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A Review of Precise Positioning for Logistics Drones in Rainy Night Conditions

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Abstract

With fast development of the low-altitude economy and ongoing improvement of intelligent logistics infrastructure, drone delivery has become an important new way to solve the "last-mile" delivery problem. Even so, complicated weather conditions, like flying at night and when it rains, create big technical problems for getting accurate location and safe landing of unmanned aerial vehicles (UAVs). This is a key bottleneck that stops logistics drones from being used widely for business purposes. This paper gives a full look at existing research on technologies for UAV precise positioning and landing, and it sums up what current domestic and international studies have achieved in four main topic areas: guidance methods that use vision, GNSS improvement techniques, ways to combine multiple sensors, and new passive microwave radiometric imaging technologies. Based on all this information, our analysis finds several key problems that are common in current work: single sensors have limits in what they can detect, multi-sensor fusion strategies don't go deep enough into how different modes interact, there are not enough systematic studies that specifically look at the combined problem of night and rainy weather, it's really hard to keep a good balance between real-time working and how much computing power you use, and there are no standard benchmark and evaluation frameworks that everyone can use. In the end, based on all the review we did above, this paper points out some possible future research directions that could guide new developments in this area.

Keywords

UAV; Positioning; Visual Guidance; Microwave Radiometric Imaging; Multi-sensor; GNSS Augmentation.

1. Introduction

Driven by the faster and faster growth of online shopping and on-demand delivery services, drone (unmanned aerial vehicle, UAV) delivery has gotten a lot of attention from big commercial companies, like Amazon, DHL, SF Express, and Meituan. It's seen as a new way to get past the "last-mile" delivery problem.[1] Even though this area has developed quickly, there are still quite a few important problems that haven't been solved. For example, when the drone does its final landing step, it fails way more often than when it's just flying normally. This problem gets even worse when it has to land on a moving platform or in an area that's really complicated, so this puts really strict demands on how accurate the location detection needs to be and how strong the whole system has to be [2,3]. When it's dark with not much light, the visual sensors get a worse signal-to-noise ratio, and it becomes harder to pick out the right features. This makes it harder for traditional vision-based algorithms to keep working steadily [4,5]. Rainy weather makes everything even more tricky: water drops block the openings for the optical parts, refraction causes interference with the light signals, and the reflectivity of the

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landing spot changes a lot; At the same time, wet and slippery ground can change how sensors like millimeter-wave radar pick up echo signals [6]. In urban canyons, GNSS signals already get much weaker. When you add all these different bad factors together, it becomes really hard for UAVs to get an exact position when it is night and raining at the same time - this is just one of many different technical problems we face right now.

Most current research has focused on three main technical areas: visual-guided landing, better satellite navigation, and combining data from multiple sensors. In existing studies, vision-based methods usually use artificial reference markers - like ARUCO codes and AprilTags - or deep learning-based object detection systems to find and follow target landing spots [2,6]. These methods are popular with many researchers because they give lots of useful information and do not cost too much for hardware. Big progress has also been made in using Simultaneous Localization and Mapping (SLAM) and Visual-Inertial Odometry (VIO) in places where GNSS does not work well [4,7]. Even so, most of the methods people have come up with are made for just one bad condition at a time. Most of the time they do not give full combined solutions that can handle many different bad weather events happening all at once [4].

2. Current Research Focus Areas

2.1. Vision-Based Guidance Methods

2.1.1. Method Proposal and Technological Evolution:

Vision-based guidance methods are one of the most actively studied sub-areas in the whole field of UAV location finding. The basic idea behind these approaches is that the UAV takes pictures of the area around it using cameras it carries, and then extracts useful visual features through digital image processing steps. These extracted features then help us estimate and keep track of the UAV's six-degree-of-freedom position over time [6,8].

