Trustworthy Multi-UAV Collaboration: A Self-Supervised Framework for Explainable and Adversarially Robust Decision-Making

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Abstract

Ensuring trustworthiness in multi-UAV collaboration is essential for deploying autonomous aerial systems in safety-critical applications such as search and rescue, environmental monitoring, and infrastructure inspection. However, UAV decision-making remains opaque and susceptible to perception inconsistencies, sensor noise, and network uncertainties, undermining reliability in real-world scenarios. To address these challenges, we propose a self-supervised framework for explainable and robust multi-UAV decision-making, enabling UAVs to generate interpretable confidence assessments, verify internal consistency, and dynamically adjust decision thresholds based on environmental conditions and mission dynamics. Mutual verification through external consistency validation ensures alignment in perception and decision logic while mitigating the effects of sensor noise and adversarial perturbations. Additionally, our dynamic network adaptation mechanism adjusts confidence propagation weights and seamlessly integrates new agents, preserving decision stability despite fleet variations. We formalize this framework through rigorous mathematical modeling, proving that confidence updates remain bounded and self-regulating, that multi-UAV consensus is consistently achievable, and that system-wide decision adaptation remains stable under operational uncertainties. By enhancing interpretability, adaptability, and robustness, this framework lays the foundation for advancing trustworthy autonomous multi-agent systems in complex real-world applications.

1. Introduction

Despite significant advances in UAV and AI technologies, the inherent opacity of deep learning models remains a critical challenge in achieving trustworthy and robust UAV collaboration [8, 16, 23]. Deep learning models, widely employed for autonomous perception and decision-making, often function as "black boxes," obscuring the rationale behind their decisions and impeding reliability assessments [9, 56, 74]. In safety-critical UAV applications such as search and rescue [1, 21, 81], environmental monitoring [14, 28, 50, 85], and infrastructure inspection [4, 12, 49, 64], the lack of decision transparency raises fundamental concerns regarding accountability, safety, and adaptability. UAVs are expected to operate autonomously in dynamic and uncertain environments; however, without a structured mechanism for explaining and verifying their decisions, neither human operators nor collaborating UAVs can reliably assess the correctness, appropriateness, or robustness of their actions [40, 41]. This opacity not only undermines trust in UAV-based autonomous systems but also limits their capacity to justify critical decisions, a crucial requirement in high-stakes missions [31, 68].

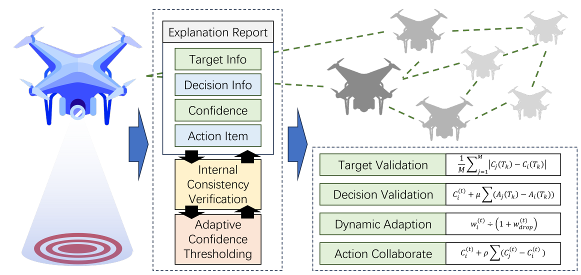

Figure 1. The proposed framework for multi-UAV collaboration enables robust and adaptive decision-making. Each UAV autonomously generates an explanation report, verifies its confidence through internal consistency checks, and dynamically adjusts its decision threshold before sharing information with the team. The multi-UAV network then conducts target confirmation, decision validation, and consensus refinement, ensuring coordinated and resilient operations while adapting to dynamic network conditions.

The challenge is further exacerbated in multi-UAV systems, where agents must coordinate and make collective decisions based on distributed, potentially inconsistent information [59, 66]. Each UAV operates with its own sensors, models, and environmental understanding, leading to variations in confidence estimation, perception accuracy, and action selection. Unaddressed inconsistencies can disrupt mission execution, induce inter-agent conflicts, and create vulnerabilities to adversarial manipulations [6, 15, 80, 90]. The absence of a formalized cross-UAV verification mechanism compounds these risks, as UAVs may reach conflicting conclusions, resulting in miscommunication, decision divergence, or mission failure [39, 45, 89]. Ensuring robust and explainable decision-making in collaborative UAV systems is therefore imperative, as UAVs must not only adapt to dynamic environments but also defend against adversarial threats that exploit decision inconsistencies [29, 42, 44, 78].

