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SORUS-DRONE-A2.2-E2 (E11)

Network Optimization II: algorithms for the orchestration of UAV 6G Networks

Abstract

In previous deliverables, we explored the state-of-the-art in algorithms for the orchestration of Unmanned Aerial Vehicles (UAVs) within Beyond 5G (B5G) networks. Building on that foundational work, this document delves deeper into two critical areas: path planning and collision avoidance. We examine advanced algorithms aimed at optimizing UAV trajectory and safety in complex environments, a challenge that becomes more pressing with the integration of UAVs into B5G systems. In addition to a thorough review of existing methodologies, we present novel contributions developed under the project, enhancing the reliability and efficiency of UAV orchestration, particularly in scenarios involving dynamic and dense environments where collision avoidance is crucial.

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Resumen Ejecutivo

Este entregable presenta un análisis en profundidad de metodologías para mejorar el rendimiento de las redes Beyond 5G (B5G), con un enfoque en la integración de vehículos aéreos no tripulados (UAVs) y superficies inteligentes reconfigurables (RIS). Se examinan métricas clave como la probabilidad de cobertura, el área de cobertura, el retardo de paquetes y el consumo de energía, explorando su comportamiento bajo diversas condiciones de B5G.

Sobre la base de trabajos previos, se investigan escenarios en los que el número de antenas del iluminador no está fijado, analizando las condiciones de identificabilidad del análisis factorial multicanal y derivando expresiones para determinar cuándo es posible separar el ruido de la señal y la interferencia. Este estudio establece cuándo es necesaria una estimación precisa de los parámetros de las antenas, incluso bajo distribuciones de observación variables.

Además, se desarrollan detectores con medidas cuantificadas. Se propone un detector basado en la prueba de Rao para medidas cuantificadas a un solo bit en radar MIMO colocalizado, como primer paso hacia un radar pasivo. Estos detectores son especialmente adecuados para aplicaciones con UAVs debido a sus requisitos de hardware simplificados y su menor consumo energético.

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Executive Summary

This deliverable presents an in-depth analysis of methodologies to enhance Beyond 5G (B5G) network performance, focusing on the integration of UAVs and Reconfigurable Intelligent Surfaces (RIS). We examine key metrics such as coverage probability, coverage area, packet delay, and power consumption, exploring their behavior under various B5G conditions.

Building on prior work, we investigate scenarios where the number of antennas on the illuminator is not fixed, analyzing the identifiability conditions of multichannel factor analysis and deriving expressions to determine when noise can be separated from the signal and interference. This study, establishes when accurate estimation of antenna parameters is necessary, even under varying observation distributions.

Additionally, we develop detectors with quantized measurements. A Rao-test-based detector for single-bit quantized measurements in collocated MIMO radar is proposed as a first step toward passive radar. These detectors are well-suited for UAV applications due to their simplified hardware requirements and reduced energy consumption.

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1. Introduction

Unmanned Aerial Vehicles (UAVs), commonly known as drones, have evolved from niche military applications to become powerful assets in modern communication networks. Their ability to act as mobile nodes or relays makes them invaluable in creating dynamic, adaptable networks capable of extending coverage, enhancing resilience, and providing real-time data transmission in complex environments. In previous deliverables, we explored the critical role of UAVs in networking, particularly in challenging scenarios such as disaster recovery, remote areas, and large-scale public events, where traditional infrastructure may be insufficient.

This document focuses to one key operational challenge: collision avoidance in UAV orchestration, specifically in scenarios where UAVs are deployed to create coverage maps. As UAVs are tasked with covering vast areas, optimizing their path planning and ensuring safe operations through robust collision avoidance algorithms becomes paramount. These algorithms directly impact network performance metrics such as coverage, latency, and energy efficiency. Furthermore, we present new contributions from this project, offering advancements in collision-free navigation and efficient path planning for UAV networks, enabling improved coverage and reliability in real-time deployments.

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2. Path Planning and Positioning: Critical Factors in Network Performance

The effectiveness of UAVs in communication networks hinges largely on their ability to position themselves strategically and follow optimal flight paths. Both path planning and positioning are crucial for maximizing network performance across several dimensions.

The way UAVs are positioned directly influences the coverage area they can provide. As aerial base stations or relay nodes, UAVs play a vital role in delivering wireless connectivity, particularly in areas lacking infrastructure or during emergency situations. Efficient path planning is key to ensuring that UAVs are optimally placed, covering the largest possible area while minimizing blind spots. Moreover, maintaining connectivity between UAVs and ground stations, or other UAVs, is essential for uninterrupted communication. Precise positioning systems help sustain line-of-sight communication, reduce signal blockage, and mitigate interference, all of which contribute to a more reliable and high-performing network.

The routes that UAVs follow can have a significant impact on network latency and data throughput, a point that was thoroughly examined in the *SORUS-DRONE-A3.1-E1* deliverable. In these simulations, we demonstrated how UAVs, acting as relay nodes or aerial base stations, must carefully minimize both the distance between themselves and other network nodes while avoiding obstacles that could degrade signal quality. Poorly planned flight paths, as highlighted in the analysis, can lead to increased latency due to extended transmission distances or frequent handovers between network nodes. On the other hand, optimized path planning can significantly reduce latency and maintain consistent data throughput, which is essential for real-time applications like video streaming, remote control operations, or urgent scenarios such as disaster response. The insights gained from these simulations reinforce the importance of strategic path planning in UAV networks.

