Narrative Review Article

Integrating Star Fixes into Multi-Drone Localization Frameworks

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ABSTRACT

Celestial navigation has recently matured into a viable backup for Unmanned Aerial Vehicle positioning, while collaborative localization frameworks have shown the benefits of sharing relative and absolute measurements across swarms. Yet, integrating star-based fixes into multi-drone architectures remains largely unstudied. This review provides an overview of work on single-platform celestial sensing, cooperative localization, and analogous leader–follower systems, and synthesizes the results to predict that sparse, asynchronous celestial star fixes, injected as absolute factors into a distributed collaborative estimator and scheduled by sky-aware planners, could achieve sub-kilometer accuracy over day-long Global Navigation Satellite Systems (GNSS) outages and surpass the capability of any single drone. To achieve this, swarm-level celestial fusion could exploit spatial diversity, temporal compression, and drift-limiting loop closures. Key research gaps remain in confirming this prediction with experimental testing, optimal sensor distribution, the balance between inter-drone and celestial measurement noise, and ensuring sky visibility through information-aware planning. Addressing these challenges is critical for building resilient positioning systems in GNSS-denied environments.

Keywords: Physics and Astronomy; Celestial Navigation (CELNAV); Collaborative Localization; GNSS-Denied Navigation; Unmanned Aerial Vehicles (UAVs)

INTRODUCTION

Unmanned Aerial Vehicles (UAVs), or drones, are aircraft flown without a human pilot onboard. They rely heavily on Global Navigation Satellite Systems (GNSS), such as the Global Positioning System (GPS), to determine their position and orientation. However, GNSS signals can be blocked by terrain, disrupted by weather, or intentionally jammed, leaving UAVs without reliable navigation (1, 2). This challenge motivates the search for alternative methods that can provide accurate, resilient positioning in GNSS-denied environments (1, 2).

With celestial navigation (CELNAV), onboard cameras called star sensors identify patterns in the night sky to provide absolute orientation or position fixes (3-6). CELNAV is highly accurate but requires clear sky conditions and relatively long exposures to capture dim stars (3, 4, 7, 8). Another promising approach is collaborative localization, in which multiple UAVs exchange relative measurements—such as inter-drone distance, bearing, or visual features—along with their own local estimates (9-11). By working together,

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swarms reduce drift and improve reliability, even when individual drones face sensing limitations (9-17).

The studies cited in this paper frame a prediction we encourage future research to test: when occasional celestial absolute estimates are shared through a collaborative estimator, the swarm may realize accuracy–throughput trade-offs unattainable by either CELNAV or collaborative localization alone. Conceptually, CELNAV supplies sparse global anchors while collaborative localization distributes their benefit, and planners create the conditions under which those anchors can be obtained with minimal mission impact (1, 3-5, 9, 11, 18). A swarm can share occasional star fixes obtained by some drones while others continue mission tasks, leveraging spatial diversity, temporal efficiency, and drift correction across the group (3, 5, 9, 12, 15, 19). Figure 1 provides a conceptual overview of this integration, showing how celestial navigation contributes absolute fixes that flow through multi-drone cooperative localization modules and are ultimately fused in a shared estimator to yield a resilient positioning system.

At the same time, the integration of celestial and cooperative localization raises open questions, such as how many drones need star sensors, how to manage the trade-off between communication and measurement noise, and how to plan flight paths that guarantee sky visibility without reducing mission effectiveness (1, 11, 18, 20). Addressing these challenges could enable UAV swarms to achieve precise, long-duration navigation without GNSS, unlocking new capabilities for both civilian and defense applications (1, 5, 11).

CELESTIAL NAVIGATION FOR LIGHTWEIGHT UAVS

Over the past decade, a series of works has shown that modern, low-cost star sensors can be hardened for flight on multirotor and fixed-wing UAVs (3, 4, 5, 7, 8). As represented in the top portion of Figure 1, the celestial-navigation layer supplies the swarm's global reference by providing absolute fixes derived from night sky imagery.

Early proofs of concept, such as Imagery Synthesis for Drone Celestial Navigation Simulation (3), demonstrated that long-exposure images rendered in a physics-based simulator are sufficient to train attitude and position estimators that run in real time on embedded processors (3, 16, 21, 22). Subsequent flight experiments (4) bolted a vision-only "strap-down" star camera onto a 3 kg airframe and achieved < 4 km position error during GPS outages, confirming that accurate celestial fixes are feasible with out gimbals, gyros, or heavy optics (4).

