Trust-Aware Dynamic Navigation for Mobile Robots with Sensor Noise

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***Abstract*— Mobile robots are increasingly using learning-based methods to navigate in dynamically changing environments. Even though achieving impressive task performance in practice, these methods at best do not take into account uncertainty on sensory observations and model predictions, which can result in unsafe or undesired behavior. In this paper, we introduce a confidence-based adaptive navigation system in which the influence of learned control is dynamically tempered by the confidence of the prediction. The framework combines uncertainty-aware learning and reactive safety controller. Passive estimation of confidence monitors the trustworthiness of learned navigation policies and adjusts control authority. Confident, adaptive control wins out when confidence is high and confidence degradation results in reactive safety behaviors. We evaluate the approach via simulation experiments in a Gazebo setup, varying sensor noise. The experimental results show that the proposed approach can greatly enhance navigation robustness, decrease collision possibility, and well preserve real-time tracking comparing with traditional learning-based or reactive methods. This confirms the significance of confidence-aware control for secure and efficient mobile robot navigation**.

***Keywords*—Confidence-guided navigation; robot navigation; Learning-based control; Reactive safety control; control architecture; Sensor noise; Robust; Safety-critical.**

I. INTRODUCTION

Learning-based navigation has emerged as a main paradigm in mobile robotics, benefiting from its capacity of managing high-dimensional sensory information and solving complex reasoning tasks. Deep RL and neural network control successfully operate in structured environments. However, they are difficult to apply in reality because of sensor noise, partial observability and non-stationary environment [1].

One fundamental shortcoming among many learning-based systems is that they tacitly assume perceptual reliability. In reality, sensory inputs are noisy or missing and will be interpreted as input uncertainties resulting in overconfident but unsafe actions. This problem is even more crucial in safety-critical robotic tasks as wrong decisions may result in collisions or complete failure of the system [2].

On the other hand, reactive control architectures provide trustworthy safety guarantees thanks to deterministic sensor–action mappings. They are strong but not flexible and efficient in diversified environments. The difficulty then becomes how to allow robots to enjoy learning-based adaptability, while maintaining the requirement of safety and dependability.

In this paper, we tackle problem by proposing a confidence-aware navigation framework to reason about the uncertainty in learned policy. Instead of directly controlling the learning-based controllers, we modulate their effects by estimated prediction confidence levels enabling safe operation in cases that unreliable decisions could occur [3].

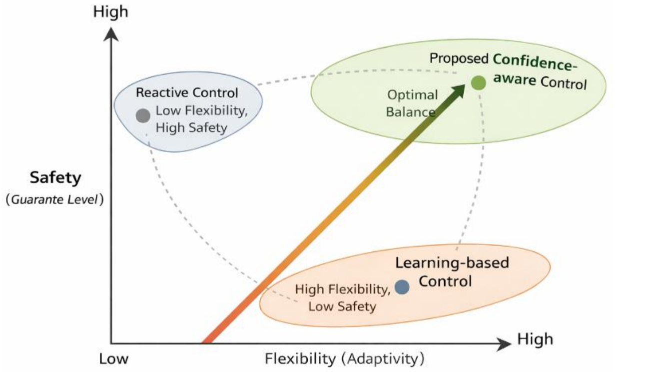

Fig. 1. Comparison of theoretical groundwork between learning based, reactive control and the proposed confidence-guided navigation approach.

The figure illustrates the tradeoff that exists between flexibility and safety and motivates the introduction of confidence-aware control arbitration.

The contributions of this paper are as follows:

A confidence-informed navigation pipeline that flexibly combines adaptive learning-based control and reactive safety control.

A confidence estimation system for learning-based navigation decisions.

A simulation validation under different sensor noise.

Quantitative evidences for enhanced robustness and safety.

II. RELATED WORKS

Robotic navigation is a fundamental research problem in robotics, which has attracted significant attention for decades as it requires reliable decision-making in dynamic and uncertain environments. Initial works were more concerned with reactive and behavior-based control in order to obtain quick and robust behaviors, while later ones integrated to the system abilities like probabilistic reasoning and learning based techniques that helped adaptability as well as performance. This section discusses the related work on learning- based navigation, uncertainty modelling and safety critical control that forms a background for our approach in this paper [4].

