Probabilistic reliability evaluation of autonomous navigation for firefighting robots in uncertain environments

Zhaowei Zhou[1)], Ruikun Li[1)], Fang Cong[1)], and Wei Shi[1, *)]
1) Shanghai fire research institute of MEM, Shanghai 200032, China, zhouzhaowei0206 @sina.com; ruikunli@sina.com; congfang@sina.com
**) Corresponding author, shiwei11005@sina.com (W.S.)*

Abstract: Autonomous navigation is a mission-critical capability for firefighting robots operating in hazardous, unstructured, and highly uncertain environments. However, existing evaluation approaches are largely based on deterministic performance metrics and provide limited support for quantifying navigation reliability under uncertainty. This limitation hinders objective benchmarking and standardized assessment across different robotic platforms and operating conditions. This paper proposes an uncertainty-aware reliability assessment framework for autonomous navigation of firefighting robots. The framework integrates multi-source sensing, trajectory reconstruction, deviation analysis, and probabilistic performance evaluation into a unified pipeline. A nearest-neighbor-based trajectory matching method is employed to quantify discrepancies between reference and executed trajectories under asynchronous and non-uniform sampling conditions. To move beyond deterministic evaluation, key performance indicators, including trajectory deviation, completion time, and obstacle avoidance success rate, are modeled as stochastic variables, from which probabilistic reliability measures are derived. Experimental studies were conducted in controlled environments with static, dynamic, and complex obstacle configurations. The results show that the proposed framework effectively captures both navigation accuracy and performance variability across scenarios. In particular, the reliability metrics provide a more informative assessment than conventional threshold-based indicators by explicitly reflecting the probability of satisfying navigation requirements under uncertainty. The proposed framework offers a systematic and quantitative approach for reliability assessment of autonomous navigation systems and provides practical value for performance benchmarking, system validation, and algorithm improvement in firefighting robotics and related mobile robotic applications.

Keywords: firefighting robot; autonomous navigation; reliability assessment; trajectory deviation

1. Introduction

Firefighting robots are increasingly deployed in hazardous environments such as industrial facilities, underground infrastructures, and disaster-response sites, where high temperatures, dense smoke, toxic gases, unstable structures, and cluttered terrain pose substantial risks to human responders. In such scenarios, autonomous navigation is a prerequisite for effective task execution, including environment exploration, obstacle avoidance, target localization, and continuous mobility under limited visibility or restricted communication conditions. Reliable navigation capability improves operational efficiency and reduces human exposure to life-threatening conditions (Al Mahmud et al., 2024; Liu et al., 2024; Usinskis et al., 2025; Waga et al., 2025).

Recent advances in sensing, path planning, and motion control have significantly improved the navigation performance of mobile robots in complex environments. Existing studies have mainly focused on obstacle detection, sensor fusion, path planning algorithms, and online replanning strategies (AlAli and Alabady, 2022; Ghauri et al., 2024; Dong et al., 2025; Deng et al., 2026). While these developments have enhanced the autonomy of robotic systems, the evaluation of navigation performance remains comparatively underdeveloped. In many cases, performance is assessed using deterministic indicators such as trajectory deviation, completion time, collision count, or task success rate. These metrics are useful at a basic level, but they are often scenario-specific, insufficiently standardized, and not explicitly linked to uncertainty (Kim et al., 2024; Raoufi et al., 2025).

This limitation is particularly critical for firefighting robots. Their operating environments are inherently uncertain due to sensing noise, communication disturbances, environmental variability, and control imperfections. As a result, navigation performance cannot be fully characterized by single deterministic values alone. Two systems may exhibit similar average trajectory errors while having substantially different levels of robustness and failure risk under dynamic obstacles or changing terrain conditions. Therefore, a meaningful evaluation framework should not only measure navigation accuracy but also quantify the likelihood that the system satisfies required performance thresholds under uncertainty (Stephens et al., 2024; Chen and Xiao, 2025; Rado et al., 2025).

The same trend is visible in localization and SLAM research. Multi-sensor fusion methods based on UWB, IMU, wheel odometry, LiDAR, and camera sensing have significantly improved the resilience of mobile robot localization, but they also make evaluation more complex because uncertainty propagates across sensing, estimation, and control stages (Ji et al., 2024; Deng et al., 2025; Cao et al., 2025; Fan et al., 2025). Foundational surveys on motion planning and SLAM remain highly relevant here because they show that performance should be discussed jointly in terms of path quality, localization consistency, and robustness to environmental variation (Paden et al., 2016; Cadena et al., 2016).

In reliability engineering, mixed uncertainties, cross-stage error propagation, and system-level risk aggregation have been addressed through probabilistic and evidence-based modeling frameworks (Mi et al., 2022; Bensaci et al., 2023; Pan et al., 2024). These ideas are highly relevant to mobile robots, yet a unified reliability-oriented framework for evaluating firefighting robot navigation remains underdeveloped. Existing robotic studies typically focus on algorithmic improvement, while standardized and uncertainty-aware evaluation frameworks are still rare (Nrioui et al., 2019). A recent digital-twin-based navigation evaluation study underscores this gap by explicitly calling for multi-metric and uncertainty-aware validation in robotics (Bergs et al., 2025).