Algorithmic developments have further reduced the payload burden and operational constraints of celestial navigation systems. Teague and Chahl demonstrated a self-calibrating wide-angle method that minimizes preflight alignment requirements (4), while Zhang and colleagues introduced super-large-field-of-view (FOV) star sensors capable of imaging nearly the entire sky

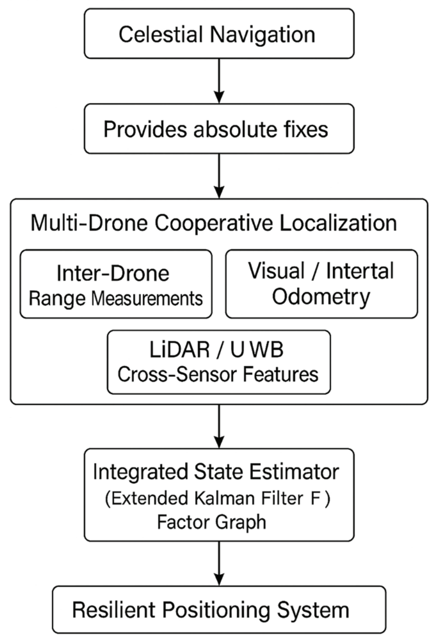

Figure 1. Conceptual architecture of multi-drone celestial–collaborative localization. This diagram illustrates how celestial navigation (CELNAV) can be fused with multi-drone cooperative localization to create a resilient positioning system for GNSS-denied environments. CELNAV provides absolute star-based fixes, which are injected into a multi-drone cooperative localization framework that combines inter-drone range measurements, visual–inertial odometry, and cross-sensor features from LiDAR or ultra-wideband (UWB) systems. These measurements are fused in an integrated state estimator, such as an Extended Kalman Filter or a factor-graph-based optimizer, which propagates the benefits of occasional celestial fixes throughout the swarm. The resulting architecture balances global accuracy from celestial anchors with local robustness from relative sensing, yielding a fault-tolerant, drift-bounded resilient positioning system capable of sustained operation without GNSS.

in a single exposure (23-25). Additional approaches have exploited extended celestial features: Tao and co-authors treated the Milky Way band as a single, continuous landmark, while Zhang and collaborators (2023) incorporated inertial motion data to predict and compensate for star streaks caused by vibration or movement (5, 26-28). Together, these studies define a credible single-platform baseline for celestial navigation against which future multi-drone or cooperative implementations can be compared (3-8, 29).

Wide–field optics improve sky coverage but reduce precision because stars occupy fewer pixels and suffer greater distortion (25). This trade-off implies that swarms may perform best when some drones act as wide-angle "scouts," while others serve as narrow-FOV "anchors." Exposure time also limits single-drone performance: long integrations blur motion, while shorter ones capture fewer stars. Yu *et al*. (2023) addressed this by introducing multi-exposure Kalman filter centroiding, which fuses several short images to reduce noise and blur (7). Unlike standard centroiding, this approach predicts and corrects a star's position over time, using the same recursive estimation logic that underlies collaborative localization itself. Similarly, Zhang *et al*. (2023) reduced motion blur through inertial-aided star tracking, though both methods depend on accurate timing and motion sensors (5).

At the opposite end of the spectrum, Gao and colleagues (2022) achieved less than one hundred meters of drift over twenty-four hours using triple star sensors and refraction correction on a high-altitude aircraft (43). While smaller drones cannot carry such payloads, swarms could collectively approach similar accuracy if multiple drones share their individual, less precise fixes. In the flowchart shown in Figure 1, these absolute star-based measurements form the inputs passed downstream to the collaborative localization framework, establishing the "Provides absolute fixes" link between the celestial and swarm subsystems.

COLLABORATIVE LOCALIZATION AND SWARM PNT

Parallel to CELNAV progress, the multi-robot community has produced mature frameworks for fusing relative observations between aircraft with each platform's own local estimates, a process known as collaborative localization. This stage corresponds to the central module in Figure 1, where inter-drone range measurements, visual-inertial odometry, and cross-sensor features from LiDAR or UWB collectively form the cooperative-localization layer that distributes and refines the absolute information received from celestial anchors.

The best-known example of this cooperative framework is Collaborative Localization for Micro-Aerial Vehicles, where drones exchange visual-inertial odometry states and pairwise relative-pose measurements; this method reduces drift by roughly 40% compared with solo visual-inertial odometry (9, 31). Follow-on studies extended the idea with ultra-wideband ranging, 3-D LiDAR (Light Detection and Ranging) or monocular cross-camera feature association (Wang & Dong 2024), routinely achieving sub-metre relative accuracy in feature-poor indoor or forest environments (11-17, 32-34).