III. MOBILE ROBOT NAVIGATION BASED ON LEARNING. SKILLS

The positioning skills of a robot may be broadly divided into two classes: dead-reckoning skill and external-sensor based skill.

In recent years, learning based approaches have been widely studied to enable robots to learn automatically instead of inputting explicit programming for navigation behaviors. Reinforcement learning is a leading approach for learning control policies in robotic systems, enabling robots to learn and adapt through action-perception loops inside the environment with reward feedback. These kinds of method have been used in obstacle avoidance, goal-directed navigation, and motion generation with potential for using large and high-dimensional state space. However, learning-based navigation methods face plenty of challenges when transferring to robotic systems in the real world. Many learned policies have been shown to be data hungry and assume stationary sensory regimes. When the assumptions are violated, because of sensor noise or environmental variation for example, performance can deteriorate dramatically and unsafe or unpredictable behavior can result. Furthermore, controller's developed using learning are known not to have explicit safety guarantees and hence they can be difficult to deploy over safety-critical applications. These constraints urge the addition of complementary mechanisms to guarantee the reliability and robustness at the time of deployment [5].

IV. UNCERTAINTY REPRESENTATION IN ROBOTIC SYSTEMS

Assisting robots will always involve some level of uncertainty due to sensor noise, limited observability and dynamic environment. As a consequence, probabilistic modeling has been of central importance in mobile robotics, delivering mathematically principled means for representing and reasoning under uncertainty. A probabilistic approach enables robots to hold belief distributions over states instead of single-point estimates, thereby increasing robustness in uncertain environments [6].

Lately, uncertainty estimation has also become of interest in learning-based architectures. Recent advances in Bayesian deep learning models have been developed to estimate prediction uncertainty and measure trustworthiness of model’s predictions. These approaches separate predictions into those that exhibit high confidence and are unsure, which is vital in safety-critical contexts. However, while uncertainty estimation is indeed a useful diagnostic information signal, it alone does not guarantee safe control behavior unless embodied within the decision-making and control cycle [7].

V. SAFETY & REACTIVE CONTROL ARCHITECTURES

Reactive and behavior-based control architectures were proposed to accommodate the requirement for quick and dependable reactions in a dynamic environment. In behavior-based robotics, control policies are implemented through direct sensor–action mappings which can provide rapid reactions and natural robustness (Arkin 1998). These architectures provide useful solutions for safety-critical driving behaviors such as collision-avoidance and emergency braking, especially in situations demanding quick reaction. Formal safety analysis and verification methods have also emerged in parallel to offer certifiable properties about system behavior. The methods of reachability-based verification, for instance, allow one to reason about safety requirements and possible ways of failing in autonomous systems. Although these methods provide strong theoretical safety guarantees, they are typically computationally expensive and difficult to incorporate directly in learning-based control policies, which restricts their applicability for real-time robotic navigation [8].

VI. RESEARCH GAP AND MOTIVATION

Studies reviewed show a clear distinction between learning-based adaptability, uncertainty understanding, and safety-controlled navigation in mobile robots. Model learning methods provide flexibility and performance but do not generalize to uncertainty-rich scenarios and lack explicit safety assurance. Probabilistic and uncertainty aware techniques offer reliability estimates of high value, however in many cases they are de-coupled from actual decisions for control at run-time. Reactive and safety-based control architectures provide robustness, but no learning capacity and adaptability.

Such elements are seldom combined into a single control system which adapts the behavior according to how confident it is on learned decision. Especially, uncertainty and confidence information have never been exploited to control a weight distribution between adaptive and safety focused behavior during online operation. This gap is addressed in this work that presents a confidence-guided navigation framework that explicitly integrates uncertainty-aware decision making within the control loop. The proposed method aiming to carry out robust, safe and adaptable autonomous navigation in uncertain environments is able to balance learning-based navigation with reactive safety behaviors using estimates of confidence [9].

