

Reconfigurable Intelligent Surfaces-Assisted System for Malicious UAV Detection

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A Thesis Presented to the
DEANSHIP OF GRADUATE STUDIES

KING FAHD UNIVERSITY OF PETROLEUM & MINERALS

DHAHRAN, SAUDI ARABIA

In Partial Fulfillment of the
Requirements for the Degree of

MASTER OF SCIENCE
In
**TELECOMMUNICATION
ENGINEERING**

DECEMBER 2023

KING FAHD UNIVERSITY OF PETROLEUM & MINERALS
DHAHRAN 31261, SAUDI ARABIA

DEANSHIP OF GRADUATE STUDIES

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Dedications

This thesis, and this degree, and all the effort, work, hardship, and sacrifices that accompanied its preparation, the successes and aspirations that come with it, all of that, is a dedication to my mother; Nadia Shuaib Al-Farra.

This thesis also serves as a fulfillment of my promise to my friend and grandfather; Shuaib Al-Farra, may he find solace in it for his late beloved companion; Nadira Abu Assi who departed to the All-Merciful, earlier this year.

Yousef

Acknowledgements

In The Name of Allah, The Most Gracious, The Most Merciful.

All praise and glory goes to Almighty Allah (Subhanahu wa Ta'ala) who gave me the courage and patience to carry out this work. Peace and blessings of Allah be upon His last Prophet Muhammad (Sallallahu-Alaihi-Wasallam) and all his companions (Radia-Allaho-Anhum) who devoted their lives towards the prosperity and spread of Islam.

Firstly and most importantly, I would like to express my sincere gratitude to my supervisor; Dr. Subail Al Dharrab, for his guidance and support throughout this journey. Since my first week at KFUPM, and even before officially being my academic advisor, Dr. Suhail has always been the first and most important source of motivation, encouragement and confidence to me. As a researcher and instructor, Dr. Suhail has set my standards high to what an academic has to be able to do. His dedication and patience towards his students as an instructor and as an advisor was something that always inspired me. I will forever be grateful to the countless numbers of hours he dedicated for me throughout my journey, starting from familiarizing me with reading and understanding different research papers, and finally ending up with a solid research results that I feel proud of. As a person, I have learned so much from his kindness, generosity, patience and most importantly, his humbleness. With that, I would confidently claim that without Dr. Suhail's presence, all my academic accomplishments would have never been possible, and his contribution on my academic path will remain unchanged for my life time.

I would also like to mention the impact of Dr. Mudassir Masood on my journey and my mindset. I feel so lucky that I had the chance to study Digital Signals Processing course with him, and being really inspired by his magical ability to make something special out of every single lecture or discussion. On a personal level, Dr. Mudassir is the

one who believed in me the most. Starting from trusting my performance at the course, my ability to lead a group research project and my ability to being among the best PhD students at any university in the world (his words) are all things that I will always keep in my heart. As a committee member, Dr. Mudassir has supported me with excellent suggestions that allowed me to take best decisions. I would also like to extend my thanks to the other thesis committee member, Dr. Ali Nasir, for his time to review my thesis and his insightful comments and discussions.

Moreover, I would like to thank my parents and my grandfather for their endless and continuous support and encouragement throughout this journey, despite the major challenges and circumstances we had. It's their prayers and support that made me stronger and encouraged me to keep working hard and keep moving forward. I would like to dedicate this thesis to them. Additionally, it's time to thank my brothers (Omar and Mahmoud), my sister and my brother in law (Sara and Ayham) for believing in me since my first day and even when things seemed to be more complicated than I anticipated.

Furthermore, I would like to thank all my friends and colleagues who given me support whenever I needed and in all possible ways. First of all, I sincerely want to thank Ali Elkhazraji, my third brother, the one who I learned from the most and the person who always believed in my ability to achieve academic excellence! The amount of time he dedicated to help me is something that I will never forget. Additionally, I would like to thank Abdulrahman Saad, Hammam Khalid, Khalil chikhaoui and Ziyad Al Swaidan, who made this whole journey a pleasant one.

Finally, and going to the part that actually makes my journey little different, I would like to express my sincere gratitude to Enova by Veolia team at King Fahd International Airport (KFIA). Being a full time employee at KFIA and a MSc student at KFUPM, in parallel, has been the biggest challenge of my life. I would like to start by thanking Eng. Mohammed Qouqas, Enova's head of operations at eastern region, and the man who never said 'no' to any request of mine in a period of around 2.5 years. Special thanks go to Eng. Mohammed Azhari and Eng. Ahmed Elhaddad, for all the things I learned from them, for treating me as a younger brother and for all the support and flexibility that I had with Enova.