Another fundamental challenge arises from the ever-changing nature of real-world UAV operations. UAVs frequently operate in complex, unpredictable, and noisy environments where external factors—such as fog, smoke, high winds, or electromagnetic interference—degrade sensor performance, leading to incomplete, erroneous, or conflicting observations [3, 10, 54, 65, 75]. Even state-of-the-art deep learning models struggle under such conditions, as their inputs may be inherently noisy, sparse, or adversarially perturbed. Additionally, real-time UAV decision-making introduces further complexity, requiring continuous confidence evaluation, inter-UAV consistency verification, and adaptive decision-making under evolving mission constraints [7, 25, 59, 60]. Without a structured framework for real-time confidence adjustment, cross-UAV validation, and collaborative decision adaptation, UAV fleets risk operational incoherence, compromising mission success in high-stakes deployments [48].

To address these challenges, we propose a mathematically grounded framework for trustworthy multi-UAV collaboration, integrating explainable self-supervision, multi-agent consensus verification, and dynamic decision adaptation to enhance the robustness, interpretability, and adaptability of UAV-based decision-making. Each UAV autonomously generates an explanation report, documenting confidence scores, decision rationales, and proposed actions, forming the basis for internal consistency verification and external peer validation. Through multi-perspective, multi-sensor fusion, UAVs conduct secondary target detection confirmation, decision process validation, and coordinated consensus formation, thereby reducing uncertainty and improving decision reliability. Furthermore, our framework incorporates a dynamic confidence adaptation mechanism, allowing UAVs to adjust decision thresholds and influence weights as agents join or leave the mission, ensuring decision resilience and stability under varying conditions.

This work provides a rigorous mathematical formulation of multi-UAV confidence evaluation and collaborative decision-making, proving that confidence updates remain bounded and self-regulating, that multi-UAV consensus is consistently achievable, and that system-wide decision stability is preserved under sensor perturbations, network fluctuations, and environmental uncertainties. By integrating explainable self-supervision, collaborative verification, and dynamic decision adaptation, our framework establishes a foundation for trustworthy multi-UAV collaboration, contributing to the development of robust, interpretable, and resilient UAV autonomy in safety-critical applications.

The contributions of this paper are summarized as follows:

- We propose a self-supervised confidence evaluation framework, enabling UAVs to generate and utilize explanation reports to enhance decision transparency and interpretability.
- We introduce a multi-UAV external consistency verification mechanism, allowing UAVs to perform mutual validation, multi-perspective target confirmation, and collaborative decision alignment, thereby improving mission robustness and reliability.
- We develop a dynamic confidence adaptation strategy, enabling UAVs to adjust decision thresholds based on environmental changes, sensor reliability, and network conditions, ensuring adaptability in real-world UAV operations.
- We provide a rigorous mathematical formulation of the framework, ensuring that confidence evaluation, decision-making, and UAV coordination remain stable, convergent, and robust under operational uncertainties.

2. Related Work

2.1. Trustworthy Decision-Making in Multi-UAV Systems

Ensuring trustworthiness in autonomous UAV decision-making is a fundamental challenge, particularly in safety-critical applications where erroneous or non-interpretable decisions can lead to mission failure. Traditional UAV decision frameworks often rely on rule-based logic or probabilistic models [36, 67, 70], which lack adaptability in complex and uncertain environments. While explainable AI (XAI) approaches have been explored to enhance UAV decision transparency, most methods focus on post-hoc interpretation rather than embedding explainability within the decision-making process itself [2, 5, 17, 32, 62, 71, 86].

Existing trust modeling in multi-agent systems frequently employs Bayesian inference or graph-based trust estimation [24, 27, 55, 61, 72, 82], yet these approaches do not explicitly address how individual UAVs should internally validate their confidence levels before making mission-critical decisions [43, 69, 76]. Furthermore, many prior methods assume static confidence assessments, overlooking the necessity of real-time adaptation to dynamic operational conditions [19, 33, 34, 77].