To address these challenges, this paper proposes an uncertainty-aware reliability assessment framework for autonomous navigation of firefighting robots. The main contributions are threefold. First, a unified evaluation framework is established by integrating scenario configuration, trajectory generation, data acquisition, and probabilistic performance analysis into a closed-loop pipeline. Second, a nearest-neighbor-based trajectory deviation quantification method is developed for asynchronous and non-uniform sampling conditions. Third, a probabilistic reliability metric system is introduced to estimate the likelihood that predefined navigation requirements are satisfied under uncertainty.

2. Methodology

2.1 Problem Formulation

2.1.1 *Trajectory Representation*

In an autonomous navigation task, the motion of a firefighting robot can be represented as a trajectory in a two-dimensional workspace. Let the reference trajectory generated by the planning module be denoted by Eq. (1).

$$\Gamma^* = \{\mathbf{p}^*(t) = (x^*(t), y^*(t)) \mid t \in [0, T_f]\} \tag{1}$$

Let the actual executed trajectory be Eq. (2).

$$\Gamma = \{\mathbf{p}(t) = (x(t), y(t)) \mid t \in [0, T_f]\} \tag{2}$$

In practice, the reference trajectory is typically available as a continuous curve or a densely sampled sequence, whereas the executed trajectory is reconstructed from discrete measurements acquired by the sensing system. Therefore, the actual trajectory is expressed as Eq. (3).

$$\Gamma = \{\mathbf{p}_i = (x_i, y_i)\}_{i=1}^{N} \tag{3}$$

2.1.2 *Trajectory Deviation Definition*

To quantify the discrepancy between the reference trajectory and the actual executed trajectory, a nearest-neighbor matching strategy is adopted. For each sampled point pi on the executed trajectory, the closest point on the reference trajectory is determined by Eq. (4).

$$\mathbf{p}_i^* = \arg \min_{\mathbf{q} \in \Gamma^*} \| \mathbf{p}_i - \mathbf{q} \| \tag{4}$$

The point-wise trajectory deviation is then defined as Eq. (5).

$$e_i = \| \mathbf{p}_i - \mathbf{p}_i^* \| \tag{5}$$

Based on the matched point pairs, the root mean square (RMS) trajectory error is computed as Eq. (6).

$$e_{\mathrm{RMS}} = \sqrt{\frac{1}{N} \sum_{i=1}^{N} e_i^2} \tag{6}$$

In addition to the RMS error, the maximum deviation and deviation variance are also considered to capture the magnitude and variability of path-tracking errors.

To further characterize deviation behavior, the maximum trajectory deviation, mean trajectory deviation, and deviation variance are defined as Eqs. (7) - (9).

$$E_{max} = \max_{1 \le i \le N} e_i \tag{7}$$

$$\mu_E = \frac{1}{N} \sum_{i=1}^{N} e_i \tag{8}$$

$$\sigma_E^2 = \frac{1}{N} \sum_{i=1}^{N} (e_i - \mu_E)^2 \tag{9}$$

These metrics jointly reflect the overall magnitude, worst-case behavior, and fluctuations in trajectory-tracking errors.

2.1.3 *Performance Variables under Uncertainty*

To characterize navigation performance, several key variables are introduced: trajectory deviation *E*, task completion time T_c, travel distance *D*, and obstacle avoidance success indicator *S*. In this study, *E* denotes a trajectory-deviation-related performance variable, which can be instantiated by metrics such as e_{RMS}, μ_E, or E_{max}, depending on the evaluation objective.

In realistic firefighting environments, these variables are influenced by multiple uncertainty sources, including measurement noise, obstacle dynamics, environmental disturbances, and actuation errors. Consequently, they are modeled as random variables rather than fixed deterministic quantities. This probabilistic formulation provides the basis for reliability-oriented performance assessment. Instead of merely reporting whether a metric exceeds a threshold in a single trial, the objective is to estimate the probability that a navigation system satisfies predefined requirements over repeated trials or uncertain operating conditions (Stephens et al., 2024; Lind et al., 2024; Pan et al., 2024).

2.2 Reliability Assessment Methodology

2.2.1 *Evaluation Framework*

The proposed framework consists of four tightly coupled components: scenario configuration, multi-source sensing and data acquisition, trajectory reconstruction and deviation analysis, and probabilistic reliability evaluation.

First, the testing environment is configured by defining the workspace geometry, obstacle layout, start and target positions, and scenario-specific constraints. The framework supports both static and dynamic obstacle settings, allowing the navigation system to be examined under different levels of environmental complexity. Second, multi-source data are collected during task execution. The experimental platform integrates ultra-wideband (UWB) positioning and inertial measurement unit (IMU) sensing to obtain robot position, motion state, and temporal information. The UWB system provides the global positioning reference, while the IMU contributes short-term motion dynamics and improves trajectory reconstruction consistency. All data streams are time-synchronized and recorded for subsequent analysis. Third, the executed trajectory is reconstructed from the measured data and compared with the reference trajectory. Deviation metrics are computed through nearest-neighbor matching, enabling robust trajectory comparison under asynchronous and non-uniform sampling conditions. Finally, the obtained performance indicators are analyzed statistically and transformed into probabilistic reliability measures. This step allows the framework to move beyond deterministic threshold checking and to explicitly quantify the likelihood that navigation requirements are satisfied (Liu et al., 2024; Usinskis et al., 2025; Bergs et al., 2025). The overall framework forms a closed-loop assessment pipeline, from controlled experimentation to quantitative reliability characterization, and supports repeatable comparison across different scenarios and robotic platforms. The reliability assessment framework for autonomous navigation of firefighting robots is shown in Figure 1.