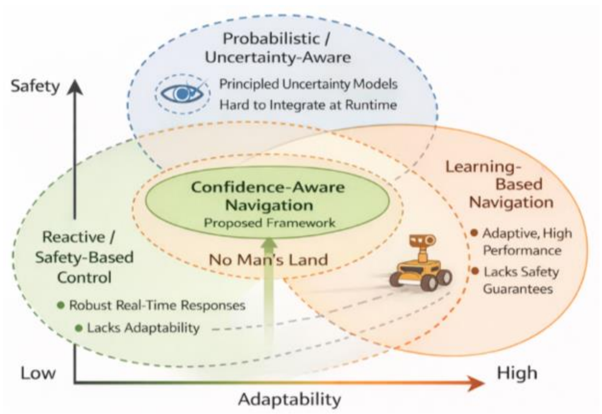

Fig.2. Taxonomy of navigation strategies for mobile robots.

The diagram suggests that different navigation paradigms occupy different regions in a trade-off space between adaptability and safety. Learning-based approaches often offer high flexibility and performance but without an explicit security guarantee, particularly in uncertain or novel scenarios. Reactive and safety-based methods, on the other hand, ensure robustness but suffer from limited adaptability. Probabilistic and uncertainty-aware strategies provide estimates of reliability, but these estimates typically remain separate from the real-time control loop. This conceptual “no man’s land” is defined by the restriction’s relationships between adaptivity, security and the expurgation of uncertainty. It is an unoccupied, which none of existing methods fully meet and reflect. Combining confidence-aware control and prediction confidence with standard PID execution allows dynamic biasing across responding to learned strategies or robust strategies based on How certain it, in fact, feels at the time. This is achieved by using information about prediction confidence in-forcing output to decide which kind of policy the system shall favor–learned or reactive. Transfer information creates trade-offs between flexibility and safety during final use. This figure clearly illustrates how our proposed paradigm builds on the strengths of previous work and bypasses their main drawbacks, facilitating robust adaptive navigation made for autonomous vehicles operating under significant environmental uncertainty.

VII. Confidence-Guided Navigation Architecture

VIII. Architecture Overview

The proposed architecture is divided into four parts:

- Learning-Based Navigation Policy
- Confidence Estimation Module
- Reactive Safety Controller
- Control Arbitration Mechanism

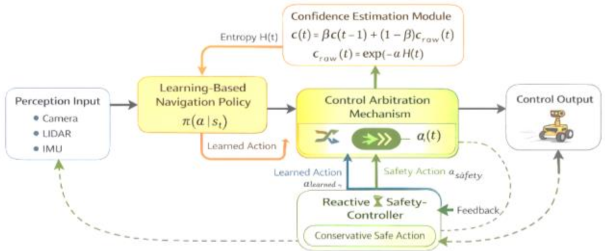

Fig. 3. Confidence-guided adaptive navigation architecture.

The Figure illustrates the proposed Confidence-Guided Navigation Architecture, which integrates learning-based flexibility with safety-aware decision making in mobile robotics. The system begins with a Perception Module that processes raw sensory input to estimate the current state of the robot. This state estimate is fed into a Learning-Based Policy, typically a neural network or reinforcement learning controller, which outputs an adaptive control action. However, since learned policies may exhibit uncertainty under noisy or novel conditions, a Confidence Estimation Module evaluates the reliability of each decision by computing a dynamic confidence score $c(t)$, derived from the entropy of the policy's output. This score reflects how certain the policy is about its chosen action. The core of the architecture lies in the Control Arbitration Mechanism, which blends the outputs of the learning-based controller and a conservative Safety Controller. The arbitration is governed by the confidence score: high confidence leads to a greater influence from the learning-based policy, while low confidence shifts control toward the safety controller. This blending mechanism ensures that the robot maintains safe behavior in uncertain situations while still benefiting from the adaptivity of learned control in familiar, reliable conditions. The final control output is thus a confidence-weighted decision that balances performance and robustness, with continuous feedback from the environment completing the closed-loop system [10].

IX. Confidence Estimation

A confidence estimation for the learning-based navigation policy is used to quantify its reliability. Entropy quantifies the lack of certainty and thus helps regularizing the action distribution output by the policy network.

Let $\pi(a \mid s_t)$denote the action probability distribution produced by the learned policy at time step t, given the current state s_t. The entropy of the policy output is computed as:

$$H(t) = -\sum_{i=1}^{N} p_i(t) \log p_i(t) \qquad (1)$$

where $p_i(t)$represents the probability assigned to action $i$at time t, and Ndenotes the number of discrete control actions.