In contrast, our framework introduces a self-supervised confidence evaluation mechanism, enabling UAVs to generate explanation reports and verify internal consistency before sharing decisions. By integrating adaptive confidence thresholding, UAVs dynamically adjust their decision reliability in response to environmental complexity, improving the trustworthiness of autonomous UAV operations.

2.2. Consensus Mechanisms and Collaborative Verification in UAV Networks

Multi-UAV collaboration hinges on effective information sharing and decision consensus, yet existing frameworks often suffer from sensor inconsistencies, misaligned perceptions, and conflicting action strategies [33, 34, 77]. Traditional consensus algorithms, such as distributed Kalman filters [26, 51, 88] and consensus-based belief propagation [11, 37, 38, 48, 53], typically assume homogeneous and synchronized observations, an assumption rarely met in real-world deployments.

Recent advances in distributed decision-making have explored cross-UAV verification and multi-view fusion techniques to mitigate perception inconsistencies [39, 66, 79, 89, 90]. However, many of these methods rely on predefined confidence models, rendering them inflexible to environmental variations [6, 20, 22, 57, 63], or lack a structured framework for resolving decision conflicts through iterative peer validation [13, 35].

Our framework advances these efforts by introducing multi-UAV external consistency verification, where UAVs not only share explanation reports but also perform secondary target detection confirmation and decision process validation to refine mission-critical decisions. By leveraging multi-perspective cross-verification and adaptive consensus refinement, our approach enhances collaborative decision alignment, mitigating the impact of sensor uncertainty and adversarial perturbations.

2.3. Dynamic Confidence Adaptation in UAV Systems

In real-world multi-UAV networks, confidence estimation must be adaptive to account for environmental noise, agent fluctuations, and task uncertainties. Most existing confidence estimation techniques rely on fixed thresholds that fail to adjust dynamically to network conditions or evolving mission demands [18, 42, 52, 73]. While some studies have explored confidence propagation in multi-agent systems, they often assume static UAV networks, where agents do not dynamically enter or leave [15, 58, 80, 87].

Another limitation of prior research is the absence of a resilient confidence adjustment strategy for handling inconsistent observations. Existing belief update models apply heuristic weighting but do not incorporate real-time adjustments based on UAV network evolution [30, 46, 47, 83, 84].

Our proposed dynamic confidence adaptation mechanism allows UAVs to adjust decision thresholds, update confidence propagation weights, and reallocate influence based on mission needs. By formulating confidence adaptation as a bounded, self-regulating process, we ensure that UAV networks maintain stability and decision robustness despite sensor perturbations, UAV departures, and task complexity variations.

3. Framework for Trustworthy Multi-UAV Collaboration

Ensuring the trustworthiness and robustness of UAV collaboration in autonomous missions remains a fundamental challenge, particularly in safety-critical applications such as search and rescue, environmental monitoring, and infrastructure inspection. Traditional UAV decision architectures often lack transparency and explainability, complicating verification and validation in complex environments. While deep learning-based UAV systems offer powerful perception and decision-making capabilities, their black-box nature and susceptibility to uncertainty and adversarial perturbations limit their reliability. Addressing these challenges requires a structured approach in which each UAV not only evaluates its own decision confidence but also engages in collaborative verification to ensure mission-level consistency.

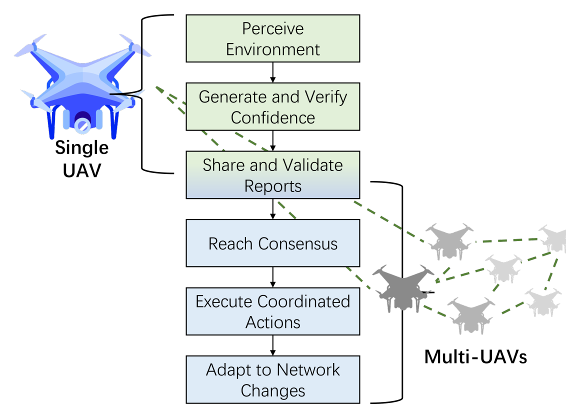

Figure 2. Each UAV autonomously generates an explanation report, validates its confidence through internal verification, and shares the report with the UAV network. The multi-UAV system then conducts target verification, decision alignment, and consensus formation, ensuring robust collaboration despite uncertainties. The framework dynamically adapts to network fluctuations and environmental variations, maintaining stability and resilience in UAV operations.