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Abstract

Due to their high mobility, low cost, and enhancement of the line-of-sight (LoS) conditions in non-terrestrial networks, Unmanned Aerial Vehicles (UAVs) are playing a significant role in the development of wireless communications of smart cities. Nevertheless, several concerns behind using UAVs are being raised over time due its ability to cause physical or social damages if they are controlled to breach into restricted areas or invading privacy. Hence, the problem of detecting unauthorized drones and improve the performance of detection has to be considered. Radio frequency (RF)-based detection techniques of malicious UAVs rely on sensing ambient RF signals emitted, which can be utilized under non-line of sight (NLoS) channel conditions with low-cost RF sensors. On the other hand, Reconfigurable intelligent surfaces (RISs), which consist of an array of elements that each scatter and phase-shift the waves differently according to the angle of arrival of the incident wave, can potentially bring detection performance gain as compared to the scenarios without using RISs. In this work, we present a novel RF-based UAV detection technique aided by RISs considering realistic air-to-ground (A2G) channel conditions in an interference environment.

ملخص الرسالة

نظرًا لقدرتها العالية على التنقل وتكلفتها المنخفضة وتعزيزها لظروف الرؤية المباشرة في الشبكات اللاسلكية، تلعب المركبات الجوية بدون طيار دورًا هامًا في تطوير الاتصالات اللاسلكية للمدن الذكية. ومع ذلك، تثار العديد من المخاوف المتعلقة باستخدام المركبات بسبب قدرتها على تسبب أضرار جسدية أو اجتماعية إذا تم التحكم بها لاختراق المناطق المحظورة أو انتهاك الخصوصية. وبالتالي، يجب مراعاة مشكلة اكتشاف الطائرات بدون طيار غير المصرح بها وتحسين أداء الكشف. تعتمد تقنيات الكشف بناءً على التردد اللاسلكي للطائرات بدون طيار الضارة على استشعار الإشارات اللاسلكية المحيطة المنبعثة، والتي يمكن استخدامها تحت ظروف القناة غير المباشرة مع أجهزة استشعار ذات تكلفة منخفضة. على الجانب الآخر، الأسطح الذكية قابلة لإعادة التشكيل، والتي تتكون من مجموعة من العناصر التي تبعث الأمواج وتغير مرحلتها بشكل مختلف وفقًا لزاوية وصول الموجة المنبعثة، يمكن أن تساهم في تحسين أداء الكشف مقارنة بالسيناريوهات التي لا تستخدم فيها الأسطح الذكية. في هذه الرسالة، نقدم تقنية جديدة لكشف بدون طيار بناءً على الإشارات اللاسلكية المعززة بواسطة الأسطح الذكية مع مراعاة ظروف القناة من الجو إلى الأرض في بيئة معرضة إلى التشويش.

1 Introduction

Unmanned aerial vehicles (UAVs) are expected to play an important role in future cognitive cities. They have been identified among new disruptive technologies, specifically in aerial communications, and an enabler in non-terrestrial networks [1]. Their unique features, for instance, having flexible positioning capabilities, make them a promising candidate for a wide range of applications. Not only in military applications, UAVs are now widely used in several applications and can provide multiple services in environmental protection, traffic events, and congestion monitoring [2] in addition to agriculture and public safety [3]. In fact, the commercial UAV market size worldwide is projected to exceed USD 795.57 billion by 2030 from USD 29.55 billion in 2022 with a cumulative annual growth of 50.92%¹. However, as the use of UAVs is rapidly increasing, the threats behind them are increasing as well especially if they have been controlled to breach into highly restricted areas such as in oil and gas facilities or possible privacy invasions of others [4].

Threats of UAVs may include physical threats such as explosives, radioactive materials, or guns that could be used or cyber threats such as hijacking, spoofing, and hacking. These man-made flying objects typically have a low altitude, slow speed, and small radar cross-section (RCS), also known as LSS targets [5] which are challenging to detect/track in real-time in urban environments [6, 5, 7, 8]. Nowadays, certain restricted locations are identified as "No Drone Zone" where UAVs can not be operated, for instance, in the proximity of airports where breach incidents can cause the closure of runways and flight disruption.

We also witness another disruptive technology using tunable metasurfaces envisioned to tackle the ever-increasing demands for high-quality and ubiquitous wireless services. Reconfigurable intelligent surfaces (RISs), which consist of an array of reflecting elements

¹Research and Markets, "Commercial Unmanned Aerial Vehicle Drones Market by Drone Type, Application- Global Forecast 2023-2030," 360iResearch, October 2023.

that reconfigure and forward the incident signals, are considered as a promising technology in wireless communication systems as they are able to modify the wireless communication environment. The flexibility of deployment into different structures, spectral efficiency enhancement, energy efficiency, environment friendly, and compatibility are some advantages of using RISs [9].