Large entropy values correspond to high uncertainty about what the policy should decide and smaller values correspond to confident predictions. In order to obtain from the entropy-level measure an inherent bounded-confidence score, we simply express an instantaneous confidence at instants as:

$$c_{\text{raw}}(t) = \exp\ (-\alpha\, H(t)) \qquad (2)$$

where $\alpha > 0$is a scaling parameter that controls the sensitivity of the confidence score to variations in entropy. This formulation ensures that $c_{\text{raw}}(t) \in (0.1]$, with higher values indicating greater confidence in the learned policy output.

To stabilize confidence over time and reduce the impact of short-term sensor noise-induced fluctuations, a dynamic confidence update is implemented by exponential smoothing:

$$c(t) = \beta\, c(t-1) + (1-\beta)\, c_{\text{raw}}(t) \qquad (3)$$

where $\beta \in [0.1)$is a smoothing factor that determines the influence of previous confidence estimates. The resulting confidence value $c(t)$represents a dynamically updated measure of policy reliability and is used in the subsequent control arbitration process.

X. Control Arbitration

The final navigation command is generated through a confidence-guided control arbitration mechanism that combines the outputs of the learning-based navigation policy and the reactive safety controller. This mechanism enables continuous and adaptive regulation of control authority based on the dynamically estimated confidence value.

Let $u_{\text{learned}}(t)$denote the control command generated by the learning-based controller at time step t, and let $u_{\text{reactive}}(t)$represent the command produced by the reactive safety controller. The final control command $u(t)$is computed as a weighted combination of the two control signals:

$$u(t) = c(t)\, u_{\text{learned}}(t) + (1 - c(t))\, u_{\text{reactive}}(t) \qquad (4)$$

where $c(t) \in [0.1]$is the dynamically updated confidence value obtained from the confidence estimation module.

$$u(t) = c(t) \cdot u_{learned}(t) + (1 - c(t)) \cdot u_{reactive}(t) \qquad (5)$$

where $c(t) \in [0.1]$is the dynamically updated confidence value obtained from the confidence estimation module.

To prevent abrupt transitions and ensure stable control behavior, the confidence value is constrained within predefined bounds using a saturation function:

$$c'(t) = \min \ (\max \ (c(t)\, c_{\min})\, c_{\max}) \qquad (6)$$

where $0 \le c_{\min} < c_{\max} \le 1$define the lower and upper confidence thresholds, respectively. The bounded confidence value $c'(t)$is then used in the arbitration process:

$$u(t) = c'(t)\, u_{\text{learned}}(t) + \big(1 - c'(t)\big)\, u_{\text{reactive}}(t) \qquad (7)$$

This formulation ensures that the reactive safety controller never loses control completely, and it always influences the vehicle by a minimum degree required for avoiding collisions and safety-critical maneuvers. Meanwhile the learning-based controller can take over when it has enough confidence, both maintain adaptability and improve efficiency. As a result, the proposed arbitration mechanism strikes a principled balance between robustness and efficiency, enabling dependable navigation even under sensor uncertainty [11].

XI. EXPERIMENTAL SETUP

XII. SIMULATION ENVIRONMENT

We perform experiments in Gazebo with an indoor cluttered environment.