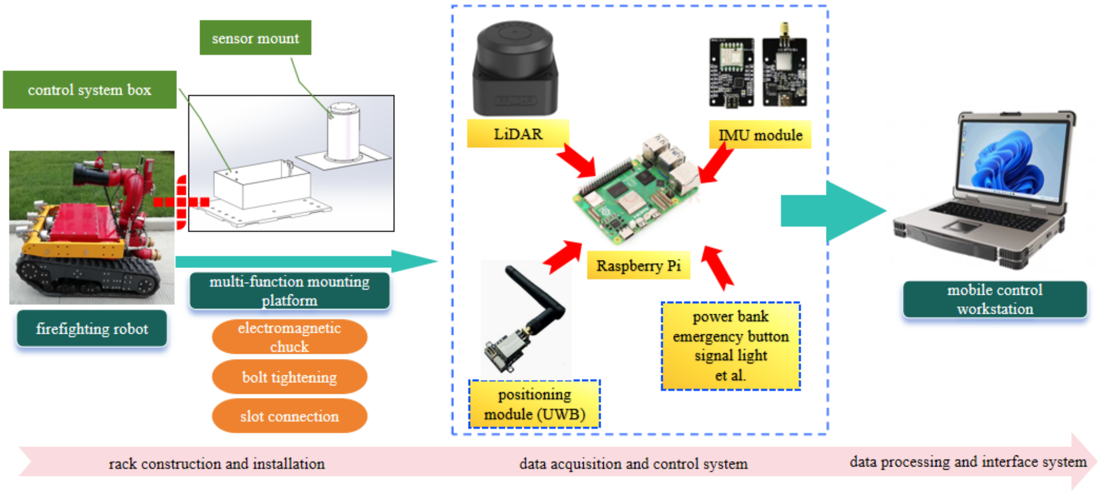

Figure 1. Reliability assessment framework for autonomous navigation of firefighting robots.

2.2.2 *Trajectory Deviation Analysis*

2.2.2.1 *Nearest-Neighbor Matching*

Trajectory comparison is complicated by the fact that the reference and executed trajectories often have different point densities and non-uniform time sampling. Direct one-to-one point correspondence is therefore generally unavailable. To address this issue, nearest-neighbor matching is employed to associate each measured point on the executed trajectory with the closest point on the reference trajectory. Compared with strict time-based alignment, this strategy is less sensitive to local speed variations and irregular sampling intervals. It provides a geometrically meaningful measure of deviation and is particularly suitable for autonomous navigation tasks in which the executed path may deviate locally due to obstacle avoidance or replanning (Xu et al., 2025; Xu, 2024).

2.2.2.2 *Statistical Characterization of Deviation*

Trajectory deviation is not fully represented by a single error metric. For this reason, the framework characterizes deviation using multiple statistical descriptors, including the mean deviation μ_E, RMS deviation e_{RMS}, maximum deviation Emax, and deviation variance σ_E^2. These indicators reflect different aspects of performance. The mean deviation represents the average path-tracking quality, the RMS deviation reflects the overall error magnitude, the maximum deviation captures the local worst-case behavior, and the deviation variance characterizes stability and fluctuation. Together, these metrics provide a richer description of navigation performance than any single error measure alone. (Katona et al., 2024; Bergs et al., 2025; Tran et Ryoo, 2025).

2.2.2.3 *Segment-Wise Analysis*

Navigation tasks often consist of several motion phases, such as straight-line travel, turning, obstacle avoidance, and path recovery. The same robot may perform well during nominal tracking but exhibit larger errors during maneuvering or dynamic obstacle interaction. To identify such localized performance variations, the trajectory can be segmented into different motion phases, and deviation metrics can be calculated separately for each segment. Segment-wise analysis improves interpretability and helps identify the specific navigation stages that contribute most strongly to performance degradation. This is particularly useful for diagnosing the impact of obstacle interactions and environmental complexity.

2.2.3 *Probabilistic Reliability Modeling*

2.2.3.1 *Uncertainty Sources*

Navigation performance variability arises from multiple sources of uncertainty. In the present framework, these sources are grouped into three categories. The first category is measurement uncertainty, including UWB positioning noise, IMU drift, packet loss, and timestamp mismatch. These effects influence trajectory reconstruction accuracy and therefore affect all downstream deviation metrics. The second category is environmental uncertainty, including changes in obstacle position, dynamic obstacle motion, terrain variation, and disturbances caused by cluttered surroundings. These factors increase task difficulty and alter the motion response of the robot. The third category is control uncertainty, including path-tracking errors, actuation delay, wheel slip, and controller response variation. These uncertainties directly influence the difference between the reference path and the executed path. The combined effect of these uncertainty sources results in variability of the measured navigation performance across repeated trials (Al Mahmud et al., 2024; Xu et al., 2025).

2.2.3.2 *Reliability Metrics*

To quantify navigation reliability, deterministic thresholds are extended to probabilistic indicators. Let δ_E denote the acceptable threshold for trajectory deviation. The reliability associated with deviation is defined as Eq. (10).

$$R_E = P(E \leq \delta_E) \tag{10}$$

This metric expresses the likelihood that the trajectory deviation remains within the acceptable range. Similarly, if δ_T is the maximum acceptable completion time, the time-related reliability is defined as Eq. (11).

$$R_T = P(T_c \leq \delta_T) \tag{11}$$

For obstacle avoidance success, the corresponding reliability can be defined as Eq. (12).

$$R_S = P(S = 1) \tag{12}$$

Where S=1 indicates successful completion of the obstacle avoidance task without collision or task failure, and S=0 indicates failure. These definitions transform conventional threshold-based performance evaluation into a reliability-oriented interpretation.