1.1 Unmanned Aerial Vehicle Detection

Drones and small UAVs are becoming ubiquitous with many potential civilian and military applications. Hence, the need of developing efficient detection techniques is increasing. Existing counter unmanned aerial systems in the market depend on radar [10], electro-optical/infrared (EO/IR) [11], radio frequency (RF) directional finding (RFDF) [6], acoustic sensors [12] and computer vision [13]. These systems are challenged to detect such malicious UAVs and can be deceived causing false alarms or false negatives (missed targets). Each one of these methods has its own pros and cons, and sometimes they are combined to enhance the accuracy of detection/tracking of the breaching UAV.

Ambient RF signals emitted from the malicious UAV can be sensed at the terrestrial RF network under mixed channel propagation conditions as shown in Figure 1. The strength of the drone signal in the presence of interference can limit the detection performance.

1.2 Reconfigurable Intelligent Surfaces

RISs, also known as Intelligent Reflecting Surfaces (IRSs), are envisioned to enable the next-generation communication and sensing systems and improve coverage and localization for mobile users [14]. Such surfaces can be labeled as active, i.e. equipped with phase shift circuits and reflecting-type amplifiers, or passive, as compared in [15]. The

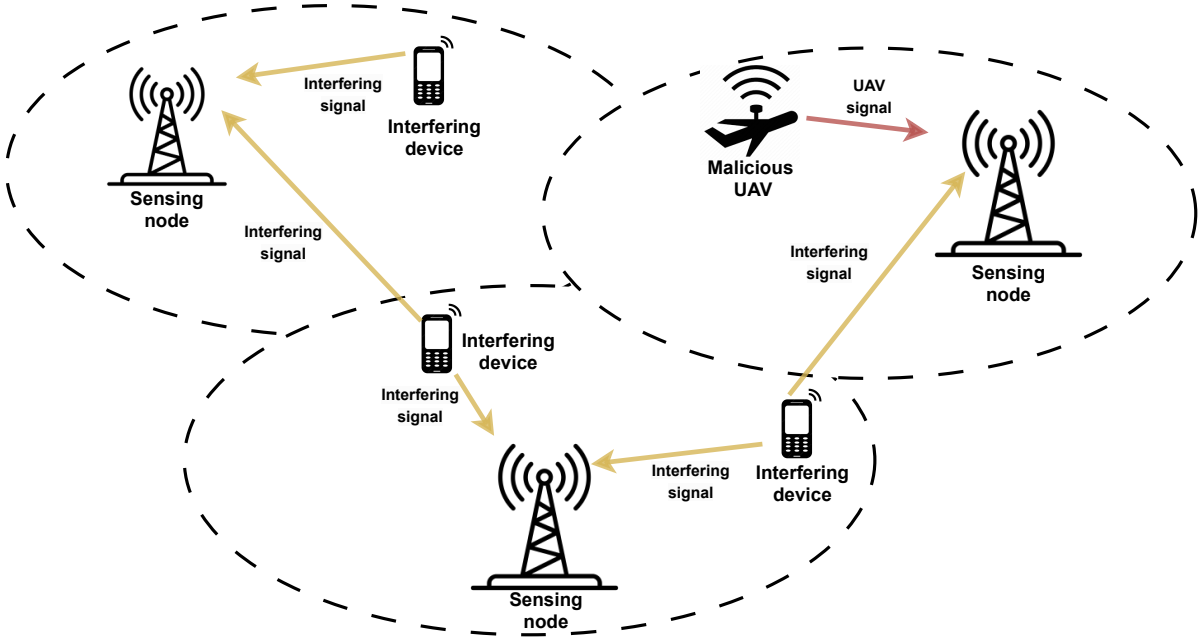


Figure 1: UAV received signal at the RF-detector in the presence of interference

RIS-supported communication scenarios, as shown in Figure 2, overcome the problem of non-line of sight (NLoS) channel condition cases by efficiently reflecting the transmitted signal towards the destination desired. In [16], a maximum eigenvalue spectrum sensing approach was developed with statistical phase shift design. Moreover, RIS for localization was studied by Elzanaty *et al.* in [17] and they derived the ultimate bound on the localization in terms of Cramer-Rao Lower Bound and proposed closed-form RIS phase design for spherical wavefronts. They performed extensive numerical simulations to elaborate on the enhancement offered by adopting RIS in terms of localization performance. Xu *et al.* in [18] recently proposed a correlated transmission and reflection phase-shift model for passive lossless simultaneously transmitting and reflecting RISs, known as STAR-RISs. They derived the outage probability of the proposed phase-shift configurations and the random phase-shift configuration as bounds. Due to the recent advancements in the RISs and their unique features in localization problems, their adoption for malicious UAV detection will be examined.