The basic logic of visual positioning tech is to build a link between the photos the UAV takes and where the UAV is in space. Gu wrote a full review of vision-based UAV position finding and navigation methods in the Journal of Electronics. In that paper, Gu split visual positioning into two main groups: absolute visual localization, or AVL, and relative visual localization, or RVL. AVL gets the full global position directly by matching what the onboard camera sees to pre-built map databases with known coordinates, like satellite maps. On the other side, RVL uses visual odometry (VO) or simultaneous localization and mapping (SLAM) methods to slowly work out position step by step. It does this by estimating how the UAV has moved between one photo frame and the next.[8]

How feature descriptor generation has evolved over time follows a pretty clear direction. Older hand-made descriptors like SIFT, SURF, and ORB are built around local image gradients and corner responses, and they show a decent amount of stability when viewpoints and scales change. When there are big changes in lighting, really big shifts in viewpoint, or lots of image noise though, these older descriptors clearly get worse when it comes to how reliable and accurate they are at matching.[6] As deep learning got better, feature extraction methods that use deep neural networks, like SuperPoint and LOFTR, have shown much better ability to tell different features apart. Tian and his team were the first people to look at how useful second-order similarity (SOS) can be in descriptor learning. They put forward a second-order similarity regularization (SOSR) method, which is based on the idea of similarity distance between pairs of matching points. When you combine it with a triplet loss function, this method worked better than older models again and again across multiple benchmark tests for local descriptors.[6]

When it comes to similarity metrics, Euclidean distance and Hamming distance are the most often used traditional measures, and they get used for floating-point descriptors and binary descriptors separately. The LIFT method uses a voting-based strategy to check how reliable matching is: for every keypoint, it does a nearest-neighbor search along many direction axes,

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sets thresholds based on how far apart descriptors are, and keeps the correspondences that meet the voting rule.[6] Right now, this whole research area is still in its early development stage.

2.1.2. Rationale and Advantages of the Method

The method offers the following advantages:

(1) Information richness. Visual sensors enable the acquisition of a broad spectrum of semantic environmental cues, encompassing colour, texture, shape, and edge information, all of which are essential for scene interpretation and object recognition. In contrast to point-cloud data generated by LiDAR or coordinate outputs from GNSS receivers, optical imagery affords a higher-dimensional representation of the surrounding environment.

(2) Economic viability. With the progressive maturation of CMOS image sensor fabrication technologies, the unit cost of high-resolution cameras has undergone a sustained decline, rendering visual sensors among the most economically attractive perception devices. This attribute carries substantial engineering significance for logistics(UAVs), where cost containment remains a critical design constraint.

(3) Compatibility with deep learning. Recent advancements in deep neural network architectures-notably Convolutional Neural Networks (CNNs) and Vision Transformers-have markedly enhanced the robustness of visual feature extraction. Under challenging operational conditions characterised by illumination fluctuations, viewpoint shifts, and partial occlusions, deep-learning-derived visual features exhibit superior adaptability relative to conventional hand-crafted descriptors.[9] Through integration with deep learning, absolute visual localisation techniques can constitute a dependable positioning recourse in GNSS-degraded environments, including urban canyons and subterranean spaces.[9]

Nevertheless, alongside these notable benefits, certain limitations also persist.

2.1.3. Limitations

(1) Optical interference in rainy conditions

When raindrops sit on the surface of a camera lens, they turn into thin layers of water or separate droplets. This makes captured images look blurry and lowers their contrast. These are tiny floating particles, and they also create a fog-like scattering effect when the camera takes a picture, which makes image quality even worse. Even more significantly, how the ground reflects light changes a huge amount when it rains. Wet and slippery surfaces make strong specular reflections, and that means the original lighting model people used does not work well anymore.

(2) Challenges in Low-Texture Environments

In environments that do not have many distinct textures, such as big open areas of concrete, snow or water, it is really hard to get clear visual features. This problem actually gets even worse when it's raining. Purely visual methods have trouble getting a reliable position in places that don't have any clear landmarks to use. [6,8]

2.2. Methods based on Single-Source GNSS Augmentation

2.2.1. Proposal and Evolution of the Method

The Global Navigation Satellite System (GNSS) is the main technology that lets us get exact absolute position data for unmanned aerial vehicles. The usual Single-Point Positioning (SPP) method usually only gives accuracy around the meter level, which does not meet the centimeter-level precision we need when logistics UAVs do their precision landing. Because of this, making GNSS positioning better by using differential techniques has become a key area of research in this field.

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This group of differential techniques can be split into two types: RTK/PPK technology, and PPP plus PPP/RTK.