In networks involving multiple UAVs or swarms, avoiding collisions is critical to maintaining network integrity. This is something we explored in depth in the deliverable *SORUS-DRONE-A3.1-E1*, where we analyzed simulations involving multiple UAVs. These simulations highlighted the significant impact that effective collision avoidance has on overall network performance. By employing advanced path planning and reliable positioning systems, UAVs can detect and avoid potential collisions with other UAVs or obstacles in their flight path. This is crucial not only for ensuring the physical safety of the UAVs but also for maintaining stable communication links. A collision or even a near-miss could easily disrupt communications, lead to data loss, or cause network downtime, which would negatively affect the network's performance and reliability.

Despite the advancements in UAV technology and path planning algorithms, several challenges remain that need to be addressed for seamless operations:

Real-Time Processing Requirements

Effective path planning and collision avoidance rely heavily on real-time data processing and fast decision-making capabilities. This poses a significant computational burden, especially when UAVs are operating in complex environments filled with obstacles or other UAVs. The faster and more accurate the processing, the safer and more efficient the UAV's operations will be.

Environmental Uncertainty

Another challenge is dealing with environmental uncertainties. Path planning algorithms must be robust enough to handle sudden changes in weather, unexpected obstacles, or sensor inaccuracies. These unpredictable factors can greatly affect a UAV's ability to stick to its planned route. Adapting to such changes in real time is crucial to maintaining both the UAV's safety and the network's overall performance.

Communication and Coordination

In operations involving multiple UAVs, reliable communication between drones becomes essential. Each UAV needs to be constantly aware of the others' positions and flight paths to avoid collisions. However, issues such as intermittent connectivity or communication delays can lead to poorly coordinated flight paths, increasing the likelihood of collisions.

2.1. UAV Positioning Systems

The positioning system of an Unmanned Aerial Vehicle (UAV) is a fundamental component that determines the UAV's location, orientation, and movement in space. Accurate positioning is crucial for UAV operations, including navigation, path planning, collision avoidance, and mission execution. UAV positioning systems typically rely on a combination of Global Navigation Satellite Systems (GNSS), inertial sensors, visual odometry, and other methods to achieve precise location awareness. Let's delve into the various positioning technologies and their integration in UAV systems. [1]

2.2. Global Navigation Satellite System (GNSS)

Global Navigation Satellite System (GNSS), such as the Global Positioning System (GPS), GLONASS, Galileo, and BeiDou, is the most widely used positioning technology in UAVs. GNSS provides geospatial positioning with global coverage by utilizing a network of satellites that transmit signals to the UAV's onboard receiver. [2]

How GNSS Works: The UAV's GNSS receiver calculates its position by measuring the time it takes for signals to travel from multiple satellites to the receiver. By triangulating these signals, the receiver determines the UAV's latitude, longitude, and altitude.

Advantages: GNSS provides high accuracy, typically within a few meters, depending on the quality of the receiver and environmental conditions. It is reliable over large geographic areas, making it ideal for outdoor UAV operations like surveying, mapping, and delivery services.

Limitations: GNSS signals can be obstructed or degraded by obstacles like buildings, trees, or mountains. They are also susceptible to interference, multipath effects (where signals bounce off surfaces), and jamming or spoofing attacks. Furthermore, GNSS is less effective in indoor environments or areas with weak satellite signal reception.

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2.3. Inertial Navigation System (INS)

Inertial Navigation Systems (INS) rely on onboard sensors, such as accelerometers and gyroscopes, to determine the UAV's position, velocity, and orientation. INS provides relative positioning information by measuring the UAV's acceleration and angular rates over time. [3]

How INS Works: The INS calculates the UAV's movement from a known starting point by integrating the acceleration and angular velocity data provided by the sensors. This process, known as dead reckoning, continuously updates the UAV's position and orientation.

Advantages: INS is independent of external signals, making it immune to GNSS signal loss, jamming, or interference. It provides high-frequency updates (typically in the range of milliseconds) and is well-suited for environments where GNSS is unreliable or unavailable, such as indoors or in dense urban areas.

Limitations: INS suffers from drift over time due to sensor errors and noise, causing the calculated position to diverge from the actual position. This drift accumulates rapidly, especially during long-duration flights, necessitating periodic calibration or integration with other systems like GNSS for error correction.

2.4. Visual Odometry (VO)

Visual Odometry (VO) uses onboard cameras to estimate the UAV's position and orientation by analyzing the motion of objects in the captured images. VO is particularly useful for UAVs operating in GPS-denied environments, such as indoors or in dense urban areas where satellite signals are weak or obstructed [4].

How VO Works: VO algorithms track feature points in consecutive images captured by the UAV's camera(s). By analyzing the changes in the positions of these feature points, VO estimates the UAV's relative motion, providing data on its position, orientation, and velocity.

Advantages: VO can provide accurate positioning in environments where GNSS is unreliable or unavailable. It is effective in both indoor and outdoor environments and can leverage existing visual information from the UAV's mission sensors (such as RGB or infrared cameras).

Limitations: VO is highly dependent on environmental conditions, such as lighting and texture. Poor lighting, lack of distinct features, or rapid movements can degrade VO performance. It also requires substantial computational resources, which can be challenging for small UAVs with limited processing capabilities.

2.5. Ultra-Wideband (UWB) Positioning

Ultra-Wideband (UWB) positioning is a short-range wireless communication technology that uses radio waves to determine the position of a UAV. UWB operates by measuring the time-of-flight (ToF) of signals between the UAV and multiple fixed anchors or beacons. [5]

How UWB Works: The UWB system transmits a series of ultra-short radio pulses between the UAV and stationary anchors. By calculating the time taken for the signals to travel back and forth, the UAV's onboard system determines its precise location relative to the anchors.