To this end, we propose a multi-level explainability and robustness framework (Fig. 2) that integrates self-supervised confidence evaluation at the individual UAV level with external consistency verification at the system level. This framework enables UAVs to autonomously generate and validate interpretable decision reports, dynamically adapt their confidence thresholds, and achieve multi-UAV consensus, thereby enhancing mission robustness.

3.1. Single-UAV Confidence Evaluation and Decision-Making

At the individual level, each UAV must assess the reliability of its own observations and decisions. Given the uncertainties inherent in real-world environments, UAV decision-making is influenced by sensor noise, environmental variability, and adversarial disturbances. To mitigate these effects, each UAV follows a structured self-supervised confidence evaluation process (Fig. 3), allowing it to autonomously generate, validate, and refine its decision-making through explainability-driven self-assessment.

Each UAV first generates an *explanation report*, which serves as a transparent record of its decision-making process. This report includes target characteristics, estimated position, predicted confidence scores, decision rationale, and the reasoning behind its autonomous action selection. By explicitly documenting its decision process, the UAV creates a structured representation that can be internally validated and later shared with collaborating UAVs for collective verification.

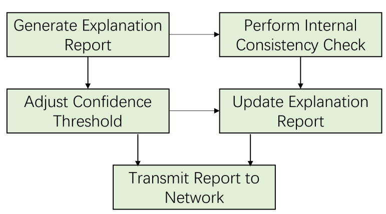

Figure 3. A UAV first perceives its environment, generates an explanation report, and performs internal consistency verification to refine its confidence assessment. It then dynamically adjusts its confidence threshold in response to environmental conditions and mission requirements. Once validated, the UAV updates its report and shares it with the network, ensuring transparent, adaptive, and reliable decision-making.

Following report generation, the UAV conducts *internal consistency verification* to ensure that its conclusions align with sensory inputs and contextual understanding. This involves cross-referencing confidence scores with raw sensor data to validate whether the assigned confidence level is supported by available evidence. If discrepancies arise, the UAV refines its confidence estimates and updates its report accordingly.

Once internal validation is complete, the UAV applies a *self-adaptive confidence thresholding mechanism*, dynamically adjusting decision thresholds based on environmental conditions and prior performance. This ensures that decision thresholds remain optimal across different operational contexts. Once confidence assessment stabilizes, the UAV refines its explanation report and prepares it for dissemination to other UAVs for external validation.

3.2. Multi-UAV Collaborative Decision-Making

While self-assessment is crucial, it alone does not guarantee system-wide robustness. UAVs must engage in *external consistency verification*, wherein each UAV shares its explanation report with collaborating UAVs to achieve system-wide agreement. This process ensures collective verification of observations, alignment of decisions, and coordinated execution of mission tasks.

Upon receiving an explanation report from a peer UAV, collaborating UAVs initiate external consistency verification, which consists of two key components: *target detection validation* and *decision process validation*.

During *target detection validation*, UAVs leverage multi-angle perspectives and heterogeneous sensing modalities (e.g., infrared, LiDAR, radar) to cross-check reported observations. Since UAVs operate from different viewpoints, their collective assessment provides a more comprehensive verification of the detected target. If shared confidence assessments align with the initial detection report, the target identification is confirmed; otherwise, additional verification steps are triggered.

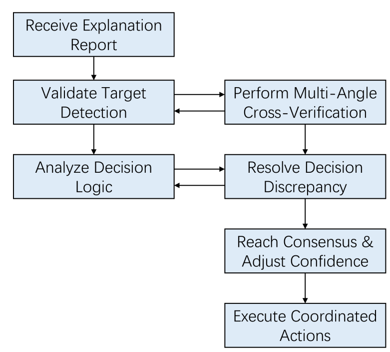

Figure 4. Upon receiving explanation reports, UAVs perform multi-angle target confirmation and decision validation to resolve discrepancies and enhance collective confidence. The system then refines decision weights and consensus alignment, ensuring coordinated UAV actions. Additionally, UAVs adapt to network fluctuations, maintaining stable operations in dynamic environments.