(1) RTK/PPK Technology: Real-Time Kinematic (RTK) and Post-Processed Kinematic (PPK) are the two most widely used high-precision GNSS positioning methods right now. RTK gets rid of most atmospheric delays, satellite orbit mistakes, and clock biases by using differential corrections from a base station to a rover receiver. This lets it do real-time positioning that gets down to the centimeter level. A review done by Jiang et al. Shows that RTK can always hit centimeter-level accuracy when the sky is open, and that is why it is the go-to technology for UAV mapping and precision farming work. [3] In contrast, PPK does not necessitate a real-time communication link and is therefore suitable for post-mission refinement in remote areas lacking network coverage. To address the challenges of elevated positioning costs and severe multipath interference in low-altitude economic scenarios, Yu proposed a low-cost optimization scheme based on RTK. The core innovation of this approach resides in the Partial Ambiguity Resolution (PAR) strategy-conventional RTK requires fixing the integer ambiguities for all visible satellites; however, in complex environments, certain satellites may exhibit degraded signal quality, and forcing a full ambiguity fix can inadvertently introduce errors. The PAR strategy resolves ambiguities by selecting a subset of high-quality satellites, thereby increasing the ambiguity fixation success rate by approximately 30% under constrained computational resources. Experimental validation demonstrates that centimeter-level positioning remains achievable even in challenging settings such as urban canyons.

(2) PPP and PPP/RTK: The biggest problem with Real-Time Kinematic (RTK) is that it needs a dense network of ground reference stations, which is really hard to set up in remote areas or cross national borders during cross-border work. Precise Point Positioning (PPP) uses accurate satellite ephemeris and clock correction products to get decimeter-to-centimeter level positioning with just one single receiver. But the time it needs to converge is usually between 15 and 30 minutes, and most UAV missions take less than 30 minutes, so this creates a basic mismatch in timing between these two methods. The combined PPP/RTK method brings together the good points of both: by making a model for regional atmospheric delays, it cuts PPP's convergence time down to 1 – 5 minutes and still keeps centimeter-level accuracy. As Jiang and other researchers have talked about in their review, PPP/RTK is a solution that "does not need much infrastructure" for high-precision positioning of low-altitude UAVs. It still needs people working on it to fix modeling errors caused by ionospheric activity and fast changes in UAV flight height.[3]

2.2.2. Rationale and Advantages of the Method

(1) Absolute positioning capability

Unlike visual positioning or inertial navigation, GNSS gives position estimates in an absolute geodetic reference frame, and this gets around the problem of cumulative drift. Because of this, positioning accuracy does not change over long flight times, and this is really important for long-endurance logistics delivery work. Jin et al. Have pointed out that GNSS and technologies that improve it make up the core base for absolute positioning in low-altitude intelligent networks.[4]

(2) All-weather operability

GNSS signals work in the L-band, which is about 1 to 2 GHz, and they have pretty good ability to go through things. Unlike optical sensors, GNSS signals can get past cloud cover, fog and even some rain, and they are not really changed much by how much light is in the environment. That means they can work normally even at night, which is a clear advantage over methods that use cameras or vision.

(3) High technological maturity

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After decades of development, GNSS tech now has high chip integration, costs less, and uses very little power. RTK/GNSS receivers have gotten much smaller over time, so they can easily be put into small UAV platforms. The RTK-SeqNet design that Ali and his team came up with shows even more clearly what we can do when we mix deep learning with RTK: it combines data from inertial measurement with velocity inputs, and uses that to predict how position will change when GNSS signals go out. Tests show that the average error can be kept under 1.6 meters for a whole 60-second gap in signal.[3]

2.2.3. Limitations and Shortcomings of the Method:

(1) Signal Loss and Interruptions: In places that have really thick tree cover or really crowded city areas, GNSS signals sometimes can't get through at all. Ordinary RTK systems can only handle signal breaks for a few tens of seconds; if the break goes longer than that, people have to start the ambiguity resolution process over again, which makes positioning accuracy drop a lot. Studies show that when you can see less than four satellites, you can't get a rough three-dimensional position and the clock offset. [3]

(2) Building Obstruction: When you work in cities, buildings reflect and block GNSS signals, which causes really bad multipath problems. Since most UAVs fly at heights lower than 120 meters, they get hit by this problem from nearby buildings much more easily. The pseudorange errors that come from multipath can get as big as several meters, or even tens of meters. This is way bigger than the normal centimeter-level accuracy that RTK is supposed to have. Even though some special ambiguity resolution methods can make this problem a little better, they can't get rid of it completely.