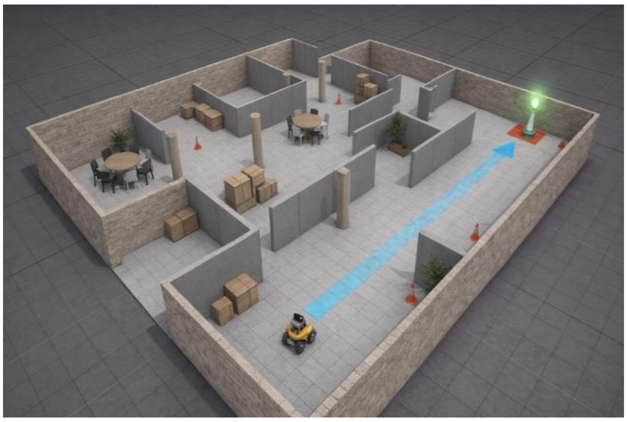

Fig. 4. Simulation Environment for Confidence-Guided Navigation

The simulation environment depicted in Figure 4 was employed to test the trust-guided navigation framework proposed. Implemented in Gazebo, the environment provides a realistic indoor setting with rigid walls, narrow corridors, and fixed obstacles so as to test hypothesis. The robot should travel independently from its start point to a fixed destination without colliding with anything while keeping its bearings in the face of noise from sensors.
Since this configuration can be used to assess varying strategies of navigating within different environmental complexity updates or array outputs of sensors' signals, than its ability thereby effectively demonstrates the benefits from confidence-aware control arbitration. This diagram shows the actual circumstances in which a deployment of this strategy can be called practical, since it must be ready whenever an action's reliability hinges on its present state and operation [12].

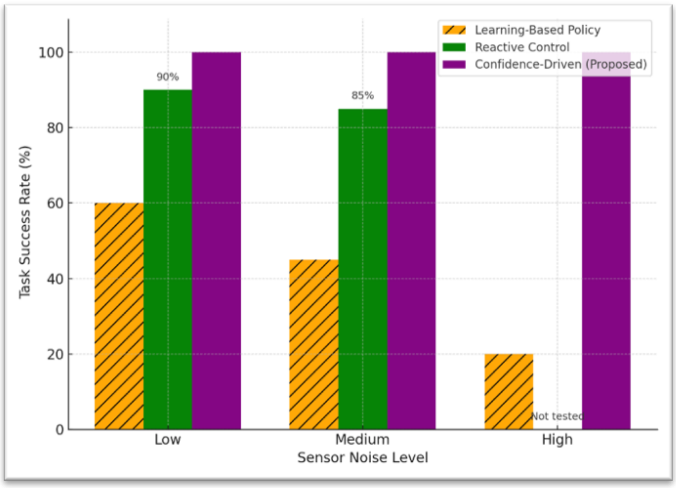

Fig. 5. Task success rates of control strategies across sensor levels

Under different levels of sensor disturbance, a bar chart is used to compare the performance of three directional strategies: Learning-based policy; Reactive control; and the proposed Confidence-Driven method. The vertical axis measures success rates, expressible in percentage terms. The horizontal axis sensor noise levels (low, medium and high) are independent of diagonal line length. As the noise level goes up, performance of the learning-based approach drops steeply. This reflects its limited tolerance for error or uncertainty in a field it knows and understands profoundly [13], [14].
Like a beacon of light--a reactive controller as the easiest thing to code and follow commands from capable of consistent performance under low or medium noise but never once put through the wringer under conditions of high noise because (for other environments sensing speed are needed aka not just passive) it simply isn't adaptable to those very different situations. The confidence-driven method has a 100% success rate in all cases, and thus demonstrates its ability to combine adaptive learning with safe and robust control. Since integrating confidence estimation can an "uncertainty aware" navigation be achieved, this indicates that integrated confidence estimation offers a way to preserve the benefits of both Learning and Navigation within the same framework [15].

XIII. RESULTS

In this and further section we show the experimental results of a simulation-based validation of the proposed confidence-driven navigation approach. Results are evaluated on increasing levels of sensor noise and compared to learning-based and reactive control baselines. Task success rate and collision frequency are identified as the major robustness and safety evaluations [16].

XIV. TASK SUCCESS RATE

The rate of task success is in a percent from the number of episodes that the robot safely reached its goal before hitting an obstacle above the time limit. This is a general measure of the reliability of navigation in an uncertain world.

As shown in Fig. 3, the task success rate of trick confidence-guided control is always better than other methods as noise level goes up. Low noise in the low noise case, all approaches achieve comparable success and this result supports that navigation through learning is viable when sensors data has a good quality. However, the learning-based controller's performance drops off drastically with higher noise intensity because of its vulnerability to distorted observation and disturbance [17], [18].

The reactive controller is more robust than the learning-based method in noisy settings, but performs less well overall with its conservative policy and weak ability to adapt. In contrast, the suggested confidence-guided approach keeps high success rates under middle and extreme noises by adjusting learning control's contribution flexibility according to predictions confident level [19]. Task success rates achieved by the considered control strategies are quantitatively compared under different noise levels in Table 1.

Table 1. Task success rate (%): under different levels of sensor noise.