Advantages: UWB provides high accuracy, typically within a few centimetres, and is effective in cluttered or indoor environments where GNSS signals are obstructed. It is also resistant to interference from other wireless systems due to its broad frequency spectrum.

Limitations: UWB requires a pre-installed network of anchors, limiting its use to environments where such infrastructure is feasible. The positioning range of UWB is also limited, making it less suitable for long-range UAV operations.

2.6. Simultaneous Localization and Mapping (SLAM)

Simultaneous Localization and Mapping (SLAM) is a method that enables a UAV to build a map of its environment while simultaneously determining its position within that map. SLAM integrates data from various sensors, such as cameras, LiDAR, and ultrasonic sensors, to achieve accurate positioning and mapping. [6]

How SLAM Works: The SLAM algorithm creates a map of the UAV's environment by identifying key features and landmarks. It continuously updates the map and refines the UAV's estimated position by comparing the sensor data with the existing map. This allows the UAV to navigate and localize itself in real time.

Advantages: SLAM provides reliable positioning in both indoor and outdoor environments, especially in GPS-denied areas. It adapts to dynamic environments, continuously updating the map as the UAV moves and encounters new features.

Limitations: SLAM is computationally intensive, requiring powerful processors and efficient algorithms to operate in real time. It also relies on sufficient environmental features for accurate mapping and localization, which can be challenging in featureless or dynamic environments.

2.7. Integration of Positioning Systems

For robust and accurate positioning, UAVs often integrate multiple positioning systems. A hybrid approach, combining GNSS with INS, VO, SLAM, or RF positioning, can compensate for the limitations of each method. For example [7]:

GNSS+INS: GNSS provides absolute positioning data, while INS offers high-frequency updates. Combining GNSS with INS allows the UAV to maintain accurate positioning during temporary GNSS outages or signal degradation.

GNSS+VO or SLAM: When GNSS signals are unavailable, visual odometry or SLAM can provide alternative positioning data. These methods are especially useful in GPS-denied environments.

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UWB+INS or SLAM: In indoor environments, UWB can offer precise positioning, while INS or SLAM can provide continuous updates and enhance accuracy in complex or dynamic settings.

By integrating multiple positioning technologies, UAVs can achieve high-precision localization, improve robustness against environmental challenges, and ensure safe and efficient operation across a wide range of scenarios.

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3. The Role of Passive Radar Systems in UAV Collision Avoidance

In certain situations where the positioning system of UAVs and/or their communication with the control center fails, it becomes necessary for the UAVs to have the ability to detect and locate other UAVs to avoid collisions. In other words, they must be equipped with a radar subsystem. However, given the energy constraints of UAVs, conventional or active radar systems are not suitable, and it is more advantageous to use passive radar systems.

Passive radar is an emerging technology that has attracted the attention of the scientific community over the past few decades [8]. Passive radar systems are a type of bistatic radar [21] in which the transmitted waveform is not controlled by the radar itself. Instead, they use opportunistic transmitters, known as "illuminators of opportunity," which can be terrestrial digital television systems, FM radio, base stations, or even the UAVs themselves, as illustrated in the following image.

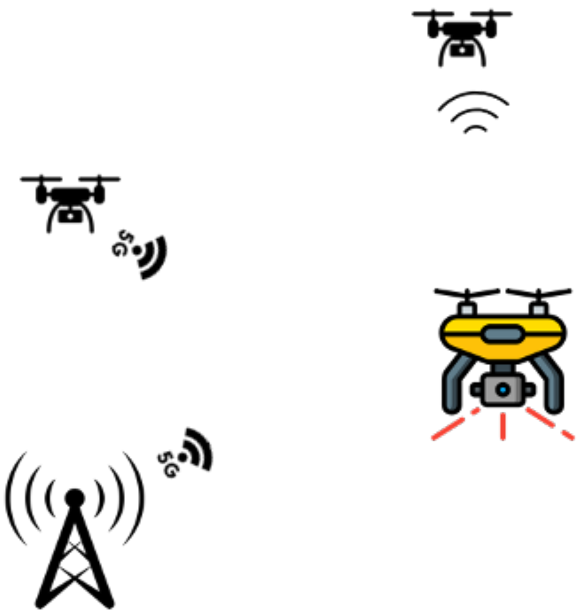

FIGURE 1 SCENARIO WITH UAVS AS PASSIVE RADARS FOR COLLISION AVOIDANCE.

The use of illuminators of opportunity is the key element that determines the advantages of passive radar systems over active radar systems [8]. Firstly, although not critical for this application, passive radar systems allow for covert operations—meaning that the system cannot be detected because it does not emit any signals. Additionally, since only the receiver needs to be deployed, these systems are simpler and less expensive. Finally, as they lack a transmitter, they are more energy efficient.

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4. Passive Radar for UAV-Based Sensing and Multi-Antenna Configurations

Passive radar has gained significant traction in recent years as a stealthy and cost-effective solution for UAV detection and UAV-mounted sensing. Unlike active radars, passive systems do not emit their own signals; instead they exploit illuminators of opportunity (IOs) (e.g. broadcast TV, cellular, or satellite signals) to detect targets. This inherently reduces power requirements and avoids high-power transmitters, which is ideal for UAV platforms with limited energy budgets. Passive radar's lack of emissions also grants it stealth and jam-resistance, making it hard for adversaries to detect or counter [9]. Recent surveys emphasize these advantages in counter-drone applications, noting that passive radar can leverage a wide variety of external signals and operate in diverse environments (urban, indoor, airspace) where active radars might be impractical.