Alternatively, exploiting spatially correlated geophysical fields tackles absolute positioning without GNSS. Yang *et al*. (2020) used a combination of ultra-wideband ranges and Earth's magnetic anomalies to bound group error below 20 m over 180 km trajectories (35, 36). Viset *et al*. (2023) and Penumarti & Shin (2024) later generalized the approach of Yang *et al*. (2020) into distributed Gaussian-process maps and information-aware path planning (10, 18, 37). The common result across these papers is that sharing complementary measurements between agents consistently outperforms simply sampling the same sensor multiple times on a single platform (9, 11-18, 35, 37).

Collaborative localization alone, though effective at reducing drift, cannot maintain absolute accuracy indefinitely. Without a global reference, small relative errors accumulate until the entire network diverges. As indicated by the downward arrows in Figure 1, without periodic celestial inputs the cooperative-localization layer lacks a top-level absolute reference, underscoring why the celestial-navigation block is essential to maintain a drift-bounded solution. Studies using magnetic-field cues show that even weak absolute measurements can constrain this drift when fused cooperatively, but their effectiveness depends on how informative the underlying map is (10, 18, 35-37). Celestial navigation faces a similar challenge: clear skies resemble informative magnetic fields, while clouds or moonlight reduce measurement quality. This parallel suggests that swarm planners should balance task-related information gain with chances to capture absolute updates, whether from magnetic readings or star sightings (11, 37).

Together, these findings indicate that collaborative localization and celestial navigation could complement each other. Relative sensing maintains consistency between absolute updates, while occasional celestial fixes could provide the global reference that keeps long-term drift bounded. We therefore predict that combining the two—relative measurements shared within the swarm and periodic absolute updates from the sky—may outperform either method alone, especially when mission planners deliberately schedule brief sky-viewing opportunities (9-18, 33, 37-39).

FUSING ABSOLUTE CELESTIAL FIXES WITH INTER-DRONE MEASUREMENTS

Surprisingly few studies directly connect celestial navigation and collaborative localization, but several provide useful analogies. Figure 1 highlights how these two previously separate streams converge within an integrated state-estimation module—typically an Extended Kalman Filter or factor-graph optimizer—that accepts asynchronous absolute (celestial) and relative (inter-drone) measurements.

In the space domain, AstroSLAM (Dor *et al*., 2022) integrates star-based absolute constraints into a monocular Simultaneous Localization and Mapping (SLAM) framework, demonstrating how celestial observations can stabilize visual navigation over time (19). In the atmospheric context, Pritzl and colleagues (2023) developed heterogeneous leader–follower architectures in which a single LiDAR-equipped “leader” drone provides absolute position updates to less-equipped followers (13-15). In both cases, one agent with access to a reliable global reference strengthens the entire network’s accuracy. A similar structure could emerge in a swarm where a few drones equipped with star sensors act as absolute reference providers, sharing celestial fixes that other drones integrate with their local relative estimates (3-5, 12, 15).

This analogy extends naturally to the algorithmic level. Both extended Kalman filters and factor-graph estimators already fuse asynchronous absolute and relative cues, such as GNSS, magnetic, or beacon data, alongside high-rate inertial measurements. In this framework, substituting a GNSS update with a periodic celestial factor requires only a different measurement model and covariance definition (9, 15, 17, 36). Likewise, information-guided motion planners (Penumarti & Shin, 2024; Zhao *et al*., 2025) can treat star visibility as another information source, planning brief loiters or coordinated pauses when clear sky conditions are predicted, much as magnetic planners seek informative gradients (11, 18, 20, 30, 33, 34, 38, 40). These examples show that the computational tools needed for integration—filtering, graph optimization, and visibility-aware planning—are already established.

The logic of fusion in these systems mirrors that of existing collaborative localization research. Combining magnetic anomalies with ultra-wideband ranging (Yang *et al*., 2020; Penumarti & Shin, 2024) or using LiDAR-based leader anchors (Pritzl *et al*., 2023) both demonstrate that even infrequent absolute updates can arrest network-wide drift (10, 13-15, 18, 35-37). Celestial navigation could fill the same role, supplying globally referenced orientation and position fixes that augment the relative measurements within a swarm. In return, collaborative localization could enhance celestial navigation by propagating and validating those updates among drones with limited sky access, maintaining accuracy during cloudy or obstructed conditions (9, 12, 15, 19, 32).