Following target detection validation, UAVs perform *decision process validation*, ensuring that the reported decision rationale is logically sound and aligned with mission objectives. Each UAV independently assesses whether the reasoning presented in the explanation report is consistent with its own situational understanding. If inconsistencies arise, the system initiates a secondary verification process to resolve discrepancies before finalizing an action plan.

Once both validation phases are complete, UAVs transition to *collaborative decision execution*, aligning their movements, resource allocations, and operational behaviors based on the validated explanation reports. This coordination ensures that all UAVs execute tasks in harmony, maintaining system-level robustness and adaptability despite environmental uncertainties and potential adversarial interferences.

Through this structured explainability-driven, self-supervised, and collaborative verification approach, the proposed framework enhances multi-UAV decision transparency, reliability, and resilience. It enables UAV teams to execute missions with high confidence, even in dynamic and uncertain conditions.

4. Methodology

To ensure trustworthy and robust UAV decision-making, we propose a self-supervised confidence evaluation framework that integrates explanation-based decision verification, multi-UAV consistency validation, and dynamic confidence thresholding. This section details the core methodology, focusing on internal and external consistency verification mechanisms that enhance decision reliability.

4.1. Explainable Self-Supervision Mechanism

Ensuring decision transparency and robustness in autonomous UAV operations requires a self-supervised confidence evaluation mechanism that enables UAVs to generate, validate, and refine their decision-making process. This mechanism is essential in dynamic environments where UAVs must operate under sensor uncertainties, adversarial perturbations, and mission constraints, necessitating both internal confidence evaluation and consistency verification before engaging in collaborative decision-making.

4.1.1. Confidence Report Generation and Internal Consistency Verification

Each UAV generates an *explanation report* that documents key aspects of its detection and decision-making process. This report serves as a structured decision trace, enabling the UAV to perform internal consistency verification before sharing its observations with other UAVs.

To verify internal consistency, the UAV cross-references its confidence assessments across different sensing modalities and historical data. If inconsistencies arise—such as discrepancies between a target's observed attributes and expected classification—the UAV updates its confidence evaluation to prevent overconfidence.

Formally, given an initial confidence estimate $C_i(T_k)$ for a detected target T_k, the UAV adjusts its self-assessment by incorporating verification results from its internal consistency check:

$$C_i^{(t+1)} = C_i^{(t)} + \lambda(C_{\text{self}}^{(t)} - C_i^{(t)}) \tag{1}$$

where $C_{\text{self}}^{(t)}$ represents the expected confidence based on prior observations and multimodal validation.

The internal consistency check evaluates whether the confidence deviation remains within an acceptable range:

$$D_{\text{self}} = |C_i(T_k) - C_{\text{self}}(T_k)| \tag{2}$$

where D_{self} represents the discrepancy between the UAV's self-evaluated confidence and the expected confidence derived from historical observations. To ensure consistency, the UAV defines a self-consistency threshold δ_{self}, where:

$$D_{\text{self}} \leq \delta_{\text{self}} \tag{3}$$

If $D_{\text{self}} > \delta_{\text{self}}$, the UAV updates its explainability report by refining its confidence estimate:

$$C_i^{(t+1)} = C_i^{(t)} + \gamma(C_{\text{self}}^{(t)} - C_i^{(t)}) \tag{4}$$

where γ controls the rate of self-correction. This ensures that confidence updates remain bounded and self-correcting, reducing the likelihood of misclassification errors.

4.1.2. Adaptive Confidence Thresholding

Environmental factors such as visibility, electromagnetic interference, and terrain complexity significantly impact sensor reliability. A static confidence threshold may lead to overconfidence in noisy conditions or excessive conservatism in optimal environments, thereby reducing mission efficiency. To mitigate these issues, UAVs employ an *adaptive confidence thresholding* mechanism, dynamically adjusting decision criteria based on environmental feedback.