Modern passive radar systems increasingly employ multi-antenna and multi-static configurations to improve detection performance. By using multiple receive antennas or spatially separated sensors, passive radar can estimate target angle in addition to range and Doppler, thus localizing UAVs more accurately [9]. For example, a multi-antenna passive radar can combine angle-of-arrival with range-Doppler measurements to filter false alarms and track UAVs more reliably [10]. Similarly, multi-static setups (multiple receivers or illuminators) provide spatial diversity and SNR gains. A recent study demonstrated UAV detection by fusing signals from multiple channels and polarizations, achieving successful tracking of small drones at ranges up to 100 km using FM radio illuminators [9]. Likewise, researchers have exploited multiple satellite transmitters simultaneously to boost detection SNR, effectively tracking UAVs across multiple reference channels for better sensitivity. Field trials have validated passive radar's capability against small UAV targets: for instance, using a digital TV (DTMB) broadcast as IO, a ~35 cm quadrotor was detected and tracked [11], and a DAB-based passive radar detected micro-UAVs at up to 1.2 km rang [12]. These results underscore that multi-antenna/multi-sensor configurations are central to state-of-the-art passive radar for UAV sensing, enabling higher precision and robustness in challenging scenarios.

4.1. Multichannel Factor Analysis and Signal Identifiability

A key theoretical advancement in the last five years is the application of multichannel factor analysis (MFA) to passive radar signal modeling and target detection. MFA provides a statistical framework to separate common signals (e.g. a target's echo) from channel-specific interference and noise across multiple sensors or channels [13]. In a passive radar context, one can model the reference and surveillance channels (each possibly multi-antenna arrays) as two channels that share a common factor when a target is present. The target reflection is a latent factor that appears jointly in both channels' data, whereas each channel also has its own independent clutter and interference factors. This common-and-unique factor model has been formulated to account for practical issues like direct signal leakage from the reference into surveillance channel. By capturing the underlying low-rank structure of shared vs. unique components, MFA-based approaches improve the ability to detect weak UAV reflections buried in strong interference.

Crucially, recent research has addressed the identifiability of these factor models – ensuring that the decomposition into target and interference factors is unique and physically meaningful. [13] introduced an MFA model with common and unique factors for multi-sensor channels and derived a maximum-likelihood estimation algorithm for it. They proved conditions under which the MFA covariance model is generically identifiable, meaning the target's contribution can be uniquely isolated from the covariance of measurements. Follow-up work has strengthened these results: for example, modern identifiability theorems show that if the number of sensors and factor dimensions satisfy certain inequalities, the shared vs. distinct factors can be separated with unique solutions (up to trivial ambiguities). In practice, these theoretical guarantees inform the design of signal processing algorithms that can, for instance, blindly separate a UAV's echo from heavy clutter by exploiting the multi-channel structure. Overall, *state-of-the-art passive radar detection algorithms leverage MFA* to enhance signal identifiability, enabling the detection of UAV targets that would otherwise be masked by interference. This line of research bridges classical array processing with modern statistical inference, providing a principled way to fuse multi-antenna data for improved UAV sensing.

4.2. Quantization-Aware Detection Techniques

Another emerging theme is quantization-aware radar processing, driven by the need for energy and bandwidth efficiency in UAV platforms and distributed sensor networks. Quantization-aware techniques acknowledge that high-rate, high-bit analog-to-digital conversion is power-hungry; instead, they explore using low-bit (e.g. 1- to 3-bit) digital samples without severely sacrificing detection performance. In the past five years, multiple studies have demonstrated that radar (and passive radar) detection can remain effective even with aggressively quantized signals:

- **One-Bit Passive Radar Detection:** In [14] is proposed a passive radar target detection method using 1-bit quantization, cleverly exploiting both pilot tones and data portions of communication signals to compensate for lost amplitude information. Their approach achieved enhanced detection of targets by treating the strong pilot signals as reference and using tailored processing for the quantized data signals. This showed that even a single-bit ADC frontend can be viable for passive radar, drastically cutting power and data-rate requirements. [15] further demonstrated one-bit passive radar for NB-IoT based localization; remarkably, with enough distributed nodes, a one-bit system showed <1% localization error increase compared to full precision, and with sufficiently many sensors it matched full-precision performance. These results validate that one-bit sensors can perform high-accuracy sensing while aligning with the ultra-low-power goals of IoT and UAV applications.
- **Low-Bit Distributed Detection:** In [16] is investigated a distributed radar on moving UAV platforms where each node uses low-bit quantizers to transmit observations with limited bandwidth. They developed a multi-target detection algorithm and even an optimal quantizer design for the network. Impressively, their simulations showed that with only 2-bit per sample

quantization, the system could achieve a trade-off between the detection performance and the used data size. This quantization strategy offers a favorable trade-off between performance and resource consumption, which is critical for swarms of small UAVs that must share data over wireless links.

- **Quantization in Radar-Communication Integration:** In the context of integrated sensing and communication, researchers have studied how quantization affects cooperative radar networks. [17] compared strategies where local radar receivers send either quantized test statistics or quantized raw measurements to a fusion center. They proved that through proper fusion, a cooperative multi-static radar system can achieve the same detection performance with fewer quantization bits compared to non-cooperative setups. Such cooperation can offset quantization loss, yielding an energy-efficient sensing network. These findings are particularly relevant if multiple UAVs or ground sensors collaboratively monitor a region they can quantize and share minimal information to save energy yet still reliably detect targets [17].