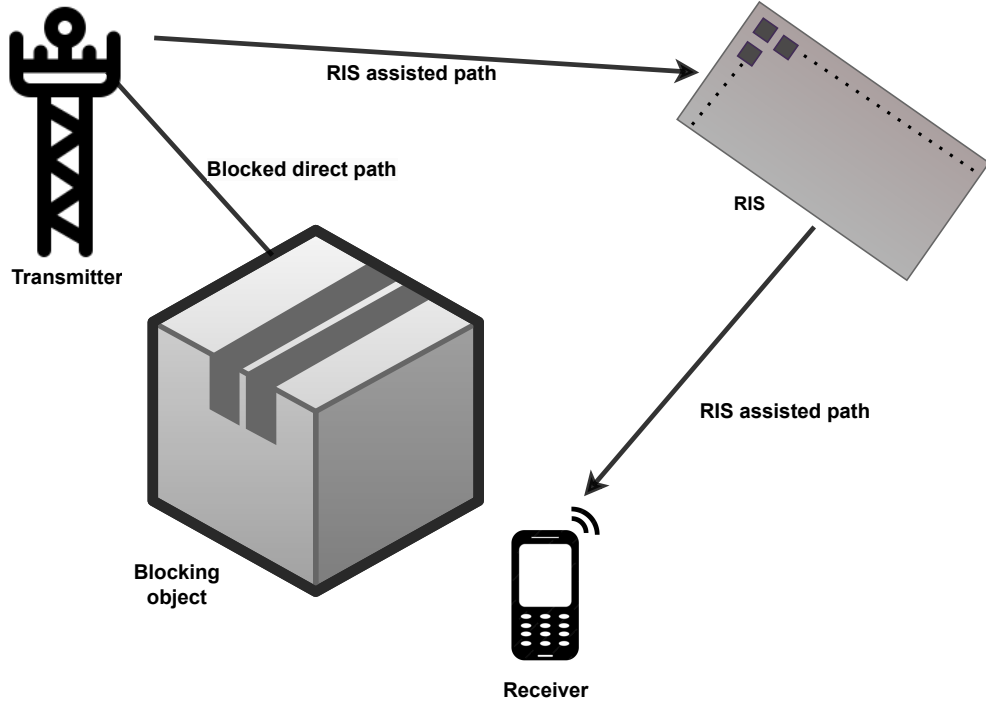


Figure 2: RIS at communication scenario

1.3 Motivation

As drones and mini-UAVs are expected to spread in the near future with many potential applications, security concerns are raising. There are several examples in which the presence of UAVs can be a real threat. One example of the harmful impact of UAVs is their unauthorized presence in critical areas, such as airports or restricted airspace. This poses significant safety risks, including potential collisions with manned aircraft, interference with air traffic control systems, and disruption of airport operations. Detecting and mitigating these unauthorized UAVs is of utmost importance to ensure the safety and security of aviation operations. Existing detection or sensing techniques depend on radar, computer vision (or visual-based), ambient RF, and acoustic-based detection. Although radar-based techniques have a relatively larger detection range of UAVs, their ability to detect low-altitude drones at NLoS conditions is a real challenge and has a

mediocre detection performance. RF-based sensing offers a relatively good detection range under LoS/NLoS scenarios, and it is superior in this sense. Besides, unlike visual and acoustic-based techniques, RF-based detection can be implemented using low-cost and low-complexity sensors.

To the best of our knowledge, no study in the literature has mathematically analyzed the use of Reconfigurable Intelligent Surfaces (RISs) in the problem of UAV detection. Motivated by this, a novel RIS-assisted RF-based detection model is proposed and investigated.

1.4 Main Contributions

In this thesis, we developed and analyzed a low-cost RF-based UAV detection scheme assisted by RISs in the presence of wireless interference. The main contributions of this thesis are summarized as follows.

- Detection performance is investigated and closed-form expressions are derived for a low-cost passive RF detector taking into consideration realistic Rician fading channel model. We have also proposed a novel low-complexity suboptimal detector for intruding UAV in urban and suburban environments, and its performance is compared with the optimal one.
- RISs have been adopted to enhance the detection and we obtain closed-form expression of the optimal phase shift design of the RISs. This is based on considering coherent addition with the direct path link at the sensing node. We derive closed-form expressions for the probability of detection and the optimal/ proposed suboptimal thresholds when RISs are utilized.
- For the elements of RISs, we derive a closed-form expression for the optimal needed elements in the case of multiple RISs to outperform the NLoS conditions. We also investigate the impact of the RIS placement in the scene and the effect of varying their locations.
- Finally, in the presence of RF interference, analytical expressions for the probability of detection are obtained where interference is modeled by Homogeneous Poisson Point Process (HPPP). We corroborate our analytical derivations with extensive Monte Carlo simulations to confirm the accuracy of the derived expressions under the aforementioned channel conditions.