2.2.3.3 *Composite Reliability Index*

In practical applications, autonomous navigation performance depends on multiple criteria rather than a single metric. To aggregate different aspects of performance into a single interpretable indicator, a composite reliability index is introduced in Eq. (13) – (14) (Mi et al., 2022; Bensaci et al., 2023; Pan et al., 2024).

$$R = w_1 R_E + w_2 R_T + w_3 R_S \tag{13}$$

$$w_1 + w_2 + w_3 = 1 \qquad w_1, w_2, w_3 \geq 0 \tag{14}$$

The weighting factors can be adjusted according to mission requirements. For example, in time-critical rescue missions, completion time may be assigned a higher weight, whereas in high-risk environments, avoidance success and trajectory control may receive greater emphasis.

2.2.3.4 *Distribution Estimation*

The proposed framework adopts a data-driven strategy for reliability estimation. Rather than assuming a specific parametric distribution for each performance variable, empirical distributions are constructed from repeated experimental trials. Based on these empirical samples, probabilities of satisfying performance thresholds are estimated directly. This approach is advantageous for experimental robotic systems because the underlying distributions may deviate from standard Gaussian assumptions, especially in the presence of nonlinear path replanning, intermittent disturbances, or heterogeneous obstacle interactions. In addition to empirical probabilities, conventional statistical descriptors such as sample mean, variance, and confidence intervals can also be reported to support interpretation (Lind et al., 2024; Bergs et al., 2025).

3. Experimental Validation and Results

3.1 Experimental Setup

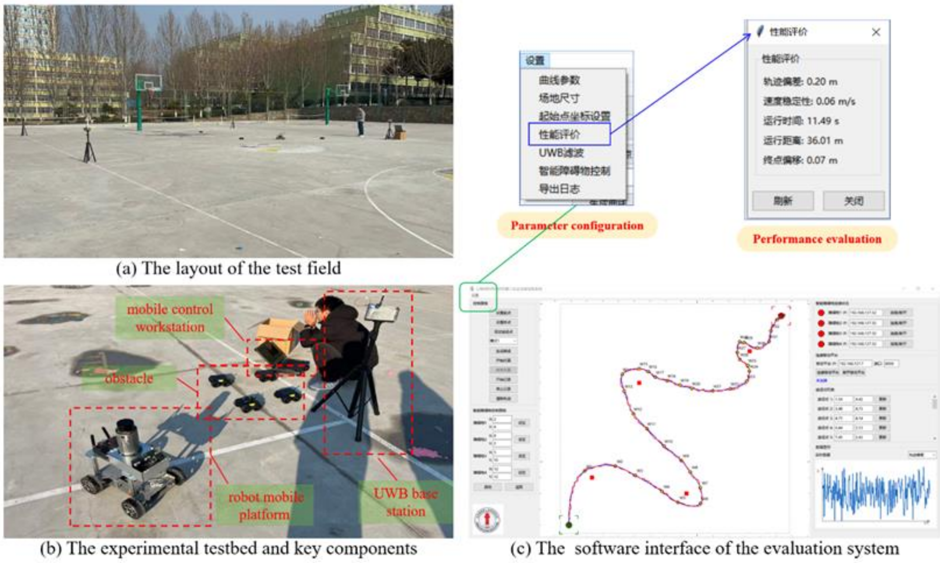

Figure 2. Layout of the test field.

The experimental platform was constructed in a controlled outdoor environment to evaluate the proposed framework under representative navigation conditions. A rectangular test field of approximately 15 m × 15 m was established, and different obstacle configurations were deployed to create static, dynamic, and complex scenarios. The robot was equipped with a multi-sensor measurement module integrating UWB positioning and IMU sensing. The UWB system provided a global spatial reference with centimeter-level positioning capability, while the IMU supplied motion-state information to improve consistency in trajectory reconstruction (Ji et al., 2024; Deng et al., 2025; Tran and Ryoo, 2025; Cao et al., 2025). A workstation was used for scenario configuration, task execution control, data acquisition, and real-time monitoring. All sensor streams were synchronized and stored for offline analysis. The position data were sampled at a sufficiently high rate to support trajectory reconstruction and statistical deviation analysis. Figure 1 presents the standardized layout of the test field, including the start point, target point, and representative obstacle configuration.