In summary, quantization-aware detection has become a vital component of the state of the art, aiming to minimize power, data, and cost footprint of radar sensors. By smart algorithm design (e.g. leveraging signal structure or network cooperation), these methods maintain high detection probability for UAV targets even under severe quantization. This paves the way for deploying passive radar on size-, weight-, and power-constrained platforms like small drones, and for large networks of simple sensors in the emerging IoT sensing paradigm.

4.3. Energy-Efficient Radar Processing for UAV Systems

Given the limited battery life and processing capabilities of UAVs, recent research has put a strong emphasis on energy-efficient radar processing techniques. Passive radar itself is an energy saver (no dedicated transmitter), but additional strategies are being developed to further reduce power consumption while maintaining performance in UAV-based sensing tasks.

One direction is optimizing the *operational aspects* of UAV radar systems. For example, mission planning and flight path optimization can dramatically influence the sensing efficiency. [18] introduced an energy-efficient passive UAV radar imaging system and showed that the UAV's flight trajectory and choice of illuminators have a large impact on imaging performance vs. energy use. They formulated a path planning problem for a UAV carrying a passive synthetic aperture radar (SAR) sensor, aiming to maximize imaging quality while minimizing energy expenditure. Their proposed algorithm (Sub-DiCoS) finds an optimal path that lets the UAV cover the area using favorable geometries with minimal extra distance or maneuvering, which in turn conserves energy. Simulation results demonstrated that by intelligently planning the UAV's route over 3D terrain, one can safely traverse in an energy-efficient manner and achieve high-quality SAR imagery and even maintain communication links. This work underscores that energy efficiency in UAV radar isn't only about electronics – it's also about *where and how* the UAV flies to gather data most efficiently.

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On the signal processing side, computational efficiency and smart resource allocation are key to saving energy. Researchers are exploring reduced-complexity algorithms (e.g., using unmatched filtering or reduced sampling rates) that trade off some processing gain for lower power usage. For instance, in passive radar workflows, skipping certain processing steps or using approximate methods can save CPU/GPU cycles on-board, which translates to energy savings—as demonstrated by Sun *et al.*, who implement an energy-efficient passive SAR imaging pipeline onboard a UAV by optimizing path planning and processing stages during flight [19]. There is also interest in cognitive radar techniques that adapt the processing or sensing schedule based on context—a UAV radar might power down or duty-cycle its receiver when no threats are present or dynamically lower the sampling rate in benign conditions to conserve energy. Additionally, integration with communication systems (as in 6G networks) allows a UAV to share sensing tasks with ground stations or other drones, balancing the energy load across the network. By offloading heavy processing or using cooperative detection (so that each node does less work), the overall system becomes more energy-efficient.In conclusion, the latest UAV radar and sensing systems prioritize energy-efficient operation through a combination of passive sensing principles, quantization and data reduction, optimized trajectories, and cooperative processing. These state-of-the-art methods ensure that even small drones can host radar sensors or detection algorithms that run persistently and reliably within tight power constraints, which is essential for real-world deployment of UAV networks for surveillance, navigation (sense-and-avoid), and remote sensing. The convergence of passive radar technology, multichannel signal processing, and power-aware design is enabling a new generation of UAV-based sensing systems that are both capable and sustainable in performance.

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5. Detection with Unknown Parameters and Known Subspaces

In passive radar systems that leverage *illuminators of opportunity*—such as digital television (DVB-T), commercial cellular base stations (4G/5G), or WiFi networks—the transmitted waveform is not designed for radar purposes and is not known a priori. As a result, the receiver faces a challenging detection problem, in which critical parameters such as the transmitted signal, propagation channel gains, and noise characteristics are either unknown or only partially observable. This challenge is particularly acute in airborne detection applications, such as UAV collision avoidance, where the sensing window is short and real-time inference is required.

To address this, our contribution builds on the framework of Generalized Likelihood Ratio Tests (GLRTs) [22] under a second-order statistical model, where the received signals are modeled as jointly Gaussian random vectors. In contrast to first-order GLRTs—which treat the unknown signal deterministically—second-order approaches enable the incorporation of signal energy and spatial statistics, thereby yielding more powerful and robust detectors under uncertainty.

Problem Formulation

The system comprises two linear arrays:

- A **surveillance array**, which observes potential reflections from the scene (e.g., from a UAV), and
- A **reference array**, which captures a copy of the signal emitted by the illuminator, either directly or via a reliable proxy.

Let $x_i[n] \in \mathbb{C}^M$ be the complex baseband sample vector at time n from channel $i \in \{s, r\}$, where s and r refer to the surveillance and reference channels, respectively. The detection problem is then cast as a binary hypothesis test:

$$\mathcal{H}_1 : x_i[n] = \alpha_i \boldsymbol{U_i} s[n] + r_i[n]$$
$$\mathcal{H}_0 : \ x_i[n] = r_i[n]$$

where:

- $\alpha_i \in \mathbb{C}$ is an unknown complex channel gain,
- $\boldsymbol{U_i} \in \mathbb{C}^{M \times d}$ is a known orthonormal basis spanning the signal subspace,
- $s[n] \in \mathbb{C}^d$ is the unknown transmitted signal modeled as $s[n] \sim \mathcal{CN}(0, \sigma_s^2 \boldsymbol{I})$
- $r_i[n] \sim \mathcal{CN}(0, \sigma_s^2 \boldsymbol{I})$ is additive white Gaussian noise.