(3) Signal Delay in Rainy Conditions: Rain makes the amount of water vapor in the atmosphere go up a lot, and that's the main thing that causes delay in GNSS signals. Even though RTK differential correction can get rid of most atmospheric delays, how well it actually works depends on how similar the space conditions are between the base station and the rover. When it's rainy, how water vapor spreads changes a lot more over time and different places. If the distance between the UAV and the base station gets bigger than 10 to 20 kilometers, the leftover differences after correction might go past what the system can handle.

2.3. Fusion of Multi-sensor Data

2.3.1. Proposal and Evolution of the Method

Multi-sensor fusion is one of the main technical ways to fix positioning problems when the environment is complicated. The basic idea behind it is that every single sensor has its own natural performance limits and limits on how it can work. If we put together data from different kinds of sensors - like vision, IMU, LIDAR, millimeter-wave radar, and ultrasonic sensors - we can use the good points of each that the others don't have. This makes the whole system stronger and more accurate even when the environment is really complicated. [6,8]

Based on how their fusion structures are different, the review written by Ye splits multi-sensor fusion methods into three main groups: [6,10]

(1) Filter-based fusion: The Extended Kalman Filter (EKF) and the Unscented Kalman Filter (UKF) are the most common examples of this approach. It combines multi-source observation data by recursively estimating the state of the whole system. Filter-based methods run fast on computers, and they work really well for real-time uses. They are really sensitive to errors that come from system linearization. When people build navigation systems through multi-source sensor fusion, you can find two different ways to make the dynamic model. The first way is to build a full state-space model, and it uses navigation parameters as the state variables. This model can accurately show the nonlinear dynamic features of the whole system. The second way uses linearization approximations to build error propagation equations. This cuts down

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the amount of calculation you need to do, but it still gets errors easily from when you truncate the Taylor series expansions.

(2) Optimization-based fusion: Methods like graph optimization and factor graph techniques build an optimization goal function, which puts all past observations together to find the best possible state sequence. Optimization-based methods give more accurate results and work better when dealing with nonlinear constraints, they do need a lot more computing power though.

(3) Deep learning fusion methods use neural networks to automatically learn how to align and weight multimodal features, which gives them really strong adaptability. For some specific real-world uses, Isilak and Oktal came up with a multi-sensor system that puts together YOLOv8 object detection and Kalman filtering. When they combined the UAV's own position data, GPS points from the moving platform, and inertial measurement data, they got a landing accuracy that's about 0.15 meters RMSE. This works even when wind speed gets up to 6 m/s and visibility is not very good, and at the same time they made the operating range of the landing process much longer, plus they got better landing trajectories.[2] Xu looked into a dynamic positioning method for autonomous UAV landing that's built on LIDAR and camera fusion.[2] When there's no GPS signal, Wajahat came up with a fusion framework that mixes the YOLOv3 deep learning obstacle avoidance method with reference marker positioning tech, and it showed really good performance when it was tested in indoor spaces and large parking lots.[6] One review article that got published in IEEE Access summed up in a systematic way what SLAM fusion, UWB fusion, odometry fusion, and Wi-Fi fusion are all used for when it comes to dynamic target positioning.[8]

2.3.2. Rationale and Advantages of the Method

Sensor Complementarity: Different sensors have different complementary features. Visual sensors can give lots of semantic information, but they are very sensitive to how much light is in the environment. IMUs can give motion information at high frequency, but they face the problem of integration drift. LIDAR can get really accurate distance measurements, but it costs a lot and gets messed up by rain and fog. GNSS gives an absolute position reference, but its signal can get blocked easily and it also has multipath issues. When you fuse these sensors together, each can use its own good points and make up for the bad points of the others[10].

Redundancy and Fault Tolerance: Multiple sensors create extra information that works as a backup. If one sensor stops working correctly in some certain situation, other sensors can take over the job of figuring out position, so the system can keep working without stopping. This ability to handle faults is especially important when UAVs are doing landing tasks, because safety has to come first above everything else.

