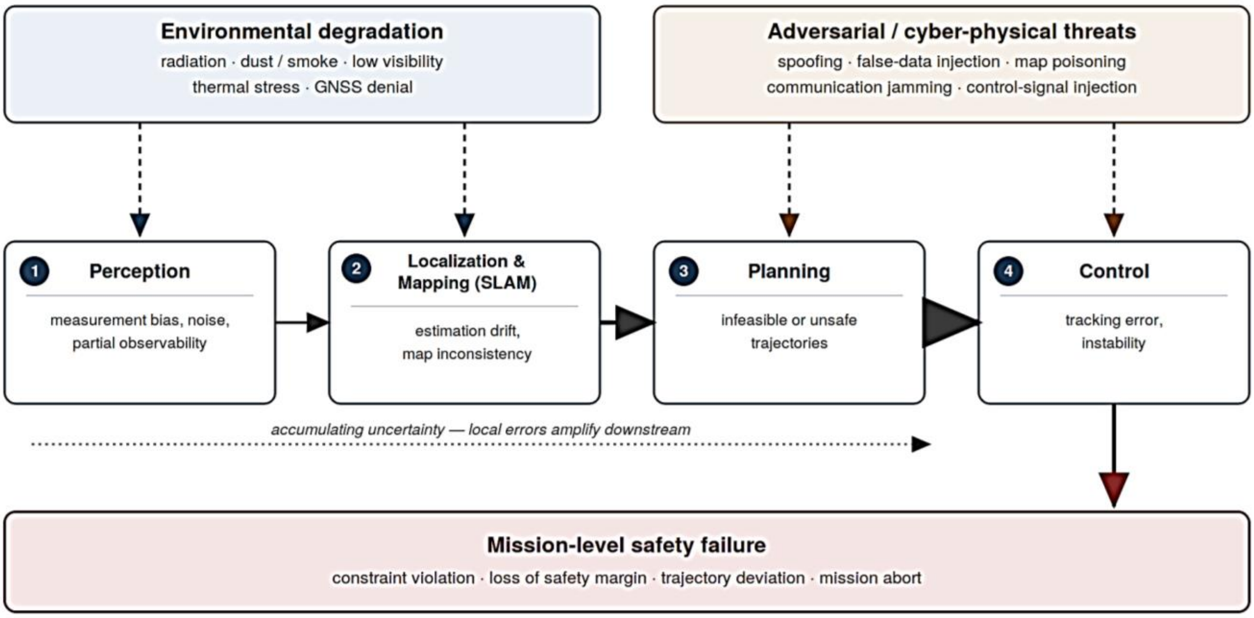


Figure 1. Cross-layer propagation of degradation in hazardous navigation.

The combination of damage, cyber threats and limitations in algorithms throughout the entire autonomy system is not fully understood. We need to look at the system to see how uncertainty affects it and how different problems interact with each other. We are motivated by these gaps; this review adopts a resilience perspective on autonomous control under hazardous conditions and makes four core contributions:

- An integrated taxonomy that maps environmental disturbances and cyber-physical threats to vulnerabilities across the perception, localization and mapping, planning, and control layers.
- A cross-layer propagation analysis explains how uncertainty diffuses through these coupled layers and how adversarial pathways can trigger cascading system failures.
- A comparative survey of autonomy methods spanning classical, optimization-based, learning-driven, and hybrid approaches with emphasis on their behavior under hazardous conditions.

- An assessment of validation and hardware resilience, examining how simulation, digital-twin, and stress-testing strategies, together with hardware design, affect mission-level reliability in safety-critical applications.

Taking together these contributions show that reliable autonomous robotic operation is a challenge. It combines physical aspects focusing on resilience. The main outcome is to help design robots that work well in hard situations and when faced with adversaries.
This review was conducted as a structured narrative synthesis of the literature on mobile robot navigation in hazardous and hostile cyber-physical environments. Relevant studies were identified using the Scopus, Web of Science, IEEE Xplore, Science Direct, and Springer Link databases, supplemented by tracking citations upstream and downstream of key works. The search combined terms such as "mobile robot navigation," "SLAM," "hazardous or degraded environments," "cyber-physical security," "hybrid and machine learning-based control," and "resilience." Articles from peer-reviewed journals and conferences published mainly between 1998 and 2026 were considered, with particular attention paid to works published from 2018 onwards. The records were first examined on the basis of the title and the abstract, then the full text, retaining those that dealt with perception, localization, planning, control or validation under environmental degradation or adverse conditions, while reports purely specific to an application, without methodological relevance for resilient navigation, were excluded.