This detection model falls under the umbrella of composite hypothesis testing, as multiple nuisance parameters must be estimated or marginalized. In practice, the basis matrices $\boldsymbol{U_i}$ are obtained through calibration or estimation from training data, and they capture the spatial filtering characteristics of the array, including direction-of-arrival (DOA) alignment.

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5.1. GLRT under the Second-Order Gaussian Model

Under the second-order model, the classical GLRT replaces the unknowns with their maximum likelihood estimates (MLEs) under both hypotheses. This process leads to a closed-form test statistic involving the sample covariance matrices projected onto the known subspaces $\boldsymbol{U_i}$. The advantage of this formulation is twofold:

1. Efficient implementation: The final detector depends only on subspace projections and covariance estimation, avoiding non-convex optimization or iterative fitting.
2. Statistical robustness: The Gaussian assumption allows the model to exploit correlation structures and improves detection reliability in the presence of noise and clutter.

This approach is aligned with the work of Scharf et al. (2016), who introduced the use of canonical correlation analysis (CCA) for passive radar detection in scenarios with spatial diversity and unknown channel conditions [20]. While their work focused on correlation between signal subspaces, our contribution advances this by explicitly modeling the signal as a random Gaussian process, thereby generalizing the detector design.

In scenarios characterized by limited sample support, such as those involving fast-moving unmanned aerial vehicles (UAVs), second-order statistical models demonstrate markedly superior performance compared to deterministic signal assumptions. The inherent dynamics of UAVs, including rapid mobility and fluctuating propagation conditions, often lead to low signal-to-noise ratios (SNRs) and sparse observations, making reliable inference challenging. Deterministic models, which rely on precise signal representations, tend to overfit or fail under such uncertainty. In contrast, second-order models leverage statistical properties—such as covariance and variance—to capture the underlying distribution of signals, providing a natural form of regularization. This statistical perspective allows for more robust estimation and decision-making by smoothing out noise and compensating for the variability introduced by limited and noisy data. Consequently, in low-SNR, high-mobility environments, second-order models are better suited to generalize and maintain performance, particularly in tasks such as channel estimation, beamforming, or trajectory prediction.

5.2. Performance and Impact

In our numerical experiments, we evaluated the proposed GLRT on a system comprising:

- Six-element surveillance and reference arrays,
- An illuminator with four transmitting antennas,
- A window of 20 coherent observations,
- A reference-channel SNR 10 dB higher than the surveillance-channel SNR.

Under these conditions, the second-order GLRT achieved a 6 dB gain in required SNR compared to the first-order GLRT—equivalent to halving the required signal power or doubling the detection range under free-space propagation, as per the radar range equation [22]. This improvement

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translates into a 40–50% increase in detection coverage, which is particularly significant for small drones with limited radar cross-section (RCS). Such gains can extend the temporal margin for evasive maneuvers by several seconds, a critical enhancement in UAV sense-and-avoid systems.

The improvement is not purely theoretical. In practical radar deployments, the 6 dB gain enables:

- **Earlier warning times** for impending collisions,
- **Reduction in antenna or power requirements**, making the system more viable for lightweight UAV platforms,
- **Enhanced resilience** to environmental clutter and multipath propagation.

These benefits underline the importance of advanced statistical signal processing, not just hardware design, in the development of next-generation passive collision avoidance systems. In other words, more advanced processing can achieve significant improvements.

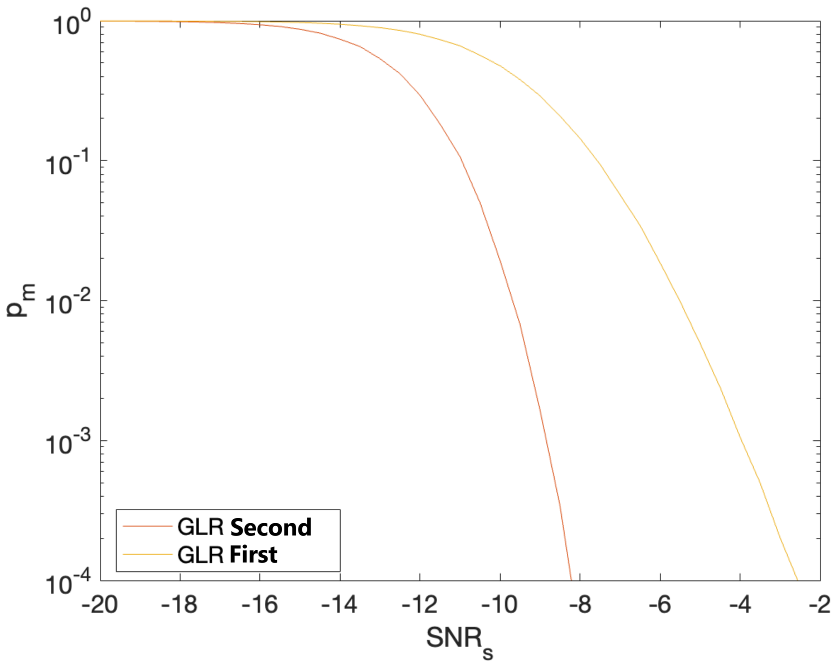

FIGURE 2 PROBABILITY OF MISSED DETECTION VS SNR

As illustrated in the figure, the proposed GLR vides a gain of nearly 6 dB, effectively doubling the radar's operational range under free-space propagation conditions. In other words, more advanced processing can achieve significant improvements.

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6. Always On Reference Channel with Coloured Noise

While passive radar systems benefit from not having to transmit any waveform themselves, this advantage comes at the cost of a more complex signal processing chain. In particular, many practical systems are configured such that the reference channel is permanently aligned with the direct path from the illuminator, capturing a clean (or nearly clean) version of the transmitted waveform. This configuration is achieved using fixed directional antennas or adaptive beamforming, ensuring continuous reception of the source signal regardless of the target presence or motion.