Better Accuracy: Past research shows that combining data from multiple sensors can greatly boost how accurate the positioning is. Isilak and Oktal's work shows that mixing visual and inertial data keeps landing errors within 0.15 meters [2]. Also, Abdelazeem did a four-constellation RTK experiment, and his results say that combining multiple data sources can make positioning accuracy around 40% better than before [11].

2.3.3. Limitations of the Method

Challenges of Spatiotemporal Synchronization: Different sensors don't work the same way when it comes to sampling frequency, time delay and how their spatial coordinates are set up. When the environment is changing fast, like when a vehicle moves quickly during landing, small errors in spatiotemporal synchronization get bigger. This makes the final fusion result less accurate. Even though fusion methods that use deep learning have made this problem a little better, they rely way too much on the data they are trained with. That means we can't be sure they'll work well in situations that aren't included in the training data. [6]

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Problems with Sensor Recognition Performance: Visual sensors get messed up when there is not enough light and when raindrops block their view. LIDAR also struggles because raindrops scatter its signals, which adds a lot of extra noise. Millimeter-wave radar can get through rain and fog pretty easily, but we still need to check how wet and slippery surfaces change the echo signals it picks up.

2.4. Novel Perception Technology Based on Passive Microwave Radiometric Imaging

2.4.1. Proposal and Evolution of the Method

The "Domestically Developed Multi-Payload Low-Altitude Unmanned Aerial Vehicle Safe Landing Guidance System" was just released by the Hubei Luojia Laboratory at Wuhan University. This is the first time that passive microwave radiometric imaging technology has been used for multi-source information fusion.[9] This new tech has opened up a new direction for building a UAV perception system that can actually work in any weather condition.

Passive microwave radiometric imaging is a type of sensing that is completely different from radar, which uses active microwave. Its basic working idea is that any object that has a temperature higher than absolute zero will send out electromagnetic energy to the outside world. The strength of the radiation in the microwave band is controlled by the object's own physical temperature and its emissivity. A passive microwave radiometer makes images by catching the microwave radiation energy that the target scene gives off by itself, and it does not need to rely on any outside radiation source to work.

2.4.2. Rationale and Advantages of the Method:

(1) Fundamentally Overcomes the Limitations of Optical Sensors: Rain and nighttime conditions degrade optical sensors primarily through light scattering and attenuation. Because microwave wavelengths are considerably longer, the Mie-scattering effect is markedly reduced; raindrops (approximately 0.5–5 mm in size) cease to act as effective scatterers relative to centimeter-scale microwave wavelengths. Consequently, passive microwave imaging possesses an inherent all-weather capability.

(2) Advantages of Passive Mode: In contrast to radar, passive microwave radiometers do not transmit signals; consequently, issues associated with echo attenuation are absent, and mutual interference among active sensors does not arise. This property confers a distinct advantage in scenarios involving high-density UAV operations.

(3) Supplementing Existing Sensors in Failure Scenarios: Under the most extreme weather conditions, visual systems, LIDAR, and even certain radar bands may become inoperative, whereas passive microwave radiometric imaging can continue to provide reliable perceptual data, thereby serving as the system’s final safeguard for perception.

2.4.3. Limitations of the Method

(1) Low spatial resolution: Because of what antenna size and the physical diffraction limit limit us, the spatial resolution of passive microwave images is clearly much worse than what optical images can do. For example, in the L-band (around 1.4 GHz, with wavelength of 21 cm), to get an angular resolution of 1 degree you need an antenna with an aperture size that's around 12 meters. That's just not possible for small UAVs, that's obvious. While you can get better resolution if you use synthetic aperture methods (like passive synthetic aperture imaging, for example), these ways of doing it add a lot more complexity to the whole system, and also make processing take much longer.

(2) High complexity of data interpretation: Images from microwave radiation are really different from what humans see with their own eyes. Instead of showing how much visible light bounces off a target, it shows how the "microwave brightness" spreads across it. Because of this, turning microwave radiation images into info that UAV navigation systems can understand, like

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landing area lines, obstacles and what kind the surface is, counts as a really hard research problem to solve.