Kalman filter centroiding provides an instructive example of how these concepts intersect. Traditional centroiding finds a star’s center of brightness in a single image, while Kalman filter centroiding, as shown by Yu *et al*. (2023), predicts the star’s future position based on earlier frames and fuses multiple short exposures into a more accurate estimate (7). The recursive filtering principle underlying this method is identical to that used in collaborative localization—combining noisy, partial measurements over time to reduce uncertainty. This shared logic suggests that both systems could operate within a unified framework, each reinforcing the other through prediction and correction cycles (7, 9, 14, 17, 18, 20).

Taken together, these connections imply that integrating celestial navigation and collaborative localization is both conceptually and technically feasible. Celestial measurements could serve as a new form of absolute factor within existing estimators, while swarm-level collaboration could expand their effectiveness by sharing and cross-validating star fixes in real time. We therefore predict that a cooperative framework combining these two methods could achieve greater long-term stability than either one alone, and we encourage experimental comparisons between single-drone celestial navigation and team-based celestial–collaborative localization under equivalent visibility and communication conditions (1, 3, 5, 9, 11, 14, 16, 30). The bottom of Figure 1 represents this outcome: by merging absolute celestial cues with cooperative-localization data inside a unified estimator, the swarm achieves a resilient positioning system capable of maintaining global accuracy through extended GNSS outages.

EXPECTED BENEFITS OF MULTI-DRONE CELESTIAL FUSION

The literature identifies three main mechanisms through which a cooperative constellation of drones could outperform a single drone, making repeated star observations.

First, the spatial diversity of the sky view enhances reliability by reducing sensitivity to local obstructions. With wide-baseline viewing angles, a constellation can overcome challenges such as cloud cover, light pollution, or temporary sensor blinding from the Moon. While one drone may have an obstructed view of the sky, another may capture a clear frame and share that positional fix with the group. This redundancy provides robustness that an individual drone cannot achieve alone (3-5, 7, 12, 23, 26-28).

Second, cooperative systems benefit from temporal compression of exposure windows. Obtaining long-exposure imagery (typically 0.5–2 seconds) is necessary for detecting dim stars, but this requirement forces single drones to hover or adopt slow, gentle flight paths. In a swarm, however, only a subset of drones needs to pause for a celestial measurement. The rest can continue moving, ensuring that mission progress is not stalled while still collecting accurate navigation data (3, 4, 11, 12, 20, 34).

Third, swarms exploit drift-limiting loop closures. Absolute star fixes from a few drones can propagate through the relative-pose graph of the swarm, constraining the entire group's navigation solution. This effect is analogous to loop closures in SLAM, where revisiting landmarks reduces cumulative error. In the cooperative case, however, the drift correction does not require revisiting ground features, since celestial observations serve as global anchors (11, 15, 17, 19, 36).

Quantitative evidence supports these advantages. Multi-agent visual-inertial odometry (Vemprala & Saripalli, 2019) has been shown to reduce drift by a factor of two, while experiments with triple star-sensor integration on a high-altitude, long-endurance UAV (Navigation, 2024) demonstrated less than 100 meters of drift over a 24-hour period (5, 9). Extrapolating from these results, it is plausible that a cooperative constellation sharing star fixes across the group could achieve sub-kilometer absolute accuracy over day-long GNSS outages, a performance level not yet attainable by a single drone operating independently (1, 5, 9, 11).

These mechanisms outline how combining CELNAV and collaborative localization could outperform either approach alone. We predict that spatial diversity will increase the chance that some agent can obtain an anchor; temporal compression will limit the opportunity cost of exposures to the mission; and absolute loop closures will periodically cap swarm drift without dependence on terrestrial landmarks (3-5, 7, 9, 11, 30). Each mechanism follows a pattern already observed when collaborative localization was fused with other absolute modalities (magnetic, LiDAR) (10-15, 18, 35, 37), but now with a terrain-agnostic anchor.

CAVEATS AND LIMITATIONS

Despite these promising directions, no prior work has explicitly compared a fleet in which one or more drones provide celestial navigation updates to the group, versus a lone drone that accumulates multiple star fixes over time. This leaves several critical questions unanswered (1, 13, 15, 19).