However, this always-on configuration introduces new challenges:

- The surveillance and reference channels are affected by distinct propagation paths, including multipath and fading, and may include unknown spatial transformations.
- The additive noise in each channel is no longer assumed white or independent, but rather coloured, with unknown covariance matrices that may vary over time or across antenna elements.

These conditions reflect realistic operating environments for UAV detection, particularly in urban or semi-structured airspace, where interference and reflections are pervasive.

6.1. Canonical Correlation-Based GLRT

Under Gaussian assumptions and unknown channel responses, the classical approach is to apply the Generalized Likelihood Ratio Test (GLRT) by replacing unknowns with their maximum likelihood estimates. A key insight from [23] is that in such multichannel settings, the GLRT can be expressed as a function of the canonical correlations k_l between the surveillance and reference data matrices:

$$GLR = \prod_{l=1}^{L} \left(1 - k_l^2\right), \qquad (2)$$

where $L \leq \min(M_r, M_s)$ is the number of spatial degrees of freedom (or data streams), and each canonical correlation $k_l \in [0, 1]$ quantifies the similarity between projections of the data onto correlated subspaces. The larger the canonical correlations, the more evidence exists in favor of the alternative hypothesis $\mathcal{H}_1$ (i.e., presence of a common signal).

Canonical correlation analysis (CCA) provides a natural way to detect statistical dependence between the two received signals while being agnostic to the transmitted waveform and the exact propagation model. This approach has also been extended to settings with coloured Gaussian noise, which discusses detection in passive MIMO radar with unknown and possibly non-white noise components.

$$\mathcal{H}_1 : \begin{cases} x_s[n] = H_s s[n] + r_s[n] \\ x_r[n] = H_r s[n] + r_r[n] \end{cases}$$

$$\mathcal{H}_0 : \begin{cases} x_s[n] = r_s[n] \\ x_r[n] = H_r s[n] + r_r[n] \end{cases}$$

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While the GLRT in this form is powerful and has theoretical appeal, it has two significant limitations in the UAV detection context:

1. **High sample complexity**: Accurate estimation of sample covariance matrices requires a sufficient number of snapshots, which may not be available for fast-moving drones.
2. **Sensitivity to noise covariance**: Ill-conditioned or misestimated noise covariance matrices can significantly degrade detection performance, especially when the background noise is spatially correlated.

6.2. Bayesian-Inspired Marginalized Likelihood Ratio (MLR)

To overcome these limitations, we build upon recent advances in Bayesian signal detection, particularly the approach introduced by [23]. Instead of maximizing over unknown nuisance parameters (as in GLRT), the Bayesian method marginalizes them by introducing conjugate prior distributions. Specifically, the unknown covariance matrices of the reference and surveillance channels are modeled as complex inverse Wishart distributions, which are conjugate priors to the multivariate complex Gaussian likelihood.

This leads to a closed-form expression for the Marginalized Likelihood Ratio (MLR), given by:

$$MLR = \prod_{l=1}^{L} (1 - \bar{k}_l^2)$$

where $\bar{k}_l^2$ are regularized canonical correlations. These are analogous to the standard k_l values, but are shrunken toward zero depending on the number of observations, effectively penalizing overfitting when sample support is low.

Importantly, this regularization arises naturally from the marginalization process and does not rely on arbitrary tuning parameters. It is mathematically grounded in the Bayesian inference framework, making the MLR detector both statistically principled and robust to model misspecification. The method reflects a growing body of research advocating for probabilistic treatments of nuisance variables in detection and estimation problems.

6.3. Performance Evaluation and Implications

To assess the performance of the MLR detector, we simulated a passive radar system with the following configuration:

- 10-element surveillance and reference arrays,
- 10-element transmitting array from the illuminator,
- 50 coherent temporal snapshots.

The simulation assumes a coloured noise background with unknown spatial correlation, modeled using random complex covariance matrices with realistic eigenvalue distributions. The results,

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benchmarked against the canonical correlation-based GLRT, reveal a consistent performance gain of approximately 0.5 dB in SNR threshold at a fixed probability of false alarm. While this may appear modest, it becomes more significant in low-SNR and low-sample regimes, where the classical GLRT begins to degrade rapidly.

This robustness is particularly beneficial in UAV applications where:

- Only a short time window is available before the UAV has left the radar's field of view,
- Reference signal quality may fluctuate due to partial shadowing, clutter, or interference,
- Computational constraints require detectors with closed-form expressions and predictable behavior.

Moreover, the MLR detector's regularization property ensures stability under imperfect data, reducing the need for pre-whitening or additional calibration procedures.

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7. Broader Implications for UAV Collision Avoidance

The growing adoption of unmanned aerial vehicles (UAVs) in civilian, commercial, and defense domains has made sense-and-avoid (SAA) capabilities an essential component of safe and autonomous flight. As UAVs increasingly operate in shared airspace with manned aircraft, the ability to detect potential obstacles or intruders early—under a variety of environmental and signal conditions—is paramount to prevent mid-air collisions and near-miss incidents. While the initial specification of UAV control-plane architecture and mission path planning algorithms was introduced in *SORUS-DRONE-A3.1-E1* [24], the current deliverable provides the necessary modeling framework to define and interpret collision avoidance zones, which were only implicitly assumed in earlier simulations. Without the formalization established here, accurate performance evaluation and efficient scenario design for SAA in UAV missions, as described in the prior deliverable [24], would remain incomplete or overly simplified.