(3) System miniaturization challenges: Current high-sensitivity microwave radiometer systems still have pretty big size, heavy weight, and use a lot of power. That makes it hard to put them directly onto small logistics UAVs. Making light antenna arrays and shrinking low-noise amplifiers are two key engineering problems that need new solutions pretty badly..

2.5. Scenario-Driven Cross-Comparison and Recommended Fusion Strategies

The four technical routes delineated above are seldom employed independently under actual rainy-night operating conditions. To inform system design, this section assesses their performance across three representative environmental scenarios, ordered from moderate to extreme severity, and proposes corresponding optimal fusion strategies.

2.5.1. Scenario 1: Light Rain + Low Light (e.g., Dusk with Drizzle)

Environmental characteristics: Light intensity 10–50 lux, rainfall rate <2.5 mm/h, intermittent raindrops, partially wet landing surface.

Performance analyzes:

(1) Vision-based: Low-light noise reduces feature-matching reliability. With active LED illumination or high-sensitivity (e.g., Sony STARVIS) sensors, ARUCO markers can still be detected within 5–10 m. Accuracy degrades to ~0.3–0.5 m.

(2) GNSS augmentation: Minimal water vapor effect; RTK maintains centimeter accuracy in open areas. However, urban canyon multi-path remains problematic.

(3) Multi-sensor fusion: VIS+IMU+GNSS fusion works robustly. Deep learning denoising (e.g., Retinex-Net) can enhance low-light images.

(4) Passive microwave: Overkill; resolution too low to distinguish small landing markers.

Recommended fusion approach: use GNSS-RTK as the main source (for absolute position), and take vision-based marker tracking as the backup (to get fine relative positioning when doing the final approach). When GNSS signal is not available, we can use VIO with visual-inertial fusion instead.

2.5.2. Scenario 2: Moderate Rain + Low Light (e.g., Night with Steady Rain)

Environmental characteristics: Light intensity <5 lux, rainfall rate 2.5–10 mm/h, continuous raindrops, water film on lens, wet ground with specular reflections.

Performance analyzes:

(1) Vision-based: Severe degradation

Rain streaks can lead to wrong matches of image features. Traditional SLAM systems often break down; only deep learning-based deraining methods (for example, DerainNet) can get back part of the performance, but the system delay goes up to more than 100 ms.

(2) GNSS augmentation: When the distance between the base station is more than 5 km, water vapor delay starts to have an impact on RTK performance. Wet surfaces on buildings make the multi-path problem even worse. Signal attenuation can reach 2 – 3 dB.

(3) Multi-sensor fusion: Fusing together data from IMU, GNSS and millimeter-wave radar becomes really important. Lidar gets a lot of extra noise from rainy weather. Radar that works at 77 GHz has a pretty good ability to work well in rain.

(4) Passive microwave: It can still work in rain, but its resolution is pretty low (only a few meters at best) so it can't help with precise landing; it can be used to roughly classify what type of terrain you're looking at, like water, pavement or vegetation.

Recommended sensor fusion plan: take GNSS-RTK plus IMU plus millimeter-wave radar as the core parts. It uses a radar altimeter to get height data. Vision sensors are only kept for backup

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use, plus we do strong rain removal processing on the input image first. When RTK loses its signal lock, we just switch over to use radar-inertial odometry instead.

2.5.3. Scenario 3: Heavy Rain + No Light (e.g., Night Thunderstorm)

Environmental characteristics: Light intensity 0 lux (pitch dark), rainfall rate >10 mm/h, dense raindrops, lens completely blurred, ground flooding, strong signal attenuation.

Performance analyzes:

(1) Vision-based: Effectively unusable. Even with active IR illumination, raindrop back-scatter creates “white noise” images.

(2) GNSS augmentation: Severe water vapor delay and ionospheric scintillation. RTK differential residuals exceed tolerance; ambiguity resolution fails frequently. PPP convergence time >30 min.

(3) Multi-sensor fusion: Conventional VIS+IMU+GNSS fails due to vision collapse. Adding radar (24/77 GHz) and barometer can sustain coarse positioning (~1–2 m error). Radar-only odometry suffers from low feature density.