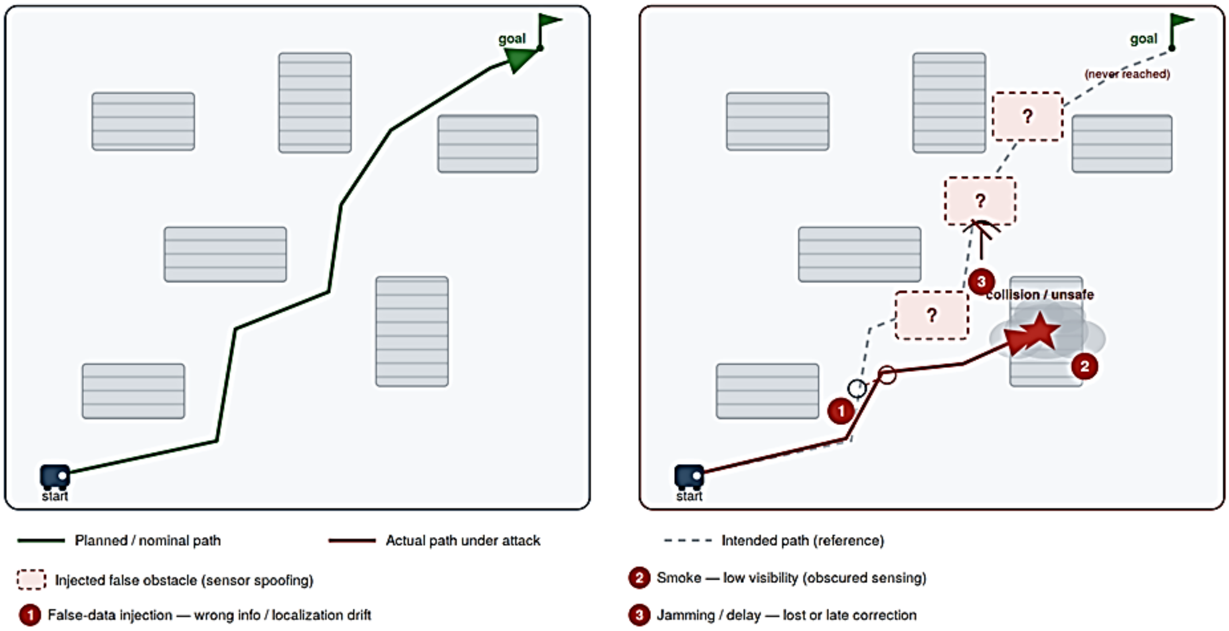
2. MECHANISMS OF DEGRADATION IN HAZARDOUS AND ADVERSARIAL ENVIRONMENTS

2.1 Environmental Degradation Mechanisms

The degradation of the environment makes navigation systems less effective. It messes up the robot's perception, estimation, and control. This may result in system failure over time **(Farrell, 2008).** It's caused by many difficult situations including radiation, dust, smoke and low light. In such cases, sensors fail and they give false readings. This adds noise and bias to data and introduces partial observability. Consequently, the information is incomplete and inaccurate, resulting in significant errors on all levels **(Concas et al., 2021; Valme et al., 2025).** The more the perception quality decreases, the more the robot is uncertain about its own localization, particularly in the case of Global Navigation Satellite System (GNSS) deprived environments where only the robot's own sensors are used for localization. As time passes, the inaccuracies grow, and fewer landmarks are visible, resulting in an incorrect map and a less precise position **(Cadena et al., 2017; Tang et al., 2025).** At the same time, temperature fluctuations, vibrations, and power supply instability impact the correct operation of the computer and the accuracy of the actuator movements, resulting in delays in the operation and making the system less stable even in the presence of partial functionality of the perception system **(Yamamoto et al., 2019; Garrett et al., 2021).** They are combined to impact on both estimation and control: they change the representation of the robot's state, and they impair the ability of the robot to track the planned trajectory **(Xiao et al., 2019).** Environmental degradation is then the primary source of uncertainty from which failures can cascade through its layers, providing a glimpse into the flaws of navigation architectures **(Fernandes and Perico, 2026).**

2.2 Adversarial and Cyber-Physical Mechanisms

Beyond ordinary unexpected problems, navigation systems also face intentional attacks where performance is deliberately degraded rather than accidentally **(Petit and Shladover, 2014; Tzafestas, 2018)**. Unlike random errors, these processes are planned and exploit the way different parts of the navigation system depend on one another **(Hossain, 2014; Mitchell and Chen, 2014).** At the perception level, spoofing and false data injection attacks can disrupt the incoming data stream by creating false obstacles or altering motion signals, thereby distorting the system's understanding and compromising its ability to determine its exact position **(Pavithra et al., 2023; Chen et al., 2025)**. The mapping process is exposed to similar risks: map poisoning and erroneous loop closures degrade the overall accuracy of the map and can lead a robot into dangerous areas. Furthermore, disturbances at the communication layer, such as jamming and data delay, confuse and add latency to interconnected systems. Even more seriously, changes to motor commands or feedback signals at the control interface can destabilize the robot, even when the system's internal calculations appear perfectly safe and correct **(Deng et al., 2021)**.



(a) (b)

Figure 2. Effect of cyber-physical attacks on mobile-robot navigation in a warehouse: (a) normal navigation, and (b) navigation under attack.

The above **Fig. 2** shows this in a warehouse-type environment: in normal conditions, the robot goes along with its programmed trajectory to its goal. If attacked, however, the actual path is corrupted by the addition of fake obstacles, fake data injection, smoke that blocks the robot's view and communication jamming, which moves the robot away from its destination and into a dangerous zone. In learning-based systems, the output of image classification and image segmentation can be slightly altered even when there is no visible physical change, demonstrating the fragility of learning-based systems **(Chakraborty et al., 2022)**. These negative effects are seldom localized but tend to propagate through estimation, communication and control, triggering additional errors in the perception, SLAM, planning and motor layer **(Pereira et al., 2026)**. To put it simply, natural environmental challenges contribute to uncertainty, while active attacks are a deliberate cause of confusion in system behavior and could cause cascading failures on different layers of the entire robotic system **(Wu, 2025).**

2.3 Cross-Layer Degradation, Propagation, and Failure Dynamics

Cross-layer degradation spread refers to the way that issues in one subsystem gradually impact the performance and reliability of later subsystems, as shown in **Fig. 1.** Where local errors remain within safe limits for the individual components, their effects can cascade through components that are closely interconnected, altering the behavior of the entire system. A ground robot driving on a rough surface at high temperatures is just one of the examples. Due to high temperatures, the processor speeds will decrease, and the state updates will come with delays, thus becoming out of sync **(Momtaz et al., 2018; Wan et al., 2022)**. Fortunately, the estimation error is within bounded limits and thus acceptable. The position information is not timely, but it also contains sufficient information for the planner to estimate the motion of the system **(Cao et al., 2014; Liu et al., 2021)**. The path planned from this out-of-step state may appear feasible given typical assumptions, but may require changes in actuators' speed or control inputs to be near their limits when executed by the robot during motion **(Ha et al., 2020; Sandakalum and Ang, 2022)**. The controller then attempts to follow this path with a time delay between its commands and the response of the actuators, causing the errors in tracking to grow and the safety margins to slowly decrease **(Hassan et al., 2023).** A simple, localized timing error in the computation layer cascades to a loss of feasibility, control saturation and potentially a safety violation **(Klugel et al., 2020)**. Generally, a timing delay, an inaccurate model, an estimation bias, or an adversarial change can affect the constraints and stability region for the following ones, and a local problem could escalate to a mission failure due to the cascading effect of the coupled estimation, planning and control **(Luo et al., 2019).**

3. PERCEPTION AND SLAM MITIGATION STRATEGIES

This section examines how uncertainty is reduced in the perception and localization layer to make it less probable that it will increase excessively, while degradation in the perception layer does not propagate to planning and control.