The UAV's confidence threshold $\theta_i^{(t+1)}$ is updated iteratively:

$$\theta_i^{(t+1)} = \theta_i^{(t)} + \beta \sum_{j \neq i} (C_j(T_k) - C_i(T_k)) \tag{5}$$

where $C_j(T_k)$ represents confidence scores from other sensing perspectives, and β controls the adaptation rate.

This mechanism ensures that the UAV's decision-making remains context-aware, reducing false positives in challenging environments while allowing for faster decision-making in clear conditions.

The updated confidence threshold is evaluated against an environmental adaptation factor:

$$\theta_i^{(t+1)} = \theta_i^{(t)} + \eta(E_i - \bar{E}) \tag{6}$$

where E_i represents environmental complexity (e.g., noise level, visibility conditions), and $\bar{E}$ is the historical mean environmental complexity. This allows UAVs to refine their thresholds dynamically, ensuring resilience under varying conditions.

Following these adjustments, the UAV updates its explainability report, integrating refined confidence estimates and revised decision justifications before engaging in multi-UAV collaboration.

4.2. Multi-UAV Consistency Verification

While individual UAVs perform self-assessment, their perception is inherently limited by sensor perspectives, environmental uncertainties, and adversarial factors. To enhance system-wide robustness, UAVs engage in *external consistency verification*, where they compare explainability reports, validate detected targets, assess decision rationales, and achieve consensus-driven action execution.

The verification process consists of three stages: secondary target detection confirmation, decision process validation, and collaborative decision-making. These stages ensure that UAVs compensate for individual sensor limitations while reinforcing system-wide trustworthiness.

4.2.1. Secondary Target Detection Confirmation

Since UAV detections are subject to sensor noise and environmental interference, all detected targets must undergo secondary verification from multiple UAVs. When a UAV i detects a target T_k, it shares its explainability report with other UAVs in the mission, which independently verify the detection using different viewing angles, sensing modalities (e.g., infrared, LiDAR, radar), and real-time environmental feedback.

The verification process involves computing a cross-UAV confidence discrepancy measure:

$$D_{\text{consistency}} = \frac{1}{M} \sum_{j=1}^{M} |C_j(T_k) - C_i(T_k)| \tag{7}$$

where M represents the number of UAVs participating in the verification, and $C_j(T_k)$ is the confidence score assigned by UAV j.

A consistency threshold δ_{target} is defined as the maximum allowable deviation in confidence scores across UAVs:

$$D_{\text{consistency}} \leq \delta_{\text{target}} \tag{8}$$

If the discrepancy exceeds δ_{target}, indicating inconsistencies in detection confidence, additional UAVs are requested to reassess the target. The final aggregated confidence score is computed as:

$$C_{\text{collab}}(T_k) = \frac{1}{M} \sum_{j=1}^{M} C_j(T_k) \tag{9}$$

ensuring that UAVs collectively validate detections while mitigating individual errors.

To further enhance robustness, the system reweights UAV contributions based on sensor reliability:

$$C_{\text{weighted}}(T_k) = \sum_{j=1}^{M} w_j C_j(T_k) \tag{10}$$

where w_j represents the reliability weight assigned to UAV j, ensuring that higher-quality observations contribute more significantly to final decisions.

If consensus is reached, the detected target is confirmed; otherwise, UAVs may initiate additional reconnaissance actions to clarify ambiguities.

4.2.2. Decision Process Validation

Beyond verifying the detected target, UAVs must ensure that the decision logic leading to action selection is internally and externally consistent. Each UAV cross-validates its decision rationale by comparing its predicted action $A_i(T_k)$ with those of other UAVs. The decision consistency measure is given by:

$$D_{\text{decision}} = \frac{1}{M} \sum_{j=1}^{M} \|A_j(T_k) - A_i(T_k)\| \tag{11}$$

where $A_i(T_k)$ represents the decision vector proposed by UAV j, and $\| \cdot \|$ denotes a norm that quantifies decision alignment.