(4) Passive microwave: The only technology that remains fully functional in principle. However, resolution (~10 m for small UAV) only provides “macro” perception (avoiding large obstacles like buildings or trees), not precise landing.

Recommended fusion strategy: We should use a step-by-step method here. We can start by using passive microwave radiometric imaging to do rough navigation work, like finding the right landing zone within a 10 to 20 meter range. After that, we can add a short-range sensor that works well even in bad conditions – things like an ultrasonic or laser altimeter would work, as long as we can fix the errors rain causes. Or another way is to guide the UAV to a special landing pad that has active signal markers, like infrared LEDs or RF transmitters. These devices keep working fine when it rains, so that's a plus. One possible good way to fix the problem is to combine passive microwave imaging with a millimeter-wave radar network. This combination can get resolution down to the decimeter level when we use synthetic aperture techniques.

2.5.4. Summary of Scenario-Driven Recommendations

Table 1. Summary of Scenario-Driven Recommendations

Scenario	Primary sensor	Secondary sensor	Fallback	Expected landing accuracy
Light rain + low light	GNSS-RTK	Vision (with marker)	VIO	<0.2 m
Moderate rain + low light	GNSS-RTK + IMU + (mm)Wave radar	Vision	Radar-inertial odometry	0.3–0.8 m
Heavy rain + no light	Passive microwave (coarse) + radar/beacon	Barometer	None (mission abort if fails)	1–5 m (coarse)

2.6. Quantitative Comparison of the Four Technical Approaches

A quantitative comparison of the performance attributes across the four technical paradigms is set forth in Table 2, encompassing multiple critical evaluation dimensions. The numerical data presented are compiled from representative peer-reviewed publications or are based on typical parameter values documented in the existing literature. Table 2 gives a numbers-based comparison of how well each of the four technical approaches works, and it covers several key ways to evaluate them. The numbers we show here come from well-known papers that have

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gone through peer review, or they are taken from common parameter values that have already been written about in past studies.

Table 2. Quantitative comparison of four positioning technologies for logistics drones under rainy-night conditions

Dimension	Vision-Based	GNSS Augmentation (RTK)	Multi-Sensor Fusion (VIS+IMU+GNSS)	Passive Microwave Radiometric Imaging
Positioning accuracy (RMSE, horizontal)	0.05–0.5 m (with markers) / 1–5 m (without) [6,8]	0.01–0.05 m (open area) / 0.5–2 m (urban canyon) [3]	0.10–0.30 m [2,10]	1–10 m (current prototype) [9]
Update rate	10–60 Hz (camera dependent)	5–20 Hz	50–200 Hz (fusion dependent)	0.5–5 Hz (synthetic aperture)
Computational latency	20–100 ms (deep learning)	<10 ms	30–80 ms (EKF/optimization)	200–1000 ms (image reconstruction)
Power consumption	2–10 W (camera+processor)	1–5 W (receiver)	5–20 W	15–50 W (radiometer+servo)
Sensor weight	20–100 g	30–80 g	100–500 g	500–2000 g (lab prototype)
Cost (USD)	20–200	100–500	300–1500	>5000 (pre-commercial)
Rainy condition applicability (1–5, 5=best)	1 (lens occlusion, specular reflection)	3 (water vapor delay, signal attenuation)	2–3 (depends on sensor mix)	5 (all-weather in principle)
Nighttime applicability (1–5, 5=best)	2 (needs active illumination or low-light camera)	5 (no effect)	4 (fusion with IR or GNSS)	5 (passive, no light needed)
Data source references	[6,8,9]	[3,11]	[2,6,10]	[9] (limited public data)

*Note: Values represent typical ranges for small-to-medium logistics UAVs (<25 kg) under rainy-night conditions. Actual performance may vary with specific implementations.