3.2 Test Scenarios

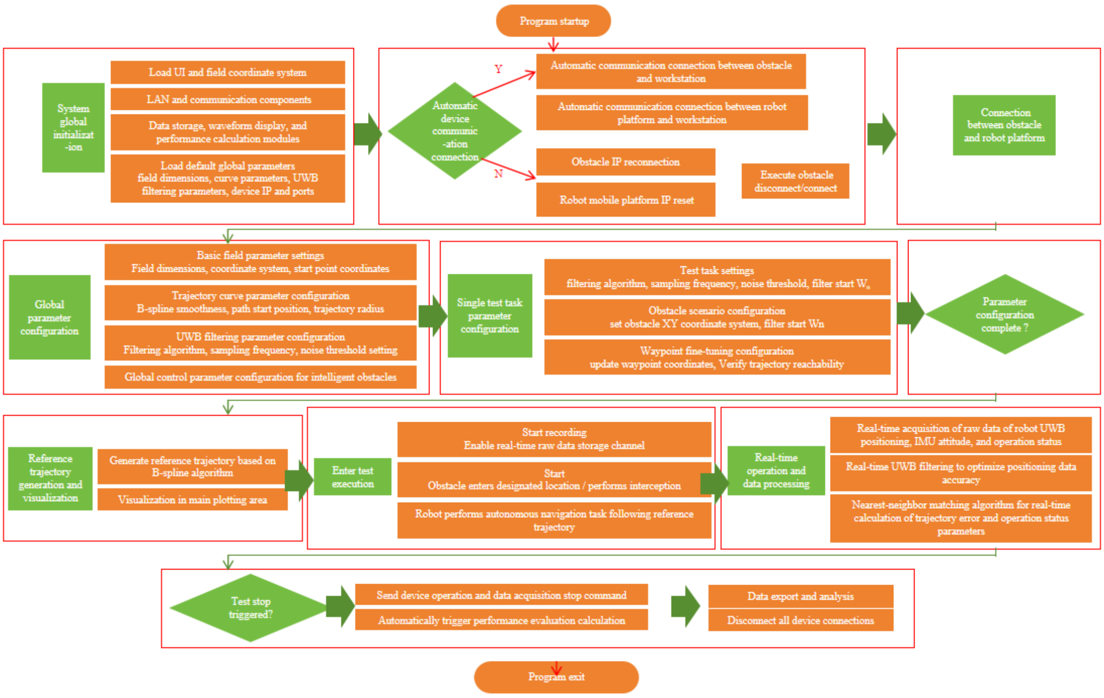

Figure 3. Flowchart of the main program.

Three types of scenarios were considered in the experiments. In the static obstacle scenario, fixed obstacles were placed along or near the planned path. The robot was required to navigate from the start point to the target while autonomously avoiding collisions. This scenario evaluates baseline path-tracking accuracy and obstacle avoidance capability in a relatively stable environment. In the dynamic obstacle scenario, moving obstacles were introduced to simulate unexpected disturbances during navigation. The robot was required to respond online to changes in obstacle position and to modify its path accordingly. This scenario emphasizes responsiveness, replanning robustness, and performance degradation under dynamic interference. In the complex path scenario, multiple obstacles were arranged in a denser and less regular pattern, generating narrow passages and multiple turning regions. This setting increases geometric constraints and better reflects cluttered or partially unstructured environments. It is intended to evaluate navigation behavior under higher environmental complexity (Chen and Xiao, 2025; Rado et al., 2025; Deng et al., 2026). For each scenario, repeated trials were conducted to obtain statistically meaningful results. These three scenarios are implemented using the software shown in Figure 2(c), and the program flowchart is presented in Figure 3.

3.3 Performance Metrics

The following performance indicators were evaluated: RMS trajectory error e_{RMS}, maximum trajectory deviation Emax, task completion time T_c, obstacle avoidance success indicator S and its empirical success probability, probabilistic reliability measures R_E, R_T, and R_S, and composite reliability index R. The deviation-related threshold δ_E and the time-related threshold δ_T were predefined according to the navigation performance requirements of the test task. These thresholds enable the estimation of probabilistic reliability from repeated trials (Bergs et al., 2025).

3.4 Results and Reliability Analysis

3.4.1 *Trajectory Comparison*

The trajectory tracking performance in static and dynamic obstacle scenarios can be quantitatively distinguished by the maximum trajectory deviation and the locations of critical deviations. In the static scenario, the system achieves an average maximum trajectory deviation of 0.098 m, which occurs only at path turning points, indicating good overall tracking consistency. In the dynamic scenario, due to obstacle interaction and online path adjustment, the average maximum trajectory deviation increases to 0.365 m and is concentrated in key regions of obstacle interaction, where local deviations become significantly larger. These results suggest that visual inspection of a single trajectory is insufficient for rigorous evaluation; instead, statistical characterization from repeated trials is necessary to effectively identify performance variability and quantify system reliability.

3.4.2 *Statistical Performance Comparison*

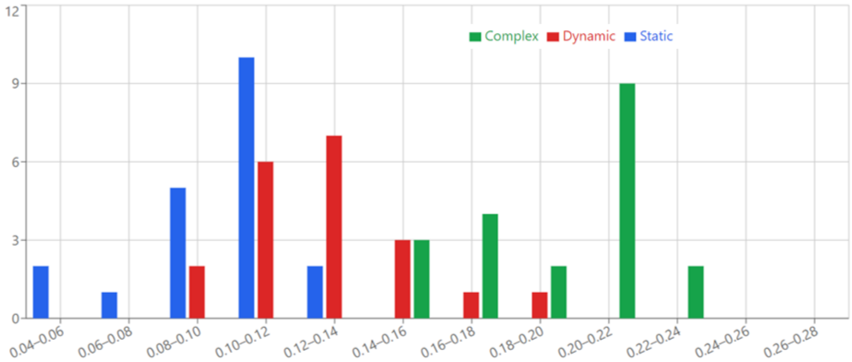

Figure 4. Empirical distribution of e_{RMS}.

(a). Box summaries of e_{RMS} (b). Box summaries of T_c

Figure 5. Boxplots of RMS error and task completion time under different scenarios.