If $D_{\text{decision}} > \delta_{\text{decision}}$ UAVs reassess their decisions and refine their explainability reports. To enforce decision consistency, UAVs engage in causal inference analysis, ensuring their justifications align with mission objectives. If a UAV's reasoning significantly diverges from fleet consensus, its confidence score is adjusted:

$$C_i^{(t+1)} = C_i^{(t)} + \mu \sum_{j \neq i} (A_j(T_k) - A_i(T_k)) \tag{12}$$

where μ is the adaptation coefficient ensuring that UAV decisions converge towards a logically consistent framework.

4.2.3. Collaborative Decision-Making

Once target detection and decision validation are completed, UAVs coordinate their actions based on validated explanation reports. The final decision is refined using a weighted consensus update rule:

$$A_{\text{final}}(T_k) = \sum_{j=1}^{M} w_j A_j(T_k) \tag{13}$$

where UAVs dynamically adjust decision weights to minimize inconsistencies and ensure optimal mission execution.

Through this structured verification-driven decision-making, UAV teams achieve a robust, coordinated, and adversarially resilient operational framework, enhancing reliability in safety-critical missions.

4.3. Dynamic Multi-UAV Network Adaptation

Real-world UAV deployments are inherently dynamic, requiring UAV teams to continuously adapt to changes in fleet composition, environmental conditions, and mission objectives. Unlike static decision frameworks that assume a fixed fleet operating under stable conditions, an adaptive UAV system must account for dynamic task allocation, variable agent participation, and evolving decision confidence. This section introduces a multi-UAV adaptation mechanism that ensures decision reliability remains robust even as UAVs enter, exit, or adjust their confidence models in response to environmental shifts.

The adaptation framework comprises three key components: dynamic UAV influence reweighting, distributed confidence propagation, and stability guarantees in dynamic networks. These mechanisms collectively ensure that UAV teams remain cohesive, resilient, and operationally robust, preventing confidence oscillations or mission failures due to network fluctuations.

4.3.1. UAV Network Dynamics and Influence Reweighting

UAV networks are inherently dynamic, with agents joining and leaving the mission space due to operational constraints, resource depletion, or emergency reallocation. If UAV decision models remain static, abrupt changes in fleet composition can introduce confidence inconsistencies and degrade mission performance. To prevent such instabilities, the system continuously reweights UAV influence based on participation status and decision reliability.

Formally, given a fleet of $M(t)$ UAVs at time t, the system maintains a dynamically updated confidence weighting factor for each UAV i, denoted as $w_i(t)$. The confidence weight is computed as:

$$w_i^{(t+1)} = \frac{w_i^{(t)}}{1 + w_{\text{drop}}^{(t)}} \tag{14}$$

where $w_{\text{drop}}^{(t)}$ represents the influence lost due to UAV departures. If a UAV leaves the network, its previous contributions are redistributed across remaining UAVs, ensuring that confidence estimation remains stable.

Similarly, when a new UAV joins the system, its confidence contribution is initialized as:

$$w_{\text{new}}^{(t+1)} = \frac{\alpha}{M(t+1)} \tag{15}$$

where α is a scaling factor ensuring that new UAVs gradually integrate into the fleet without causing abrupt confidence shifts.

Through this dynamic influence reweighting mechanism, the system adapts seamlessly to network changes, mitigating instabilities due to UAV entry or exit while preserving robust confidence aggregation.

4.3.2. Confidence Propagation and Distributed Adjustment

In a dynamically evolving UAV network, decision confidence must be continuously propagated and adjusted to maintain mission-wide consistency. Each UAV maintains an evolving confidence score $C_i(T_k)$, which is updated using a distributed consensus mechanism.

Given the previous consensus confidence $C_{\text{collab}}^{(t)}$, the confidence update rule under network changes is:

$$C_{\text{collab}}^{(t+1)} = C_{\text{collab}}^{(t)} + \lambda \sum_{j=1}^{M(t+1)} w_j (C_j^{(t)} - C_{\text{collab}}^{(t)}) \tag{16}$$

where λ controls the adjustment rate, and w_j represents the reweighted influence factor introduced in 4.3.1.