3.1 Robust Perception Under Degradation

To ensure reliable perception in hazardous environments, it is essential to have strong hardware and software tests to safeguard data. If hardened sensors are incorporated into a design that considers reliability, they are less sensitive to radiation, heat stress and particle interference **(Zhuo-hua et al., 2005)**. Decreasing changes in delay and drift, and ensuring that state updates are aligned in time, requires calibration considering temperature, in addition to adaptive timing control **(Hague et al., 2000; Konrad et al., 2018).** In addition to physical strength, modern perception systems also check data quality while operating. For example, statistical consistency checks across different sensors, along with sensor-health tests, can spot unusual measurements and automatically shut out sensors that are degraded or compromised **(Xiang et al., 2023)**. In order to prevent the system from mixing up with fake or modified data, the secure sensing systems employ password-protected communication lines and error-checking tools to help detect fake or altered data **(Hasan et al., 2018).** The system doesn't rely on unbiased data, but rather on smart software that analyzes the features and rates their reliability. This allows the system to selectively filter what to listen to, discarding corrupted data heavily depending on trusted signals **(Fayyad et al., 2020)**. These are probabilistic models which constrain the effect of each measurement to a known uncertainty range. Furthermore, low latency edge infrastructure facilitates the timely synchronization of sensor data which minimizes the sequential inconsistencies in perception and estimation modules **(Shahian Jahromi et al., 2019).** These strategies make it possible together to develop an active self-monitoring subsystem that reduces the possibility of polluting the measurement data and limits the early propagation of errors in the navigation process **(Martí et al., 2012). Fig. 3** summarizes this strong perception pipeline, the estimation process receives reliable perception with low uncertainty, if perception data from one or more sensors are faulty/manipulated, the pipeline detects such errors and down-weights the perception before fusion.

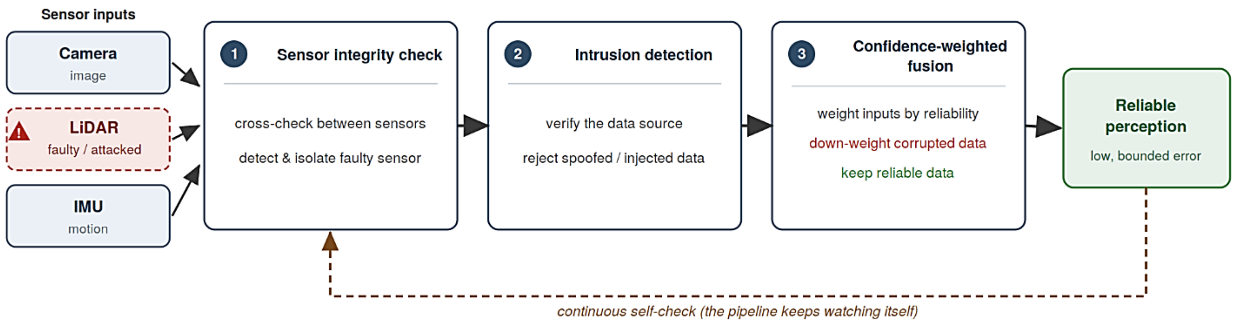


Figure 3. Robust perception pipeline.

3.2 Robust EKF-SLAM with Delay Features Initializations

The architectures show in **Fig. 4** implement an Extended Kalman Filter (EKF)-based SLAM that estimate the joints robot–maps states over recursive Bayesians belief updated processing **(Dissanayake et al., 2001),** theoretically represent as:

$$\text{Belief}_k = \text{Prediction}_k + \text{Correction}_k \quad (1)$$

The lower blocks depict the basic EKF-SLAM cycle as shown in **Fig. 4**. The prediction stage utilizes motion data from the Attitude and Heading Reference System (AHRS) unit and GPS to propagate the state, and to produce a prior pose estimate. This estimate suffers from process noise and modelling uncertainty and may drift with time **(Fang et al., 2024).** Measurement correction is completed by a visual update module which recalibrates the state estimate and covariance based on the measurements taken by the camera compared to the features predicted from the camera. This correction phase helps to keep uncertainty growth limited and keeps estimators consistent **(Maybeck, 1979; Nielsen and Madsen, 2001).** The top half of **Fig. 4** shows the delay time of the system before adding features. The system doesn't add a visual landmark to the main tracking list right away if it locates it. It is regarded as a temporary candidate by the system. Then the system follows it through a number of frames of the camera, measures its distance and verifies it from various angles which is similar to a parallax test. The test has the function of ensuring the accuracy and reliability of the position. The new feature is not actually added to the state vector (the map) until it passes these stringent checks **(Davison et al., 2007).** This can be done carefully to avoid the presence of unreliable landmarks to break the covariance matrix, which would lead to false connections and propagate large errors throughout the map **(Guerra et al., 2014).** The robot system operates in such a manner that it determines the time of information arriving. This allows for the estimation algorithm to perform in a stable manner throughout time. It is not only a fusion of the sensors, GPS and camera information. It's actually the manager of how errors occur. Prevents them from growing too large while determining their location. This allows the robot system to maintain awareness of its position over long distances. The estimation algorithm keeps its computations stable and consistent over time by controlling the timing of when new data enters the robot system. This helps the robot system to keep a sense of where the robot is over long trips **(Bailey et al., 2006; Changwani, 2025).**