3. Summary and Outlook

This paper gives a systematic review of recent research progress on precise positioning and landing tech for logistics UAVs when it is rainy and dark at night. We look at four main technical approaches and analyze their basic theories and main problems one by one. Vision-based methods have lots of information and cost less on hardware, but their sensing ability drops a lot when there is rain and not enough light. GNSS augmentation methods can get absolute geographic coordinates and work in any weather, but they easily lose signals in urban canyons,

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and also face interference from water vapor weakening when it rains. Multi-sensor fusion methods use different sensors' good points and system backup to greatly improve stability and accuracy. This makes it the most useful combined solution people have found so far; but there are still problems with how well different sensors work together and how to keep them matched in time and space when the environment is really bad. New passive microwave radiometric imaging, which is based on basic physical rules, gives a new way to get past the problems with seeing things in rainy and night-time conditions. Right now, though, it has some clear limits. Most important are its low spatial resolution and the fact it can't be made small enough yet, so we need big new tech advances really soon.

If you look at all current research together, most studies only talk about single bad weather conditions, and there's a clear lack of systematic testing when nighttime and rainy weather happen at the same time. To fix this missing part, future research work should focus on these four areas: (1) building adaptive sensor fusion structures that can change the weight of each sensing method on the fly, based on real-time checks of surrounding conditions like how heavy the rain is and how much light there is; (2) setting up standard benchmark tests and evaluation frameworks made just for UAV positioning on rainy nights, which also includes making public reference datasets that have accurate ground-truth position labels; (3) working on small lightweight passive microwave radiometers that add synthetic-aperture signal processing, to get spatial resolution that's less than one meter; and (4) using a three-part coupled co-design idea that links perception, environment and mission together, which gets improved through repeated closed-loop adjustments between simulated settings and real-world working environments.

The main limits of this review mostly come from the fact that it mostly relies on newly published English papers, plus just a selection of representative domestic research results. Because of that, we don't cover enough of the private technical solutions that companies in industry haven't made public yet. People who work on this topic in the future are expected to pay more attention to new research directions. These directions include the close combination of passive microwave radiometric imaging with existing multi-sensor fusion structures, and also how to estimate sensor degradation models in real time when the working environment is hard to deal with.

References

[1] Wei, H. C., Shi, J. M., Liu, Z., Zhang, J., & Liu, C. H. (2023). A review of drone delivery models and path planning for last-mile delivery. *Journal of Computer Systems Applications*, *32*, 1–18.

[2] Yan, F. T., Lin, H., Xuan, H., Huang, Y., Cao, Y., Hu, H., & Liu, P. (2023). Passive sensor detection and tracking of UAVs in urban environments: A survey. *Applied Sciences*, *13*, 11320.

[3] Jiang, C., Zhou, X., & Chen, H., Liu. (2026). UAV positioning using GNSS: A review of the current state. *UAV*, *10*, 91.

[4] Jin, Y., Deng, Z., Zhang, H., Ding, Z., Tang, X., & Wang, Z. (2026). A review of UAV positioning in LAIN: Toward a 5G-core "space-air-ground" integrated and cooperative architecture. *Information Technology & Electronic Engineering*, *27*, 1–16.

[5] Li, Z. (2019). Research on key technologies for visual localization and mapping of UAVs in low-light environments. https://doi.org/10.27406/d.cnki.gxbgu.2019.000141

[6] Liu, H., Long, Q., & Li, B. (2025). A review of sensor-based autonomous unmanned aerial vehicle (UAV) localization techniques. *Complex Systems*, *11*, 371.

[7] Yan, F. T., Lin, H., Xuan, H., Huang, Y., Cao, Y., Hu, H., & Liu, P. (2023). Passive sensor detection and tracking of UAVs in urban environments: A review. *Applied Sciences*, *13*, 11320.

[8] Gu, M., Li, H., & Zhang, J. (2025). A review of vision-based UAV localization and navigation methods. *Journal of Electronics*, *53*, 651–685.

ISSN: 2664-9640

[9] Miao, Z., Zhou, R., & Liu, J. (2025). Research progress on absolute visual localization of unmanned aerial vehicles. *Chinese Journal of Liquid Crystals and Displays*, *40*, 942–955.

[10] Georgiadis, D., Politi, E., & Solmaz, S. (2026). A review of positioning and sensing technologies for UAV swarms in search and rescue missions. *EURASIP Journal on Advanced Signal Processing*, *8*.

[11] Abdulazim, M., Kamal, H. A., Abazid, A., & Mohammed, M. O. A. (2025). Four-constellation RTK and relative GNSS using cost-effective smartphones for transportation applications. *Geoinformatics*, *5*, 56.