Figure 4 shows the empirical distribution of the RMS trajectory error eRMS for the three tested scenarios. The static scenario exhibited the smallest deviation and the narrowest distribution, indicating relatively stable tracking performance. The dynamic scenario showed larger deviation and higher variability, reflecting the influence of moving obstacles and replanning behavior. The complex scenario exhibited the broadest distribution, suggesting that environmental complexity substantially increases the uncertainty of navigation performance. Figure 5 compares the RMS error and completion time across scenarios using boxplots. Both the median value and dispersion increased from static to dynamic and complex settings. This trend indicates that the navigation task becomes progressively more difficult as obstacle interaction and geometric constraints increase. These observations are consistent with the expected effect of uncertainty and environmental complexity. They also demonstrate that repeated-trial statistics provide more informative evidence than single-trial deterministic measurements.

3.4.3 *Reliability Evaluation*

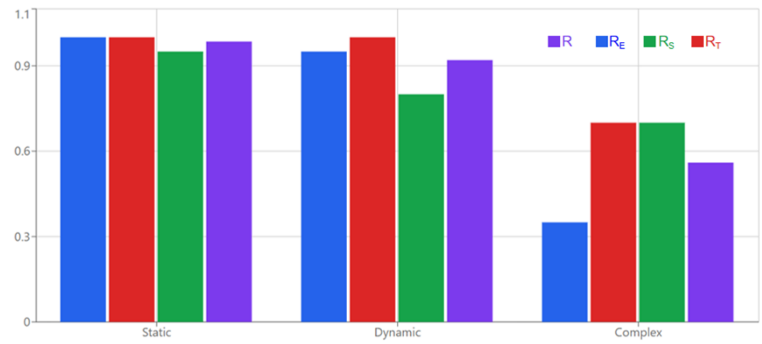

Figure 6. Reliability metrics comparison.

Based on repeated trials, probabilistic reliability measures were estimated for each scenario. The deviation-related reliability RE reflects the probability that trajectory deviation remains below the acceptable threshold. The time-related reliability RT reflects the probability that task completion time satisfies the required upper bound, and RS represents the empirical success probability of obstacle avoidance. Figure 5 compares the reliability metrics across scenarios. The static scenario achieved the highest reliability values, while both the dynamic and complex scenarios showed reduced reliability, particularly in deviation-related performance. The composite reliability index also decreased with increasing environmental complexity.

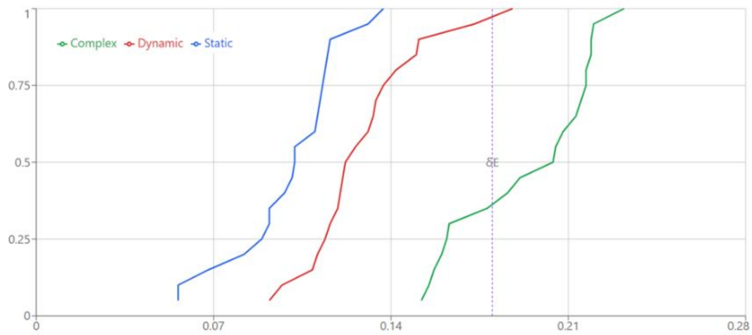

Figure 7. ECDF of e_{RMS}.

To further explain the deviation-related reliability, Figure 6 presents the empirical cumulative distribution functions (ECDFs) of the RMS trajectory error e_{RMS} under different scenarios. In correspondence with the bar-chart results shown in Figure 5, Figure 6 provides a direct visualization of the cumulative probability that $e_{RMS} \leqslant \delta_E$ for a given deviation threshold δ_E. The static scenario exhibits the leftmost and steepest cumulative curve, indicating smaller overall deviation and the highest probability of satisfying the threshold. The dynamic scenario shows intermediate behavior, whereas the complex scenario is shifted to the right, implying larger errors, stronger dispersion, and a substantially lower probability of meeting the same requirement. This distribution-level evidence further confirms the comparative results of R_E shown in Figure 5. In this sense, the ECDF provides a graphical interpretation of the deviation-related reliability R_E.

These results demonstrate that the proposed reliability formulation captures not only average performance but also performance consistency under uncertainty. In particular, two scenarios with similar mean values may still differ substantially in reliability if one scenario exhibits a larger spread or more frequent threshold violations. The distributional evidence provided by Figure 6 further illustrates that, compared with conventional deterministic evaluation, probabilistic reliability measures offer a more informative characterization of navigation performance under uncertainty.

4. Discussion

The experimental results demonstrate that autonomous navigation performance cannot be adequately described by deterministic metrics alone. Although trajectory-related indicators such as e_{RMS}, Emax, and T_c are useful baseline measures, they do not directly reveal the consistency of performance across repeated trials or the likelihood of satisfying operational requirements under uncertainty. The proposed framework addresses this limitation by transforming key performance indicators into probabilistic reliability measures.

Another important observation is that environmental complexity has a clear and systematic influence on navigation reliability. As the task environment changes from static to dynamic and complex obstacle configurations, both performance variability and threshold violation frequency increase. This result is consistent with the practical challenges encountered by firefighting robots in real applications, where sensing noise, local disturbances, and unstructured surroundings interact in a non-negligible manner (Pan et al., 2024; Bensaci et al., 2023).