If significant inconsistencies arise due to network fluctuations, UAVs iteratively refine their confidence values through a stability-controlled diffusion process:

$$C_i^{(t+1)} = C_i^{(t)} + \rho \sum_{j \neq i} (C_j^{(t)} - C_i^{(t)}) \tag{17}$$

where ρ is the diffusion coefficient ensuring that confidence propagation remains bounded and non-divergent.

This distributed confidence propagation mechanism maintains decision coherence across UAVs, preventing mission disruptions due to misaligned decision-making or delayed confidence adjustments.

4.3.3. Stability Guarantees in Dynamic Networks

To ensure the proposed UAV adaptation framework remains stable under continuous network fluctuations, we analyze the boundedness and convergence properties of the confidence update mechanism.

A necessary condition for system stability is that confidence adjustments must not amplify oscillations or induce instability in decision consensus. This is achieved when the confidence deviation variance satisfies:

$$\text{Var}[C_{\text{collab}}^{(t+1)}] = (1 - \lambda W_{\text{eff}}^{(t)})^2 \text{Var}[C_{\text{collab}}^{(t)}] + \text{Var}[\xi^{(t)}] \tag{18}$$

where $W_{\text{eff}}^{(t)}$ is the dynamically adjusted weight factor, and $\xi^{(t)}$ represents external perturbations.

To ensure long-term stability and bounded confidence variance, the adaptation parameters must satisfy:

$$0 < \lambda W_{\text{eff}}^{(t)} < 2, \quad \forall t \tag{19}$$

which guarantees that confidence updates remain self-correcting rather than oscillatory or divergent. Additionally, the UAV network topology must preserve a connected graph structure, ensuring that all UAVs receive sufficient confidence propagation signals to maintain decision consistency.

By satisfying these stability conditions, the system prevents unbounded confidence drift, ensuring that UAV networks remain resilient to agent fluctuations while maintaining decision coherence across missions.

Thus, the proposed *Dynamic Multi-UAV Network Adaptation Mechanism* provides a mathematically grounded approach for resilient confidence evaluation, self-regulating UAV influence, and stable mission execution, forming a comprehensive theoretical foundation for trustworthy UAV collaboration.

5. Discussion and Conclusion

This paper presents a theoretical framework for multi-UAV confidence evaluation and collaborative decision-making, ensuring robustness, adaptability, and consistency in dynamic, uncertain environments. The proposed self-supervised confidence evaluation mechanism enables UAVs to generate explainable confidence reports, validate their decisions through internal consistency checks, and adaptively adjust decision thresholds. Furthermore, external consistency verification allows UAVs to engage in mutual validation, enhancing collective decision accuracy while mitigating sensor noise and adversarial perturbations.

By rigorously modeling dynamic network adaptation, we ensure that UAV teams remain resilient to agent fluctuations, enabling seamless integration of new UAVs and reallocation of decision influence when UAVs depart. The mathematical formulation of confidence updates and decision propagation establishes theoretical guarantees for bounded confidence variance, convergence of multi-UAV consensus, and long-term system stability under real-world operational constraints.

Despite these theoretical guarantees, several practical challenges remain. First, while our framework assumes that UAVs can estimate confidence levels with reasonable accuracy, real-world sensor limitations, environmental noise, and adversarial attacks may introduce biases that affect decision reliability. Second, our approach ensures stability under cooperative conditions but does not explicitly address scenarios involving malicious UAVs or adversarial interference. Future research should explore integrating trust modeling and adversarial robustness strategies to mitigate deceptive confidence updates.

Additionally, real-world multi-UAV systems often encounter communication delays, bandwidth limitations, and asynchronous decision cycles, which may affect the efficiency of distributed confidence propagation. Future work will focus on extending the framework to incorporate network-aware confidence adjustments, ensuring effective coordination despite communication constraints. Furthermore, exploring machine learning-driven confidence calibration, real-time consensus optimization, and hybrid trust-aware mechanisms will further enhance UAV collaboration in safety-critical applications.

By providing a rigorous theoretical foundation for trustworthy UAV decision-making, this work advances interpretable, resilient, and adversarially robust autonomous multi-agent systems, contributing to the broader development of trustworthy foundation models in autonomous vision applications.

6. Acknowledgments

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