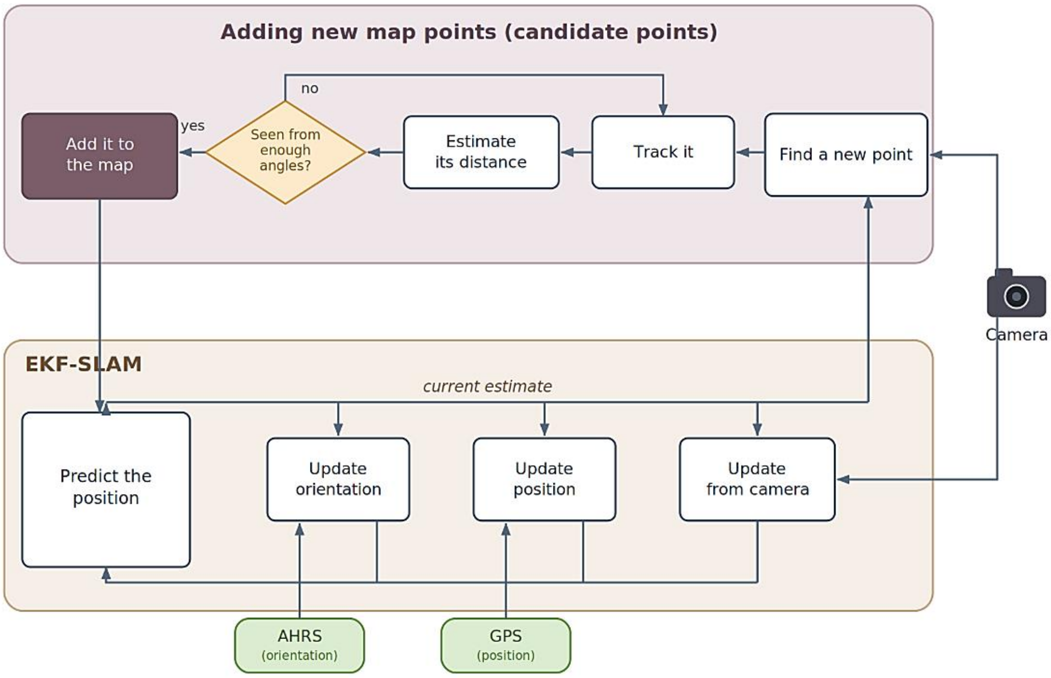


Figure 4. EKF-SLAM architectures with delayed initialization of landmarks, redesigned and adapted by the authors from (**Munguía et al., 2016**).

3.3 Adaptive Correction Strength

In EKF-SLAM, the corrections strengths are controlled by a Kalman gain K_k which is calculated as:

$$K_k = P_k^- H_k^T \left(H_k P_k^- H_k^T + R_k \right)^{-1} \tag{2}$$

where P_k^- denote the predicted covariance, H_k the measurements Jacobian, and R_k the measurements-noise covariance **(Thrun, 2002)**. In the proposed framework, we update the R_k parameter depending on the visual characteristics of the tracked features in real-time. The quality of the observations is estimated by various indicators such as quality of the features we see, persistence of features given in the observations, and the extent to which the features match **(SPEYER et al., 1982; Jetto et al., 1999).** The innovation-based scaling mechanism updates R_k to accommodate the changes in the sequence. This implies that the strength of the correction is related to the dispersion of the actual measurements **(Huang et al., 2008).** As the residual variance decreases and the feature geometry becomes more stable, the Rk decreases. This makes the Kalman gain bigger and helps to correct the pose. As the conditions are not favorable, residual dispersion increases. Then R_k also increases as well. As a result the gain gets smaller to limit the effect of observations that're not reliable **(Mei et al., 2011).** By setting the R_k at the covariance level, the estimator remains statistically consistent and thus provides a correct estimate of its confidence in its estimates and restricts the uncertainty of new measurements. This adaptive correction accounts for changes in the state and does not allow it to become corrupted, which reduces the chance that the estimator will get "off track" in the event of a short period of loss of sensing or corruption of a few of the data elements **(Thrun, 2002).**

4. ROBUST PLANNING AND CONTROL FRAMEWORK

4.1 Planning Under Uncertainty

In navigation the robot state x, which is represented as a Gaussian belief, shows where the robot thinks it is:

$$x \sim N(\hat{x}, p) \tag{3}$$

where $\hat{\mathbf{x}}$, is the estimated pose and the covariance matrix P shows how sure the robot is about its state **(LaValle, 2006)**. Not only the estimated pose, but the dispersion described by P should be considered when checking for collisions. Let's take σ^2 the variance, from the diagonal of P. Suppose that the state of the robots follows Gaussian distribution, then a safety margin can be obtained by a normal confidence factor α. For example, when we use $\alpha = 2$ gives about 95% confidence and $\alpha = 3$ gives about 99.7% confidence. We inflate obstacle boundaries by $\alpha\sigma$. That provides us with a collision-avoidance constraint **(Stephens et al., 2024):**

$$d(\hat{x}, \text{obstacle}) > r_{robot} + \alpha\sigma \tag{4}$$

Here $d(\hat{x}, \text{obstacle})$ is the estimated distance, to the obstacle. The robot's radius is r_{robot}. In this manner we make collision checking a safety constraint with a guaranteed lower bound. The safety margin is directly proportional to the uncertainty. Therefore, it is more difficult to seek a solution **(Guo et al., 2025)**. A viable path might not be safe in high state dispersion when SLAM drift and/or GNSS degradation are present **(Shetty and Gao, 2019)**. The application of uncertainty- constraints is influenced by planning paradigm. The sampling based planner is similar to the RRT variant, but only accepts a candidate node when the obstacle-free domain of its inflated collision region is found **(Meng et al., 2022).** Adding covariance-penalty terms to the cost function is possible for planners based on graphs, such as A*. This helps to prevent propagation of uncertainty in trajectories **(Pairet *et al.*, 2022).** Static inflation doesn't capture the time-varying propagation of uncertainty and doesn't capture the time-varying evolution of obstacles through the covariance. This restriction inspires us to develop belief-space planning and chance-constrained formulations. They both propagate the state distribution and safety probability, in a long time **(Cai et al., 2021).**