1.5 Thesis Structure

This thesis is organised as follows. In Chapter 2, a comprehensive literature review for the UAV detection problem is presented along with a survey on the use of reconfigurable intelligent surfaces. Our analysis is presented in Chapters 3-5. More specifically, Chapter 3 introduces our system model with a single sensing node considering only the Air to Ground (A2G) channel with the derivation of a closed-form expression for the probability of detection and the detection thresholds. Reconfigurable Intelligent Surfaces (RISs) are introduced in Chapter 4 with further insights on the detection gain at the sensing node, number of elements to be utilized for each RIS and the possible placement for the RISs with respect to the location of the sensing node and the UAV. RF interference is presented in Chapter 5 modeled by Homogeneous Poisson Point Process (HPPP) with an analytical framework for the probability of detection. Finally, the conclusion and possible future works are presented in Chapter 6.

2 Literature Review

In this chapter, we present a comprehensive literature review for our problem which includes two main aspects. First, the UAV detection problem in general, focusing more on RF-based detection solutions. Then, we survey the literature on Reconfigurable Intelligent Surfaces to enhance communications and how they are incorporated with UAVs.

2.1 UAV Detection

Our considered approach is based on radio frequency directional finding (RFDF), where we focus on the research works using RF-based techniques, then we elaborate on other possible detection methods for intruding UAVs.

2.1.1 RF-Based Detection

Ambient RF signals emitted from the malicious UAV can be sensed at the terrestrial RF network under mixed channel propagation conditions. In [6], Sinha *et al.* investigated the fundamental limits on the drone detection probability under mixed line of sight (LoS) and non-line of sight (NLoS) conditions using directional three-dimensional (3D) antenna patterns. They evaluated the detection probability numerically, which requires averaging over all possible locations of interfering sources and base stations using the Stable probability distribution. Soltani *et al.* in [19] proposed RF fingerprinting with multi-classifier scheme using two-step score-based aggregation method to enhance the overall accuracy of UAV detection and classification. Massive IoT network with multiple RF-based sensors was considered in [20] assuming Rayleigh fading channel, and the detection performance was investigated using Neyman-Pearson criterion. In [21], Nie *et al.* presented detection and identification schemes based on Wi-Fi signal and RF fingerprint under both indoor and outdoor scenarios.

Furthermore, learning-based algorithms have been merged with RF-based detection more often recently. For instance, the problem of detection and classification of UAVs in the presence of wireless interference signals was investigated by Ezuma *et al.* in [22] specifically for Wi-Fi and Bluetooth emitters using proper machine learning technique. In [23], the authors are proposing a software defined radio (SDR) platform called DronEnd, which has the ability to scan the spectrum of RF signals for detecting the presence of the drone. Its location is identified via angle-of-arrival (AoA) estimation algorithms and disrupting the communication between the operator/controller and the drone through jamming signals.

In [24], the k -nearest neighbor (k -NN) machine learning classification method merged with RF Fingerprints were utilized for micro-UAV detection and classification with an average accuracy of 0.96. In [25], multiple deep learning algorithms have been used for detection and classification of drones based on RF compressed signals. Experimental results in [26] showed that the proposed hierarchical learning approach has outperformed other techniques with an accuracy rate of 0.99. Convolution neural network (CNN) has been utilized in [27] to develop a noise immune UAV signal classification system which has been tested at different signal-to-noise ratios (SNRs). Support vector machine (SVM), artificial neural network (ANN), decision tree (DT), and random forest (RandF) classifiers have been utilized in [28] for detection and classification of drones in the presence of Wi-Fi interference using UAV video signal (VS) fingerprints where indoor and outdoor experiments have been carried out with high accuracy rates, especially by using RandF.

Hu *et al.* derived the optimal decision rule using the log-likelihood ratio (LLR) in [29] where multiple antennas were utilized with beam sweeping at the sensing node. Moreover, in [30], a data integrity technique called MaDe was utilized to identify malicious UAVs using a generalized likelihood ratio test. The performance analysis demonstrated that

MaDe has identified malicious UAVs with high accuracy under a limited time delay.

2.1.2 Other Detection Techniques

Due to their robustness and versatility, radar-based sensors are nowadays important for UAV detection and classification [5, 31, 32, 33]. In [10], a UAV classification model has been proposed using Deep Convolutional Neural Network (DCNN) where the training data set contains a Range-Doppler (RD) map of a Frequency-Modulated Continuous-Wave (FMCW) radar of a moving UAV. Generative Adversarial Network was further used for data augmentation, where an accuracy rate of 0.909 was achieved in large data scenarios. Authors in [34] provide experimental and analytical investigation of micro UAV detection in a rocky terrain using a low grazing angle, surface-sited 24 GHz dual polarized frequency modulated continuous wave (FMCW) radar. The problem of defining the type of the detected UAV was considered as an M-ary hypothesis testing problem by Ezuma *et al.* in [35]. In target classification, the authors used maximum a posteriori probability (MAP) decision rule, which is optimal for a given set of RCS data. Such RCS-based UAV statistical recognition system determines the class membership of the UAV.