The present study has several limitations. The experiments were conducted in controlled test conditions and therefore do not yet include all factors present in real fireground environments, such as dense smoke, severe thermal interference, uneven surfaces, or reduced sensor visibility. The current reliability estimation is based on empirical repeated-trial statistics, which are appropriate for data-driven evaluation but could be further enhanced by more advanced uncertainty quantification techniques. The experiments focused primarily on trajectory-level performance and did not explicitly model semantic perception reliability or mission-level task success (AlAli and Alabady, 2022; Dong et al., 2025; Kilic et al., 2025).

Despite these limitations, the proposed framework provides a practical and extensible basis for standardized performance evaluation of firefighting robot navigation. It is particularly suitable for benchmarking, iterative algorithm testing, and comparative assessment under controlled scenario variations.

5. Conclusion

This study proposed an uncertainty-aware reliability assessment framework for autonomous navigation of firefighting robots. By integrating nearest-neighbor-based trajectory deviation analysis with probabilistic reliability modeling, the framework extends conventional deterministic evaluation into a quantitative uncertainty-aware assessment scheme.

Experimental results from static, dynamic, and complex obstacle scenarios show that the proposed method captures both navigation accuracy and reliability degradation under increasing environmental complexity. The results also demonstrate that probabilistic reliability metrics provide a more informative characterization than conventional deterministic indicators.

Future work will focus on more realistic fireground conditions, including smoke interference, uneven terrain, and multi-robot cooperation, as well as on advanced uncertainty quantification and learning-based reliability modeling.

Acknowledgements

This work was supported by the National key research and development program project under Grant 2023YFC3011005.

End Notes

Table I. Nomenclature

symbol	Definition	Unit / Type	Remarks
Γ^*	Reference trajectory	Trajectory set	
Γ	Executed trajectory	Trajectory set	

$p^*(t)$	Point on the reference trajectory at time t	Position vector	
$p(t)$	Point on the executed trajectory at time t	Position vector	
$x^*(t)$	x-coordinate of the reference trajectory	m	
$y^*(t)$	y-coordinate of the reference trajectory	m	
$x(t)$	x-coordinate of the executed trajectory	m	
$y(t)$	y-coordinate of the executed trajectory	m	
t	Time	s	
T_f	End time of the navigation task	s	
p_i	i-th sampled point on the executed trajectory	Position vector	$p_i = (x_i, y_i)$
x_i	x-coordinate of the i-th sampled point	m	
y_i	y-coordinate of the i-th sampled point	m	
i	Sample index	Integer	i=1, 2,…
N	Number of sampled trajectory points	Count	
p_i^*	Nearest matched point on the reference trajectory for p_i	Position vector	
q	Candidate point on the reference trajectory	Position vector	
$\|\| \cdot \|\|$	Euclidean norm	Operator	Used to compute point-to-point distance
e_i	Point-wise trajectory deviation	m	Distance between pi and pi∗
e_{RMS}	Root mean square trajectory error	m	
E_{max}	Maximum trajectory deviation	m	
μ_E	Mean trajectory deviation	m	
σ_E^2	Variance of trajectory deviation	m^2	
E	Trajectory deviation performance variable	Random variable	
T_c	Task completion time	s	
D	Travel distance	m	
S	Obstacle avoidance success indicator	Binary / random variable	S=1 for successful task completion
δ_E	Acceptable deviation threshold	m	
δ_T	Acceptable time threshold	s	
$P(\cdot)$	Probability operator	Operator	
R_E	Deviation-related reliability	Probability	
R_T	Time-related reliability	Probability	
R_S	Success-related reliability	Probability	
R	Composite reliability index	Dimensionless	
w_1	Weight for deviation-related reliability	Dimensionless	
w_2	Weight for time-related reliability	Dimensionless	
w_3	Weight for success-related reliability	Dimensionless	

References

Al Mahmud, S., Kamarulariffin, A., Ibrahim, A. M., and Mohideen, A. J. H. Advancements and Challenges in Mobile Robot Navigation: A Comprehensive Review of Algorithms and Potential for Self-Learning Approaches. *Journal of Intelligent & Robotic Systems*, 110:120, 2024.

AlAli, Z. T., and Alabady, S. A. A survey of disaster management and SAR operations using sensors and supporting techniques. *International Journal of Disaster Risk Reduction*, 82:103295, 2022.

Bensaci, C., Zennir, Y., Pomorski, D., Innal, F., and Lundteigen, M. A. Collision hazard modeling and analysis in a multi-mobile robots system transportation task with STPA and SPN. *Reliability Engineering & System Safety*, 234:109138, 2023.

Bergs, L., Huber, M., Moriz, A., Göppert, A. M. R., Schmitt, R. H., Chan, F. K. S., Law, Y. N., Pan, X., and Drescher, B. Evaluating mobile robot navigation behavior in flexible assembly systems through digital twin and real-world experiments. *Discover Robotics*, 1:10, 2025.

Cadena, C., Carlone, L., Carrillo, H., Latif, Y., Scaramuzza, D., Neira, J., Reid, I., and Leonard, J. J. Past, Present, and Future of Simultaneous Localization and Mapping: Toward the Robust-Perception Age. *IEEE Transactions on Robotics*, 32(6):1309-1332, 2016.

Cao, Y., Usai, A., Gu, W., and Rizzo, A. Localization Handover for Mobile Robots: A Seamless Indoor-Outdoor Approach. *Journal of Intelligent & Robotic Systems*, 111:82, 2025.