4.2 Planning with Dynamic Obstacles

If there is some uncertainty about the robot and the moving obstacles, this uncertainty can be modeled as a changing position of these robots over time. The robot's position is seen as a Gaussian belief with variance $\sigma^2(t)$ **(Aoude et al., 2013),** and the predicted position of moving obstacle o(t), which have a variance $\sigma_0^2(t)$. The uncertainty about their positions is then determined as

$$\sigma_{rel(t)} = \sqrt{\left(\sigma^2(t) + \sigma_o^2(t)\right)} \tag{5}$$

Which follow, the ideas from standard stochastic state-estimation theory **(Park et al., 2008)**. To make sure we are safe and that we can really trust the results at a level α, the collision-avoidance constraint is obtained as:

$$d\left(\hat{x}, o(t)\right) > r_{robot} + r_{obs} + \alpha\sigma_{rel}(t) \tag{6}$$

Here, r_{obs} denote the limiting (physical) radius of the moving obstacle, which is added to the robot's radius and the relative positional uncertainty $\sigma_{rel}(t)$ from Eq. (5), so that the safety margin reflects the combined extent of the robot and the obstacle. The formulation of uncertainty inflation concerns not only what is happening at the present moment, but also how this inflation will evolve over time **(Andersson, 2020).** As the prediction uncertainty increases if the motion model assumes more errors in the prediction process and if the obstacles' behavior is unpredictable or unpredictable, then there is a need for a safety margin **(Du Toit and Burdick, 2012)**. These time limits can be a part of a type of optimization known as receding-horizon optimization in practice. This is similar to a method called stochastic model predictive control **(Andersson et al., 2018),** Velocity-space methods are important because they help us understand how to make things move around each other safely, they use velocity obstacles to do this **(Fiorini and Shiller, 1998)**, planners that sample possible paths and also account for timing **(Covic et al., 2025)**. In this method, we consider how feasible a plan is based on the expected future geometry, not just the future geometry at any single instant. It is important to explicitly consider dynamic uncertainty propagation, as otherwise a nominally collision-free trajectory may be unsafe due to prediction error, or motion of the obstacles that are unmodeled. The proposed formulation is a deterministic dynamic avoidance extended to a time-dependent safety constraint with bounds on the confidence level, which is highly applicable to the real world operating under uncertainty **(Hardy and Campbell, 2013)**.
Under state uncertainty, probabilistic constraint inflation provides a mathematically sound safety mechanism to deal with uncertainty **(Castillo-Lopez et al., 2020)**. However, for a real world application, the robot must be designed to ensure such guarantees even if the position estimation is not perfectly accurate, the computing speed fluctuates or the robot has to react to moving objects around it. If the estimation is unreliable. If the robot's degree of confidence is less, then the SLAM is less accurate. So does the safety-limit that is based on the SLAM **(Lindqvist et al., 2022)**. Moreover, the system should keep on being reliable and able to enforce its constraints at each cycle without relying on a receding-horizon scheme **(Venturino et al., 2025).** Where the available computation time can be distributed among the different cycles. As a result, uncertainty-aware planning is extended to hybrid, learning-integrated control systems. To this end the modern navigation systems extend uncertainty-aware planning to hybrid, learning-integrated control systems. These systems feature several layers of algorithms, with several different algorithms being responsible for ensuring feasibility, adapting to changing conditions, and enforcing safety rules while operating, as opposed to one algorithm being responsible for each **(Durlik et al., 2025).**

4.3 Intelligent Navigation for Mobile Robots in Hazardous Environments

Classic SLAM, deterministic graph-based planners and optimization-based controllers provide mathematically rigorous means to estimate a robot's state and meet safety requirements when the surrounding noise is known and predictable but their performance is ultimately constrained by their assumption of fixed models and probabilistic structures **(Guaragnella et al., 2026)**. The strength of these lies on Gaussian error approximations that might not be applicable in the presence of high-dimensional perceptual distortion and non-stationary environmental dynamics **(Zhou and Ho, 2022)**, and that they do not guarantee validity for all observations. Uncertainty evolves over time and becomes partially unpredictable in hazardous environments like when radiation corrupts the sensor, when smoke makes visibility poor, when the infrastructure is unstable, when GNSS is denied, and when it is attacked by bad people. That is why it is not possible to completely address these dynamic challenges with static cost estimates or fixed analytical representation **(González-Rodríguez and Plasencia-Salgueiro, 2021)**.

Recent studies have shown that model-based navigation methods are insufficient in dealing with wide diversity and large-scale changes in environmental data **(Zhang et al., 2026)**. This means that artificial intelligence (AI) is moving from being an all-encompassing replacement for model-based navigation (MBN) **(Nahavandi et al., 2025),** to being a flexible overlay on top of this. Convolutional neural networks allow direct interpretation of space from raw sensor data and offer high-quality image labelling and real-time terrain analysis and feature tracking, even in sub-optimal conditions **(Zaki et al., 2021; Raj and Kos, 2024b).**

Online and continuous learning methods reinforce this capability by making continuous system adjustments throughout a mission. This helps the framework adjust to completely new environments, rather than having to be trained from scratch (Wu, Ding and Huang, 2026). It enables the framework to transfer to totally different scenarios without having to be trained from the start **(Liu et al., 2025).** Deep reinforcement learning, like actor-critic and entropy-regularized methods, builds on these abilities in the decision-making layer, generating very flexible control rules **(Jha et al., 2024)**. These approaches can then be used in more dynamic, less predictable environments, where robots can cope much better with changes than traditional, rule-based approaches, particularly in complex navigation situations **(Mehta et al., 2016).** However, despite the clear benefits of using learning-based control in real robots, recent evidence indicates that safety guarantees should never be left entirely to the AI model's discretion **(Brunke et al., 2022).** With additional layers of safety filtering, constraint-aware optimization and probabilistic belief propagation, learning-based modules can also have more expressive capability and flexible generalization while still abiding by formal safety requirements **(Zhang et al., 2024b)**.

The hybrid architectures are a complementary combination of learned adaptation and model-based guarantees **(Tang et al., 2023)**. **Table 2** compares the three paradigms, showing the pros and cons of learning-based methods and formal guarantees for model-based control.