One open question concerns the optimal ratio of star-sensor-equipped to non-equipped drones within a swarm. Determining this balance depends on mission geometry, communication bandwidth, and the trade-off between equipping more drones with celestial sensors versus relying on relative-pose propagation (11, 20, 30, 34, 40). A second issue involves understanding how inter-drone range noise interacts with celestial measurement noise when fused into the swarm's state covariance. This trade-off determines whether communication errors could negate the benefits of shared star fixes (9-18, 35, 37). A third question is whether information-aware planners can guarantee sufficient sky-view opportunities for star observations without compromising overall swarm coverage or task performance (11, 18, 20, 30, 33, 34, 40).

Addressing these challenges would help close the current gap between single-platform celestial navigation research and the broader literature on cooperative localization. More importantly, it would provide direct guidance for designing resilient positioning systems capable of operating in GNSS-denied environments, enabling distributed aerial robots to navigate robustly over long missions (1-5, 9, 11).

We predict that properly tuned covariance schedules, redundant anchors (≥2 star sensors), and sky-aware, safety-certified planners will be required to realize the anticipated advantage of combined CELNAV and collaborative localization, and we encourage future studies to quantify the margins by which each element contributes (11, 18, 20, 38, 39, 41, 42).

CONCLUSION

This review brings together two previously separate bodies of research—celestial navigation and collaborative localization—and analyzes how their integration could provide a new foundation for resilient UAV navigation in GNSS-denied environments. Prior studies have already shown that each approach is effective on its own: celestial navigation delivers absolute orientation and position fixes based on star observations (3-6), while collaborative localization enables teams of UAVs to reduce relative drift through shared visual, inertial, and ranging data (9, 11-17). The unique contribution of this review is to move beyond summarizing those independent results and to identify how their fusion could outperform either technique alone. Specifically, we predict that integrating celestial fixes into a collaborative estimator would exploit spatial diversity among drones, temporal compression of exposure requirements, and absolute loop closures that propagate drift correction across the network. Together, these mechanisms point toward a cooperative architecture that could bound long-term error even during extended GNSS outages.

The practical implications of this synthesis extend well beyond academic interest. For defense applications, integrating celestial and collaborative approaches could ensure reliable navigation in environments where GNSS is intentionally jammed or spoofed. In disaster response, such as wildfire monitoring or post-earthquake search operations, a swarm capable of navigating at night or through communications disruptions could significantly improve situational awareness and coverage. In long-endurance inspection and environmental monitoring, celestial fixes could sustain absolute accuracy over many hours, allowing small UAVs to operate with minimal human intervention (1, 4, 5, 11, 22, 34, 43). The key advantage of celestial navigation—its independence from ground-based infrastructure—makes it particularly suited to these conditions, while collaborative frameworks distribute its benefits across an entire swarm.

To make this vision achievable, several clear research directions emerge. First, sensor deployment strategies should determine the optimal number and placement of star-equipped drones by considering occlusion probabilities, field-of-view accuracy trade-offs, and expected communication delays (4, 23, 24, 25, 30). A heterogeneous fleet that mixes wide-FOV “scouts” with narrow-FOV “anchors” may balance availability and precision more efficiently than identical platforms. Second, algorithms for noise and covariance balance are needed to manage how absolute celestial measurements interact with relative inter-drone data. Adaptive or federated fusion strategies, like those used in marine navigation (9, 14, 20, 35, 41), could prevent one noisy channel from degrading the global solution. Third, sky-aware planning must be developed to ensure that drones maintain line-of-sight to the stars when possible, without compromising safety or mission coverage. Incorporating star-visibility forecasts and control-barrier-function safety layers could allow brief, scheduled exposure pauses while maintaining collision avoidance and information gain (11, 18, 33, 38-40, 42-44).

Finally, to test the predictions identified here, we recommend a structured experimental comparison between a single-drone celestial navigation system and a multi-drone collaborative swarm using shared celestial updates. This experiment—comparing “Solo-CELNAV” to “Team-CELNAV”—should evaluate metrics such as long-term position error, coverage efficiency, exposure duty cycle per agent, and communication bandwidth. Simulated environments (3, 16) can provide controlled visibility and occlusion conditions (3, 16, 21), while field trials under real sky conditions can validate the robustness of communication and sensor performance (5, 9, 11-16).

In summary, this review’s contribution lies in articulating a conceptual bridge between celestial navigation and collaborative localization. By uniting absolute sky-based estimation with distributed multi-agent cooperation, we outline a pathway toward navigation systems that are not only accurate but also inherently resilient—capable of maintaining global awareness when traditional satellite-based methods fail.

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CONFLICT OF INTEREST

The authors declare that there are no conflicts of interest regarding the publication of this article.

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