Sensor Noise Level	Learning-Based Control	Reactive Control	Confidence-Guided Control
Low	95.0	93.0	96.0
Medium	78.0	85.0	92.0
High	61.0	72.0	88.0

This table presents the success rate of the learning-based, reactive and confidence-directed control methods at varying sensor noise. As shown in Table 1 the confidence-based control policy outperforms baseline methods across all noise level values. The learning-based approach suffers the most drastic performance deterioration with increased sensor noise, while the reactive controller is modestly robust at the cost of not being adaptive. The developed approach strikes a good balance between robustness and flexibility, thus leading to higher navigation reliability under uncertainty.

XV. Collision Rate

The collision rate is the mean of the number of collisions between ego-vehicle and vehicles in an episode, which reflects the safety performance during navigation. Less frequent collisions suggest more robust obstacle evasion, especially in noisy sensing. See Table 2, which shows the collision rate for each control architecture at different sensor noise levels [16], [17].

Table 2. Comparison in collision rate between different control architecture under sensor noise.

Sensor Noise Level	Learning-Based Control	Reactive Control	Confidence-Guided Control
Low	0.08	0.05	0.04
Medium	0.21	0.12	0.07
High	0.39	0.24	0.11

This table shows the average number of collisions per navigation episode for the learning-based, reactive and confidence- guided methods under different noise levels.

From Table 2, collision frequency rises with the increment of sensor noise under all control strategies. The learning-based controller demonstrates the worst performance in terms of collision ratio for medium and high noise, which indicates that while it is input/output robust to partial sensor failures, its behavior with respect to noisy sensory inputs is ambiguous. The high safety performance of the reactive controller in the propositional logic allows us to conclude that its obstacle avoidance behavior being deterministic, is significantly affected by the increase of cases.

On the contrary, confidence-guided control approach consistently results in the least number of collisions even with different levels of noise. This is because it can filter out its unreliable learned actions and select favorable reactive safety behaviors when the prediction confidence becomes low. These findings validate the significant contribution of confidence-weighted arbitration to navigation safety when sensors quality can be uncertain [16].

XVI. Summary of Results

In conclusion, experimental results show that the confidence-guided navigation has better robustness and safety compared to standard learning-based or reactive control methods. Through the direct integration of confidence estimation into control arbitration, the system trades off adaptability and safety, while still being able to provide robust navigation even in presence of very high levels of sensor noise.

XVII. Discussion

The experimental results show that confidence-guided control yields a significant gain in navigation robustness in the presence of uncertain sensors. Because that confidence is transparently measured by monitoring the prediction, this framework can adjust its control in the face of degraded sensory input. As the confidence drops, control authority is increasingly transferred to defensive safety behaviors, enabling the system to counterbalance the effects of possibly insecure learned decisions.

This adaptive transition is essential for avoiding catastrophic failures, which arise often in pure learning-based navigation systems with uncertainty. Rather than deciding to take overconfident but risky actions, the robot keeps conservative and safety-based behavior under low confidence. Meanwhile, the framework can exploit learning-based control freely when sensors are reliable to maintain adaptability and efficiency.

These results support the need of integrating confidence awareness in robotic control architectures. By not treating uncertainty as an afterthought confidence information can be exploited explicitly to balance safety and performance in a principled way, leading to a more reliable autonomous exploration of changing and cluttered scenes.

XVIII. Performance Metrics

The performance of the proposed navigation framework is evaluated using task success rate and collision rate as primary metrics, reflecting navigation reliability and safety, respectively.

The task success rate is defined as the ratio between the number of successful navigation episodes and the total number of evaluation episodes:

$$\text{Success Rate} = \frac{N_{\text{success}}}{N_{\text{total}}} \tag{8}$$

where N_{success} denotes the number of episodes in which the robot successfully reaches the goal without collision, and N_{total} represents the total number of executed navigation episodes.

The collision rate is defined as the average number of collisions per navigation episode:

$$\text{Collision Rate} = \frac{N_{\text{collisions}}}{N_{\text{total}}} \tag{9}$$

where $N_{\text{collisions}}$ represents the total number of collision events observed during evaluation. These metrics provide complementary insights into the robustness and safety of the navigation system under increasing levels of sensor noise and environmental uncertainty.