Chen, Y., and Xiao, J. Target Search and Navigation in Heterogeneous Robot Systems with Deep Reinforcement Learning. *Machine Intelligence Research*, 22:79-90, 2025.

Deng, R., Ding, S., Ding, Y., Wang, M., Huang, X., and Usmani, A. S. Autonomous navigation of non-perception firefighting robot through CCTV-informed vision sharing. *Expert Systems with Applications*, 296(Pt D):129210, 2026.

Deng, Z., Zhang, S., Chen, X., and co-authors. Fusion-Based Localization System Integrating UWB, IMU, and VIO. *Applied Sciences*, 15(12):6501, 2025.

Dong, D., Wang, Z., Guan, J., Xiao, Y., and Wang, Y. Research on key technology and application progress of rescue robot in nuclear accident emergency situation. *Nuclear Engineering and Technology*, 57:103457, 2025.

Fan, Z., Zhang, Z., Deng, F., and co-authors. LiDAR, IMU, and camera fusion for simultaneous localization and mapping: a systematic review. *Artificial Intelligence Review*, 58, 174, 2025.

Ghauri, S. A., Sarfraz, M., Qamar, R. A., Sohail, M. F., and Khan, S. A. A Review of Multi-UAV Task Allocation Algorithms for a Search and Rescue Scenario. *Journal of Sensor and Actuator Networks*, 13(5):47, 2024.

Ji, P., Duan, Z., and Xu, W. A Combined UWB/IMU Localization Method with Improved CKF. *Sensors*, 24(10):3165, 2024.

Katona, K., Neamah, H. A., and Korondi, P. Obstacle Avoidance and Path Planning Methods for Autonomous Navigation of Mobile Robot. *Sensors*, 24(11):3573, 2024.

Kilic, K. I., Samir Maity, and co-authors. Challenges and AI-driven solutions in maritime search and rescue planning: A comprehensive literature review. *Marine Policy*, 178:106692, 2025.

Kim, Y.-J., Kim, H., Ha, B., and Kim, W.-T. Advanced fire emergency management based on potential fire risk assessment with informative digital twins. *Automation in Construction*, 167:105722, 2024.

Kristoffersson Lind, S., Xiong, Z., Forssen, P.-E., and Kruger, V. Uncertainty quantification metrics for deep regression. *Pattern Recognition Letters*, 186:91-97, 2024.

Lee, D., Jung, M., and Kim, A. LiDAR odometry survey: recent advancements and remaining challenges. *Intelligent Service Robotics*, 17:531-558, 2024.

Liu, Y., Wang, S., Xie, Y., Xiong, T., and Wu, M. A Review of Sensing Technologies for Indoor Autonomous Mobile Robots. *Sensors*, 24(4):1222, 2024.

Mi, J., Lu, N., Li, Y.-F., Huang, H.-Z., and Kang, R. An evidential network-based hierarchical method for system reliability analysis with common cause failures and mixed uncertainties. *Reliability Engineering & System Safety*, 220:108295, 2022.

Niroui, F., Zhang, K., Kashino, Z., and Nejat, G. Deep reinforcement learning robot for search and rescue applications: Exploration in unknown cluttered environments. *IEEE Robotics and Automation Letters*, 4(2):610-617, 2019.

Paden, B., Cap, M., Yong, S. Z., Yershov, D., and Frazzoli, E. A Survey of Motion Planning and Control Techniques for Self-Driving Urban Vehicles. *IEEE Transactions on Intelligent Vehicles*, 1(1):33-55, 2016.

Pan, F., Zhang, Y., Liu, J., Head, L., Elli, M., and Alvarez, I. Reliability modeling for perception systems in autonomous vehicles: A recursive event-triggering point process approach. *Transportation Research Part C: Emerging Technologies*, 169:104868, 2024.

Raoufi, M., Telikani, A., Zhang, T., and Shen, J. Fire front path planning and tracking control of Uncrewed Aerial Vehicles using deep reinforcement learning. *Robotics and Autonomous Systems*, 186:105076, 2025.

Stephens, A., Budd, M., Staniaszek, M., Casseau, B., Duckworth, P., Fallon, M., Hawes, N., and Lacerda, B. Planning under uncertainty for safe robot exploration using Gaussian process prediction. *Autonomous Robots*, 48(7):18, 2024.

Tran, Q.-K., and Ryoo, Y.-J. Multi-Sensor Fusion Framework for Reliable Localization and Trajectory Tracking of Mobile Robot by Integrating UWB, Odometry, and AHRS. *Biomimetics*, 10(7):478, 2025.

Usinskis, V., Nowicki, M., Dzedzickis, A., and Bucinskas, V. Sensor-Fusion Based Navigation for Autonomous Mobile Robot. *Sensors*, 25(4):1248, 2025.

Waga, A., Benhlima, S., Bekri, A., Abdouni, J., and Saber, F. Z. A survey on autonomous navigation for mobile robots: From traditional techniques to deep learning and large language models. *Journal of King Saud University Computer and Information Sciences*, 37:198, 2025.

Xu, N., Guan, M., and Wen, C. A survey on Ultra Wide Band based localization for mobile autonomous machines. *Journal of Automation and Intelligence*, 4(2):82-97, 2025.
Xu, T. Recent advances in Rapidly-exploring random tree: A review. *Heliyon*, 10(11):e32451, 2024.