Recently, the aid of computer vision in target detection and tracking has developed rapidly due to its ability to provide high performance systems [36, 37, 38, 39]. In [13], a Dalian University of Technology (DUT) Anti-UAV dataset was used on several existing detection algorithms for performance evaluation and comparison with a proposed detection and tracking algorithm that showed high performance by experiments. Opromolla *et al.* in [40] proposed a template matching and morphological filtering-based detection and tracking algorithms on cooperative applications. The algorithm's performance was assessed by a flight test campaign where the accuracy of target position was in the order of one pixel and the percentage of correct detection decisions was in the range of 0.85-0.95.

On the other hand, acoustic-based algorithms has proven to be promising and feasible

Table 1: Comparison of UAV Detection Systems

Method	Advantages	Disadvantages
Ambient RF	works in NLoS, passive, weather independent	autonomous UAV flights, jamming scenarios
Radar	detect autonomous UAVs, micro-Doppler signature accurate in LoS conditions	power consumption, small RCS of drone, high cost and complexity
Computer Vision	fits all UAV types, passive, accuracy (optical sensors)	requires LoS, affected by weather, high cost
Acoustic	low cost (microphones), works in NLoS	acoustic background noise and weather

for short range drones surveillance [41, 42, 43]. In [12], support vector machines (SVM)-based method has been used for UAV sounds classification among birds, airplanes or thunderstorms. An accuracy of 0.97 was achieved using Mel-frequency cepstral coefficients (MFCC) features extraction technique. In [44], a 24/7 detection and localization scheme was proposed using time delay of arrival (TDOA) estimation algorithm, which is based on the Bayesian filter. Experimental results showed that the proposed model can achieve high detection and localization accuracy. Finally, a real-time detection was proposed by Liu *et al.* in [45] using pruned-YOLOv4 model and compared to RetinaNet, FCOS, YOLOv3 and YOLOv4. Experiment results showed that the proposed model has achieved higher accuracy and faster processing time. A brief comparison of different UAV detection techniques is summarized in Table 1.

2.2 Reconfigurable Intelligent Surfaces (RISs)

As wireless communication sixth-generation (6G) is expected to be revolutionary and encompassing applications such as instantaneous, ultra-massive, data-driven, and ubiquitous wireless connectivity, where new technologies are required to meet the application standards [9]. Reconfigurable intelligent surfaces (RISs), which comprise an array of re-

flecting elements for reconfiguring the incident signals, can potentially modify the wireless communication environment and be utilized as an important tool in 6G network.

First, in [46], the free-space path loss modeling is considered in an RIS-assisted beam-forming scenario, where the received signal power is maximized for a single specific user and an RIS-assisted broadcasting scenario where the signal evenly covers all users in a specific area. Experimental measurements were obtained to reassure the proposed path loss model. Moreover, a comparison between active and passive RIS was closely studied in [15] where both systems have the same overall power budget at the base station (BS) and the RIS. The proposed results state that active RIS would be superior if the power budget is not very small and the number of RIS elements is not very large. Björnson *et al.* in [47] proved that the independent and identically distributed Rayleigh fading channel model does not apply when using a RIS with rectangular geometry. Further, a closed form expression for the SNR approximation was derived where simulation results show that the asymptotic expression is accurate as long as the power of the direct path is low and the number of elements of the RIS is high. A comparison between the new RIS technology with the classic decode-and-forward (DF) relaying was carried out in [48]. It was shown that in terms of power efficiency, DF outperforms the RIS in most setups unless large number of RIS elements is deployed. The energy efficiency of the RIS can perform better than DF only when the required rate exceeds about 8.48 bps/Hz.

RIS-assisted UAV communication models have been presented in literature as well. For instance, Li *et al.* in [49] applied successive convex approximation (SCA) technique to maximize the average achievable data rate by obtaining a closed-form phase-shift solution for the RIS and optimizing the UAV trajectory around the RIS where the derived technique has shown an improved average bit rate. In [50], SCA was also utilized to maximize the energy-efficiency of the UAV, optimize the UAV trajectory along with task

offloading and cache with the phase-shift design of the RIS. Finally, in [51], a UAV-assisted RIS radio system was proposed where the goal was to minimize the bit error rate (BER) by optimizing the UAV trajectory, RIS scheduling and the phase shift matrix.

Based on the existing literature reviewed, there is no study that analyzed mathematically the use of RISs in the problem of UAV detection using RF-based techniques. Motivated by this, a novel RIS-assisted RF-based detection model will be investigated.