Table 2. Comparison of traditional, learning-based, and hybrid navigation approaches.

Criterion	Traditional / model-based	Learning-based	Hybrid
How it works	Fixed physical models and equations	Learns from data	Learning for flexibility + models for safety
Robustness in harsh conditions	Good in known conditions; weak when the environment keeps changing	Adapts to new or degraded sensing, but can fail when conditions differ from training	Best: flexible, yet kept safe by the model

Adaptability to new situations	Low	High	High
Computational cost	Low to moderate	High (training and running)	Moderate to high
Safety guarantees	Strong, mathematically proven	None built in	Strong: a safety layer keeps final control
How it is verified	Well-established proofs	Mostly tested by experiment; hard to prove	Partly proven; full checking across all layers still open
Reported success rate	Baseline	Up to 99% vs. ~48% for a basic single-network model	~93% even when the robot's own sensors fail (using external cameras)
Main weakness	Not flexible; adapts poorly to new conditions	Hard to trust; safety not guaranteed	More complex to build; heavier to run in real time

4.4 Hybrid Navigation Architectures for Hazardous Environments

Hybrid navigation architectures combine the complementary strengths of model-based and learning-based methods: model-based navigation gives strict analytical guarantees but adapts poorly beyond its assumptions **(Ficco and Russo, 2009; Fei et al., 2024).** while learning-based navigation can be very expressive and adaptable, but cannot guarantee safety and stability **(Jungers and Athanasopoulos, 2021; Willard et al., 2023)**. The integration of learning with probabilistic estimation and constraint aware control is hybrid architectures that embed learning modules into probabilistic estimation, coupled with verifiable constraints **(Aljamal et al., 2025)**. The layered structure is depicted in **Fig. 5**. As for the perceptual end of the framework, operation at the perception-mapping level entails integrating deep representations systematically into probabilistic SLAM back-ends, thus creating a double layer of the spatial understanding **(Rodríguez-Martínez et al., 2025)**. The features we have acquired remain un-changed even in the presence of other factors such as sensor failures, particles and light, while the tools we have acquired to help us understand the bigger picture keep everything consistent and connected **(Fei et al., 2024)**. The aim is to keep estimator consistency when empirical observations differ from pre-existing theoretical models as a way to reduce conflicts in operations. Thus, with learned residuals that fail to follow the standard Gaussian assumption, the architecture selectively uses mathematical formulations that include robust loss functions, dynamically adapts confidence bounds through adaptive covariance scaling and applies uncertainty re-weighting mechanisms to handle non-standard error distributions **(Al Shafian and Hu, 2024; Mukherjee et al, 2024; Srinivasan and Senthilkumar, 2025).**

The planning and control sub-systems are modified by introducing dedicated neural modules that are capable of dynamically changing the mathematical cost landscape and are used to add complex semantic risk priors that augment the foresight of the system without replacing the core analytical planner completely **(Tang et al., 2023; Li et al., 2025)**. At the same time, the geometric feasibility and probabilistic state-space constraints are explicitly and continuously checked during execution to guarantee the physical viability **(Aoude et al., 2013; Heald et al., 2023; Min et al., 2026).** Learning-augmented model predictive control or chance constraints and/or constrained optimization and/or control barrier functions **(Zhang et al., 2016; Nakka and Chung, 2023; Xu et al., 2026)**, project the candidate actions on the admissible set, which prevents input and collision bounds violation and guarantees the stability of the closed loop in spite of adaptive exploration **(Polycarpou,**

2001; Brunke et al., 2022). A level separation where learning takes place at the semantic level and deterministic controllers at the execution level, learning is confined and stability is maintained **(Iñigo-Blasco et al., 2012; Zheng et al., 2021; Raj and Kos, 2024a).** There are a number of open problems. The first one is probabilistic versus learned representations and the online/computational constraints of integrated inference **(Ouni et al., 2019).** The second is the formal description of stability and safety in the context of stability of learned representations that change the observability of the system and/or the cost geometry **(Zhang and Chen, 2023)**. The overarching research challenge of this project is then how to develop a principled co-design of adaptive representation and uncertainty-aware estimation-control that is scalable, consistent, feasible, and certifiably safe **(Trevelyan et al., 2016; Huang et al., 2025).**

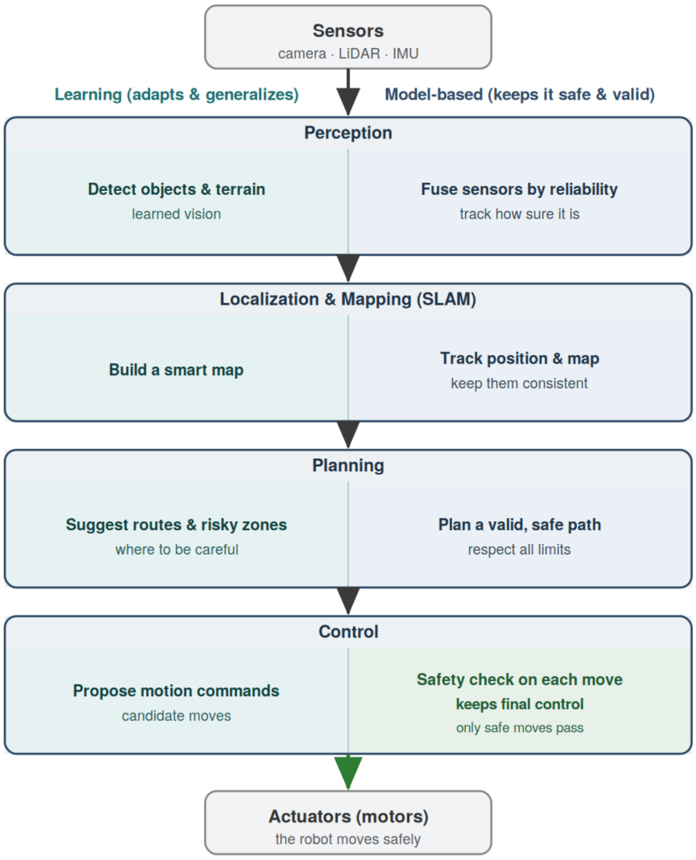


Figure 5. Hybrid navigation architecture.