XIX. Results

Follows the presentation of experimental results acquired by simulation evaluations of the proposed confidence-guided navigation framework in this section. Simulation evaluation The performance of the proposed approach is tested in simulated conditions with varying degrees of sensor noise, and is compared to two baselines: a learning-based controller that operates without a model and an all-reaction-based safety control scheme. The analysis is centered around task success rate, confidence patterns as well as collisions in order to measure robustness and safety.

XX. Task Success Rate

The task success rate denotes the percentage of navigation episodes where the robot successfully reaches the goal without a collision under a time constraint. This measure offers a general picture of navigation stability in response to unreliable sensory cues.

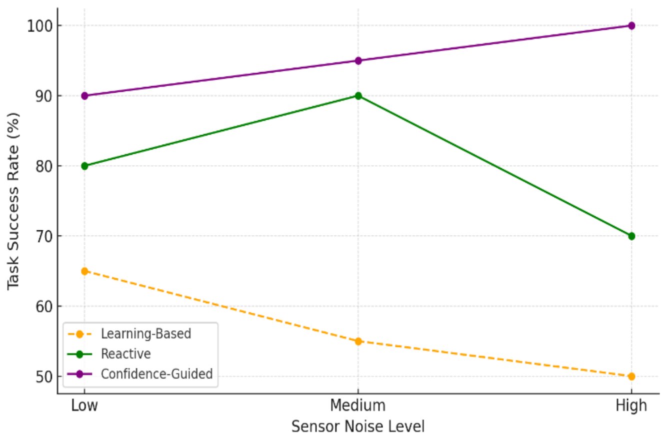

Fig.6 Task success Rate Across Sensor Noise Level

As can be observed from figure 3, all the control strategies attain similar success rates when sensor noise is low, suggesting that learning based navigation can work well if sensory information is also reliable. But as the sensor noise grows, a performance gap becomes apparent. The learning-based controller shows a drastic drop of the success rate in medium and high levels of noise, which is evidence for its vulnerability to corrupted observations and uncertainty in perception.

Compared with reference learning-based method, the proposed reactive controller is more robust to noise that remains smoother. However, it is not as prudent and flexible and thus achieves overall lower rates of success over all noise levels. On the other hand, the proposed confidence-guided navigation framework consistently outperforms all these methods and still achieves the highest task success rate as sensor noise goes up. Through dynamically tuning the influence of learnt control in accordance with prediction confidence, our method maintains robust navigation performance in the face of challenging observations.

We report the task success rate of three types of navigation strategies—learning-based, reactive, and confidence-guided—under different levels of sensor noise, as shown in Figure 6.

The performance is demonstrated and the percentage of the navigation episodes successfully completed is shown on the y-axis, and the x-axis corresponds to the magnitude of sensor's noise (low-medium-high).

The learning-based controller (orange dashed line) behaves quite well at the low noise level, while it gradually decreases as sensor noise increases, indicating that it is sensitive to perception uncertainty. The performance of the reactive controller (green line) is high at low and moderate noise because of its very cautiousness nature, but it drops heavily under a high noise due to its limited adaptively.

On the contrary, the blue line decreases sharply under various noise conditions while confidence-guided controller (purple line) holds not only highest success rate but also better usability in all types of noises. This showcases its capacity to dynamically moderate learning-based control's influence and then fallback to more cautious reactive behavior is confidence is not high enough, leading to robust navigation under uncertainty.

XXI. CONFIDENCE DYNAMICS

Besides the overall performances, also the dynamics of the confidence signal yields relevant information about how our approach adjusts to new environmental conditions. For this purpose, the evolution of the confidence feedback c(t) is studied over time within a typical navigation episode.