3 UAV Detection over Rician Fading Channel

3.1 Chapter Outline

The aim of this chapter is to propose a low-cost passive method for identifying malicious UAVs in a variety of channel and environment states. The analysis of this chapter, however, rely on the direct Air to Ground (A2G) without the utilization of any intelligent surfaces. Although some other works in literature have presented RF-based detection methods, this work substantially differs from any other, as clarified in Table 2 which presents the related contribution of the state-of-the-art papers mentioned in our literature review where N/A stands for not applicable.

3.2 System Model

We consider a flying UAV ² and a sensing node, that can be placed on a roof in an urban/suburban environment, as shown in Figure 3 and both the UAV and sensing node are equipped with omni-directional antenna. The analysis is based on the assumption that the sensing node antenna is able to detect the UAV command, control and communication signals. We assume that both the sensing node and the UAV are placed in the 3D cartesian coordinate system where the sensing node is located at $(x_d, y_d, z_d) \in \mathbb{R}^3$ with an elevation of z_d . On the other hand, the UAV can fly over higher altitudes, i.e. $z_u > z_d$ and the UAV is located at $(x_u, y_u, z_u) \in \mathbb{R}^3$.

In the presence of a target drone, the received signal $y \in \mathbb{C}$ at the sensing node, is

$$y = \sqrt{P}h_i s + w, \quad i \in \{N, L\} \quad (3.1)$$

²The analysis of this thesis assumes the detection of a single malicious UAV, the analysis and derivations will change for multiple UAVs.

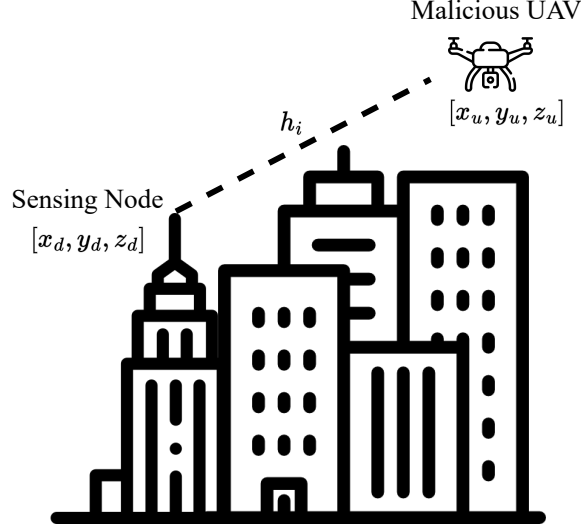


Figure 3: Received UAV signal at the sensing node.

Table 2: Related Works on UAV Detection

	This Chapter	[6]	[20]	[30]	[29]	[21]	[22]	[19]
Analysis Type	Analytical/ Simulation	Stochastic geometry/ Simulation	Analytical/ Simulation	Data analysis	Analytical/ Simulation	Experimental/ ML	Experimental/ ML	Experimental/ ML
Decision Criteria	LLR	N/A	Neyman- Pearson	LLR	LLR	Fixed threshold	Fixed threshold	Probability and ratio thresholds
Fading Channel Model	Rician (realistic)	Rician (realistic)	Rayleigh	N/A	Rayleigh	N/A	N/A	N/A
Interference Analysis	N/A	Cellular mobile users	N/A	N/A	N/A	N/A	Wi-Fi and Bluetooth	N/A
Complexity (cost)	Low	Moderate	Low	Low	Moderate	High	High	High

where P is the UAV transmitted power, s is the unit-energy transmitted signal with zero mean and statistical expectation $\mathbb{E}[|s|^2] = 1$, h_i is the air-to-ground (A2G) fading channel gain where $i \in \{N, L\}$ denotes the NLoS or LoS channel conditions, respectively, and w is the complex additive white Gaussian noise (AWGN) with zero mean and variance $\sigma_0^2 = N_0/2$ for each of the in-phase and quadrature components.

3.2.1 Air-to-Ground (A2G) Channel

Owing to the UAV's flights at high altitude, the A2G link from the UAV to the sensing node will more likely have a LoS component compared to terrestrial links. Such channel, however, will consider both LoS and NLoS propagation conditions. As a result, the

probability of a link having a LoS component at n th observation time is [52]

$$P_{\text{LoS}} = \frac{1}{1 + a \exp \left\{ -b \left[\frac{180}{\pi} \psi_u - a \right] \right\}} \quad (3.2)$$

where a and b are environment dependant constants, $\psi_u = \tan^{-1}((z_u - z_d)/r_u)$ is the UAV elevation AoA of the LoS link at the sensing node and $r_u = \sqrt{(x_u - x_d)^2 + (y_u - y_d)^2}$ is the horizontal distance from the UAV to the sensing node. The channel has NLoS components with a probability of $1 - P_{\text{LoS}}$.