5. SIMULATION-DRIVEN VALIDATION AND HARDWARE RESILIENCE

5.1 Simulation-Based Hazard Modeling and Pre-Deployment Validation

Simulation-driven validation provides a controlled and scalable way to evaluate hybrid navigation architectures under compound environmental degradation before real-world deployment **(Sini and Violante, 2020).** Modern robotics simulators can reproduce high-fidelity, real-time stochastic perturbations, including radiation-induced sensor corruption, smoke and dust interference, GNSS denial, structural instability, and thermally induced computational latency **(Leguizamo et al., 2022).** These perturbations are propagated through the perception, SLAM, planning, and control layers, producing cross-layer uncertainty amplification in which corrupted measurements raise covariance estimates, shrink planner feasibility regions, and narrow closed-loop stability margins **(Das et al., 2026)**. Domain randomization and stochastic terrain generation expose learning-based modules to a wide range of hazard distributions, partly closing the simulation-to-reality gap **(Valdivia et al., 2024)**. A fundamental limitation, however, is the difficulty of accurately reproducing compound environmental and adversarial uncertainty, especially for adaptive neural modules that must handle distribution shift **(Da Lio et al., 2020).** Simulation-based validation therefore acts as a pre-deployment resilience filter that allows cascading failure modes to be identified systematically before hazardous field operations.

5.2 Digital Twin Frameworks and Time-Varying Risk Replication

Digital twin technology is a major improvement forward from conventional simulations. It does this by using models with real world data from hardware and environment. This is a connection that allows us to see how phenomena change over time by using the digital twin technology. For instance, we can observe deterioration of structures, changes in the terrain, aging of sensors and communication delay. The motion of obstacles can also be seen **(Tian et al., 2022)**. This will enable us to gauge the strength of navigation in the presence of radiation fields, smoke density gradients, collapse dynamics, and stochastic object movement. All these elements are part of changing hazard landscapes. In this way, a digital twin with these models is capable of assisting with navigation **(Nahavandi et al., 2025)**. Propagation of time-dependent uncertainty directly restricts the acceptable confidence level for probabilistic constraint satisfaction in planning and helps to strengthen constraints in the context of safety-filtered control **(Eichstädt et al., 2016).** But to achieve precise physical parameterization and real-time synchronization, substantial computing power and a strong communication infrastructure are needed. However, these types of systems can fail in these circumstances **(Kabashkin, 2025).**

5.3 Adversarial and Cyber-Physical Validation

Adversarial and cyber-physical testing are essential for verifying the security level of machine-enhanced navigation systems. Simulation environments now often incorporate falsified sensor data, corrupted maps, blocked communications, and fake command signals. These additions aim to replicate real-world attacks against navigation systems. The goal is to protect the navigation chain from interference. It is necessary to validate navigation modules against threats. Machine-enhanced navigation systems are tested in these environments, where their vulnerability to different types of attacks is assessed **(Bhattacharya et al., 2020).** Perception and planning components are susceptible to these types of problems because attacks can distort high-dimensional feature embedding in ways that are difficult to detect. This can lead to malfunctions in learning-based perception and planning components **(Tang et al., 2023).** The system must be tested for robustness, which involves deliberately attempting to force it to fail. This is done through stress tests rigorous checks designed to determine whether the system can detect abnormal or unusual elements as well as tests evaluating its ability to return to normal after an incident. The goal is to measure the extent to which the system can prevent its own degradation, continue to comply with constraints, and regain stability when subjected to intentional manipulation **(Chen et al., 2025)**. Although cyber-physical resilience is receiving increasing attention today, we still lack many standardized adverse tests for robotic navigation. Comparing the results of studies on robotic navigation also remains difficult **(Francis et al., 2025).**

5.4 Hardware-Level Resilience and Physical Robustness

At the physical source level, we can protect the robot from environmental stress in several simple ways. First, we use radiation-hardened electronics to prevent radiation damage. Second, we employ thermally insulated processors to protect them from heat. Third, we use vibration-damped sensor mounts to limit shocks. Finally, we use shock-absorbing mechanical structures to protect the robot from violent impacts **(Kivrak et al., 2024).** Multimodal sensor redundancy relies on numerous sensors such as LiDAR, cameras, and specialized units that measure motion (inertial measurement units). We also use a process called odometry. If one of the sensors fails, the others can take over and compensate for their failure. This preserves system safety and ensures stable localization and estimator continuity, so the robot always knows its precise position **(Fayyad et al., 2020).** Electromagnetic shielding and a stable power supply also protect computing modules from failures and interference **(Kivrak et al., 2024).** Consideration should also be given to how to incorporate hardware degradation behavior into simulation and digital twin environments. This way, what is predicted during testing more closely reflects what actually occurs during real-world use.

5.5 Evaluation of Metrics for Mission-Level Reliability

When we evaluate dangerous navigation, we cannot just look at the best path or how fast the computer works. Instead, we must measure mission-critical reliability under compound uncertainty. These evaluation metrics cover both estimation and control, including the bounded growth of state-estimation error under degradation **(Bailey et al., 2006),** the probability of constraint violation in chance-constrained planning **(Chakraborty and Raghuvanshi, 2025),** and the preservation of recursive feasibility in hybrid control **(Anand et al., 2026)**. They also measure the mission-success probability under combined environmental and adversarial uncertainty **(Bhattacharya et al., 2020),** and the recovery latency after losing sensors or communication **(Anand et al., 2026).**

As real evidence, recent studies show that multi-step and hybrid learning controllers reach a success rate as high as 99% in unknown environments, while a single-network baseline only reaches about 48% **(Korayem and Takzare, 2026).** Additionally, an external-perception fallback sustains a 93% success rate to keep the robot going when its onboard sensors fail **(Fernandes and Perico, 2026)**. Together, these metrics connect subsystem performance to overall mission-level reliability, which helps us easily compare classical, learning-based, and hybrid navigation frameworks under real danger.