The two detection strategies explored in this work—namely, the second-order Generalized Likelihood Ratio Test (GLRT) and the Bayesian Marginalized Likelihood Ratio (MLR)—have direct and compelling implications for the development of practical, high-performance SAA systems based on passive radar architectures.

7.1. Enhanced Detection Range for Early Avoidance

Perhaps the most critical benefit of the proposed detectors is their contribution to detection range extension. In particular, the second-order GLRT offers up to 6 dB of SNR gain over first-order detectors, corresponding to a 40–50% increase in detection range under free-space propagation [23]. For small UAVs flying at speeds of 10–20 m/s, this range increase translates into several additional seconds for threat recognition, path planning, and evasive maneuver execution. These extra seconds can be decisive in environments with tight maneuvering constraints, such as near airports, in urban canyons, or during autonomous delivery operations.

Extending the radar's operational radius also enhances cooperative deconfliction, enabling networked UAVs to share sensed data and predict potential conflicts earlier.

7.2. Robustness in Complex Electromagnetic Environments

The MLR detector, by incorporating Bayesian marginalization of nuisance parameters, is inherently more robust to covariance mismatch and noise coloration. This is particularly important in real-world scenarios where:

- The electromagnetic environment is cluttered, e.g., in urban or suburban areas with strong multipath,
- Interference from other users or emitters may distort the reference signal,
- Snapshot availability is limited, due to short dwell times or agile scanning patterns.

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Robust detection under such conditions is a key enabler for operating in GNSS-denied or high-RF-density environments, where traditional active sensors may suffer from degraded performance or regulatory constraints.

Moreover, the MLR's statistical regularization allows the system to maintain stable detection thresholds under variable SNR and limited training data—an advantage not shared by conventional matched-filter or correlation-based methods.

7.3. Enabling Lightweight and Stealthy UAV Platforms

UAVs—particularly micro and mini drones—often operate under strict Size, Weight, and Power (SWaP) constraints, which limit the use of traditional radar systems with high-gain antennas and bulky transceivers. Passive radar systems, by contrast, require:

- No power-hungry transmit modules,
- Smaller antenna apertures (e.g., compact phased arrays or directional panels),
- Lower data-rate front ends, since they often operate at lower bandwidths (e.g., 5 MHz for DVB-T).

The use of advanced signal processing algorithms such as the GLRT and MLR detectors allows UAVs to compensate for hardware limitations through software intelligence. In other words, detection performance can be boosted not by transmitting more power, but by processing more effectively. This shift is especially attractive for battery-powered UAVs operating beyond visual line of sight (BVLOS), where stealth and low detectability are also operational requirements.

Furthermore, passive systems do not emit radio-frequency energy, allowing UAVs to operate in spectrum-constrained environments—including proximity to airports, military zones, or sensitive installations—without contributing to RF pollution or violating emission regulations.

7.4. Toward Integrated, Multi-Sensor Collision Avoidance Systems

The developments in passive radar detection presented in this work are well suited to integration within multi-sensor SAA architectures, combining: Optical or infrared sensors for short-range detection, ADS-B or transponder data for cooperative aircraft, Passive radar for long-range, all-weather coverage.

Such hybrid approaches have been proposed in recent SAA frameworks (e.g., [2], [3]), and our results suggest that passive sensing should not be relegated to backup or secondary roles, but instead considered a primary source of early detection, particularly when enhanced with Bayesian inference and multichannel processing.

In networked airspace scenarios (e.g., urban air mobility, drone corridors), passive radar-equipped UAVs can also serve as cooperative surveillance nodes, contributing their detection tracks to a shared situational awareness framework without increasing the electromagnetic noise floor.

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8. Summary and Conclusions

In this deliverable, we focus on an in-depth analysis of various methodologies aimed at enhancing the performance of Beyond 5G (B5G) scenarios. These scenarios aim at enhancing the capabilities of UAV-networks through the strategic integration of Unmanned Aerial Vehicles (UAVs) and Reconfigurable Intelligent Surfaces (RIS). To evaluate the performance, we delve into fundamental metrics such as coverage probability, area of coverage, sojourn time of delay suffered by packets, power consumption, meticulously examining their dynamics under the influence of key factors that shape the B5G landscape. Through analysis and experimentation, we aim to unravel insights into the intricate interplay between UAVs, RIS, and the dynamic elements that impact network performance.

The previous contributions, like most of the state-of-the-art, consider that the number of antennas on the illuminator is known. In many scenarios, this can be an adequate assumption since the communication standard is known, but in others, it may not be. For example, if such a standard has a mode with an adaptive number of antennas. In this contribution, which led to the publication [4], the conditions under which it is necessary to estimate this parameter accurately or not are studied. Specifically, the identifiability conditions of the multichannel factor analysis are studied, and expressions depending on the number of antennas of the illuminator and the radar system are obtained to determine when it is possible to separate noise from the signal and, in turn, when it is possible to separate the signal into desired signal (the reflected signal) and interference generated by the direct beam. It is also demonstrated that the same asymptotic results are obtained regardless of the distribution of the observations.

The final contribution presented in this report is the development of detectors with quantized measurements, which resulted in the publication [7]. Specifically, a detector based on the Rao test was derived for quantized measurements with a single bit in collocated MIMO radar systems, serving as the initial step toward extending it to passive radar. The derived detectors for quantized measurements have great potential for use in UAVs since they allow for simpler hardware systems and, consequently, lower energy consumption.

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