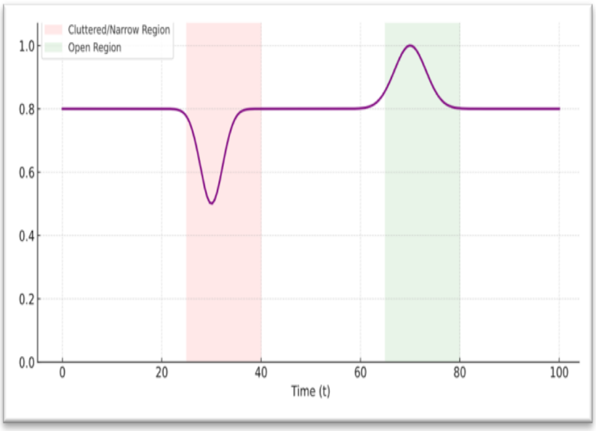

Fig.7. Temporal Evolution of Confidence Signal During Navigation

As illustrated in Figure 4, the X-axis corresponds to time and Y-axis gives us an estimated confidence value c(t) between 0 and 1. In the beginning of the navigation episode, confidence is rather high which is indicative to reliable perception and decision making while moving through free space in the environment. A sharp drop in confidence is detected when the robot moves into a small overgrown area, depicted as the shaded red interval in Figure 4. This decrease may be attributed to the growing uncertainty introduced by the nearby obstacle and the reduced sensorimotor states. During that period, the resulting lack of confidence emerges into a more dominated behavior from the reactive safety controller in order for the system to perform more limited (conservative) and "safe" maneuvers. The robot exits the clutters region approaching that to the open space (shaded green area in Figure 4) and the confidence value consistently increase over time and level off at a higher threshold than before. This rise indicates increase of sensory reliability and re-enables influence of the learning-based controller resulting in an improved navigation efficiency. Notably, the trajectory of confidence changes gradually and smoothly instead of jumping abruptly. The behavior demonstrates that the proposed transient confidence smoothness mechanism is effective and that control authority is changing in a stable and consistent way when the environment is changed. In summary, the time course of the confidence signal provides empirical support for the idea that our framework captures relevant changes in uncertainty and mediates adaptive, online control behavior during navigation.

XXII. COLLISION RATE

The collision rate is the mean number of collisions per navigation episode and is an important indicator for safety in navigation. A more reliable dodging behavior can be achieved by reducing the collision rate (especially under uncertain sensory regimes).

The collision frequency with each different control strategy and a variety of levels of sensor noise is shown in Table 2. As observed from the results, for all controllers when the sensor noise is more severe there will be an increase in the number of collisions. The learning controller has the highest collision rates in both medium and high noise, showing it is less robust with unreliable sensory inputs.

The reactive controller experiences fewer collisions than the learning based strategy because of its deterministic obstacle avoidance behavior. But it still does not avoid a significant increase in collisions when strong noise is present. In comparison, the navigation framework with confidence always shows better collision rate than other methods whatever level of noise. This better performance can be explained by its ability to avoid unreliable learned actions and favour reactive safety behaviors when confidence diminishes.

XXIII. SUMMARY OF RESULTS

In summary, experimental results show that our confidence-guided navigation framework has better robustness and safety than learning based/reactive control methods. The system successfully balances between adaptability and safety by explicitly integrating confidence estimation with control arbitration. The framework achieves high task success rates, shows informative trust dynamics, and remarkably reduces collision rate as sensor noise increases which validate the effectiveness of using it for trusted autonomous navigation in unknown environments.

CONCLUSION AND FUTURE WORK

This paper proposed a confidence-based on-line adaptive navigation scheme for resource-investigating mobile robots equipped with noisy sensors. The learning based navigation and reactive safety control are in turn combined following a confidence-aware arbitration scheme which permits the dynamic adjustment of controllability according to the reliability learned decisions and sensorial observations.

Simulation-based experiments in Gazebo environment show that the proposed framework considerably boosts navigation robustness and safety with respect to only learning based, and reactive control policies. The results demonstrate that increased sensor noise leads to reduced task success rates and higher collision frequencies, however including confidence values explicitly in the controller loop successfully settles the effects of uncertainty.

The results of this work found the significance of uncertainty-awareness in robotic autonomous systems and their interactions. Dynamic Allocation Buffering allows control to be moved towards safety minded proactive behavior when confidence erodes and yet avoids catastrophic failures while keeping adaptability under favorable conditions. This trade-off between safety at horsepower is crucial to enable PI based robust autonomous navigation in unstructured and vying conditions.

As future work, the proposed framework will be extended to learn confidence in online and by adaptive threshold. Verification on the robotic platforms in the physical world will also be demonstrated to judge deployment obstacles outside of simulation. Furthermore, the exploration of confidence-sensitive coordination in multi-robot systems and richer formulations of uncertainty estimation is a promising area for future work.

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