5.6 Open Challenges and Future Research Directions

The preceding analysis highlights not so many definitive solutions as clear directions for future work. The most urgent is inter-layer verification: methods that jointly certify the consistency of the estimation, recursive feasibility, and probabilistic safety across the entire chain, from perception to control, rather than validating each layer in isolation **(Guaragnella et al., 2026)**. A second direction is real-time certifiable inference, in which the depth of the integrated estimation, optimization, and learned evaluation is bounded, so that safety guarantees remain valid within the limits of the available computational budget **(Klugel et al., 2020)**. A third approach is the rigorous co-design of the learned representation and the uncertainty-accounting estimation-control. This design allows adaptive modules to modify the observability or geometry of the costs. Most importantly, it achieves this without compromising formal guarantees of stability and security **(Anand et**

al., 2026). The field would also benefit from standardized assessment protocols covering adversarial attacks and compound risks. These standardized tests will make resilience results easy to reproduce and compare across different studies **(Francis et al., 2025).** Advances in these areas will move resilient hybrid navigation from the realm of simple laboratory experiments to certified deployment in hazardous environments.

5.7 Synthesis and Resilience-Oriented Perspective

Throughout the preceding sections, a recurring theme emerges. In hazardous environments characterized by degraded perception, unstable structures, GNSS deprivation, or adverse interference, systems relying solely on rules or solely on machine learning are structurally fragile. They exacerbate uncertainty in the face of compound risk **(Guaragnella et al., 2026).** Hybrid navigation is deliberately designed to overcome this fragility. It combines adaptive representation, formally constrained control, and hierarchical uncertainty management. From this perspective, resilience does not reside in the robustness of a single algorithm. Rather, it consists of distributing authority across the system architecture: learning ensures adaptation, while model-based reasoning preserves the consistency of estimation, recursive feasibility, and the application of safety constraints, which maintains ultimate control. This perspective redefines navigation design as the co-design of an adaptive representation with estimation and control that takes uncertainty into account.

6. CONCLUSIONS

This article focuses on hybrid navigation of mobile robots in hazardous environments. Our goal is to prevent failures and maintain safe robot movement through the perception, localization, planning, and control layers under compound uncertainty. Traditional model-based methods offer good safety and stability but fail when unforeseen changes occur. Newer machine-based methods adapt well to change but lack safety guarantees such as recursive feasibility and constraint satisfaction. Hybrid architecture combines the best aspects of both approaches: machine learning handles perception and representation, while model-based reasoning retains final control to ensure safety and consistency. This combination prevents errors from escalating, even when sensors, structures, or communication links fail. We use simulation and digital twins to test these systems. However, these methods are expensive, rely on imperfect physics, and lack safeguards when learning alters observability or optimization. Today, the main challenge is to jointly test estimation, planning, and control across all layers, rather than in isolation. Nevertheless, combining strict rules and intelligent learning within an uncertainty-aware design framework represents a major shift: moving from robots optimized for rapid performance to systems with certified resilience. We must continue to connect control theory, statistical learning, formal methods, and cyber-physical systems engineering to make robotic navigation truly safe.

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Credit Authorship Contribution Statement

Lina M. Mahmoud: Conceptualization, Methodology, Writing – original draft. Muna Hadi Salah: Validation, Formal Analysis and Nizar H. Abbas: Writing – review and editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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أنظمة الملاحة الهجينة المعتمدة على الذكاء الاصطناعي المرِن للروبوتات المتنقلة في البيئات السيبرانية الفيزيائية عالية الخطورة: مراجعة علمية

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الخلاصة

نقدم في هذا العمل مراجعة شاملة حول كيفية التعامل مع المهام التنافسية والصعبة لملاحة الروبوتات المتنقلة في البيئات السيبرانية–الفيزيائية المعرضة للأعطال. وتتمثل المساهمة الرئيسية لهذه الورقة البحثية في تقديم معيار لتقسيم النظام، أي كيفية توزيع سلطة التحكم بين الأنظمة الفرعية المختلفة من أجل منع حدوث عطل مفرد من تحفيز سلسلة متتالية من أعطال النظام. وتحقيقاً لهذه الغاية، نقوم بتحليل تأثيرات ثلاثة أنواع من التدهور البيئي وهي: الاضطرابات البيئية، وعدم الاستقرار الهيكلي، والاضطرابات السيبرانية–الفيزيائية على الطبقات المختلفة للروبوت التقليدي، والتي تشمل: الإدراك، والتموضع وبناء الخرائط الآني (SLAM)، والتخطيط، والتحكم. بعد ذلك، نستعرض جميع الأساليب الحالية المستخدمة في الملاحة، مثل الطرق الاحتمالية لتقدير عدم اليقين، وطرق التعلم، والأنظمة الهجينة لمختلف الطبقات، مع تقديم مراجعة شاملة لأساليب اختبارها. كما نطرح عدداً من الملاحظات الهامة، مثل الأداء الملاحي العالي لأنظمة التعلم الهجينة متعددة الطبقات والتي يمكن أن تصل نسبة نجاحها إلى 99%، في حين تفشل الشبكات المفردة في الوصول حتى إلى 48%، بالإضافة إلى الكفاءة العالية للإدراك المدمج الذي يحافظ على نسبة نجاح تصل إلى 93% عند تعطل الإدراك على متن الروبوت. ونعرض أيضاً طريقة نمذجة لمثل هذه الأنظمة من خلال دمج تمثيل التعلم مع تمثيل قائم على النموذج، والذي يمكن استخدامه للتحقق من الجدوى العودية وضمان الأمان. وأخيراً، نسلط الضوء على التحدي البحثي المفتوح المتمثل في التحقق عبر الطبقات لمثل هذه الأنظمة المعقدة.

الكلمات المفتاحية: ملاحة الروبوتات المتنقلة، البيئات عالية الخطورة، الأنظمة الهجينة للذكاء الاصطناعي، المرونة في الأنظمة السيبرانية–الفيزيائية، التحكم المعتمد على النماذج.