First, the multipath propagation under the NLoS condition follows the Rayleigh fading model, and channel gain is defined as [53]

$$h_N = \sqrt{\beta d^{-\rho}} \tilde{X} \quad (3.3)$$

where ρ is the corresponding path loss exponent of the link, β is the reference path loss at distance 1m, $d = \sqrt{r_u^2 + (z_u - z_d)^2}$ is the Euclidean distance between the UAV and the sensor, and $\tilde{X}$ represents the random scattering component modeled by a zero-mean and unit-variance circularly symmetric complex Gaussian (CSCG) random variable.

Furthermore, under the LoS conditions, the small-scale fading is modelled by Rician distribution, and channel gain is given by

$$h_L = \left(\sqrt{k\beta d^{-\rho}} + j\sqrt{k\beta d^{-\rho}} \right) + \sqrt{\beta d^{-\rho}} \tilde{X} \quad (3.4)$$

where k is the Rician factor. The SNR for both cases in the presence of a target is

$$\gamma_i = \frac{P |h_i|^2}{2\sigma_0^2}, \quad i \in \{N, L\}. \quad (3.5)$$

Unlike communication scenarios, where the aim at the receiver is to decode the signal,

our interest here is to detect the presence of the UAV from its energy emitted. Hence, the decision criteria is based on the received signal strength (RSS) for a given UAV coordinates and channel conditions.

3.3 UAV Detection Problem Formulation

The received signal in (3.1) has both in-phase and quadrature components, i.e. $y = y_I + jy_Q$, and the RSS at the sensing node can be expressed as

$$R = y_I^2 + y_Q^2. \quad (3.6)$$

We consider binary hypothesis testing to detect the UAV presence based on the RSS at the sensing node. Here, the null hypothesis, $\mathcal{H}_0$, represents the state in which no drone is detected, and $y = w$ is a zero mean complex Gaussian random variable with variance $\mathbb{E}[yy^*] = \mathbb{E}[y_I^2] + \mathbb{E}[y_Q^2] = 2\sigma_0^2$, i.e. $y \sim \mathcal{N}_{\mathbb{C}}(0, 2\sigma_0^2)$. Under this hypothesis, the RSS is sum of the squares of two independent and identically distributed (i.i.d) Gaussian random variables that follows exponential distribution, i.e. $R|\mathcal{H}_0 \sim \exp\{2\sigma_0^2\}$. For the alternative hypothesis, $\mathcal{H}_1$, representing the presence of the target drone, the distribution of the received signal is based on the LoS and NLoS conditions.

Considering the NLoS case, the received signal $y \sim \mathcal{N}_{\mathbb{C}}(0, 2\sigma_1^2)$ with $\sigma_1^2 = N_0/2 + P\beta d^{-\rho}$. Hence, the RSS under the alternative hypothesis follows exponential distribution, i.e. $R|\mathcal{H}_{1N} \sim \exp\{2\sigma_1^2\}$. As for the LoS case, the signal received under the alternative hypothesis is $y \sim \mathcal{N}_{\mathbb{C}}(\frac{\mu}{\sqrt{2}}, 2\sigma_1^2)$ and the RSS distribution is a non-central Chi-squared with two degrees of freedom, i.e. $R|\mathcal{H}_{1L} \sim \chi_2^2(\mu)$, where $\mu = \sqrt{2kP\beta d^{-\rho}}$ is the non centrality parameter.

Furthermore, we represent the null and alternative hypotheses in terms of the condi-

tional probability density function (PDF) of the RSS as

$$\mathcal{P}_{R|\mathcal{H}_0}(r|\mathcal{H}_0) = \frac{1}{2\sigma_0^2} e^{-\frac{r}{2\sigma_0^2}} \quad (3.7)$$

$$\mathcal{P}_{R|\mathcal{H}_{1i}}(r|\mathcal{H}_{1i}) = \begin{cases} \frac{1}{2\sigma_1^2} e^{-\frac{\mu^2+r}{2\sigma_1^2}} I_0\left(\frac{\mu}{\sigma_1^2} \sqrt{r}\right), & \text{for } i = L \\ \frac{1}{2\sigma_1^2} e^{-\frac{r}{2\sigma_1^2}}, & \text{for } i = N \end{cases} \quad (3.8)$$

where $I_0(\cdot)$ denotes the zero-order modified Bessel function of the first kind.

3.4 UAV Detection Performance

3.4.1 Probability of Detection Analysis

In this section, the probability of detection, $\mathbf{P}_D$, and the probability of false alarm, $\mathbf{P}_F$, are derived along with the probability of detection in terms of false alarm probability. Since the conditional PDF under $\mathcal{H}_0$ does not depend on the channel state, the expression of the probability of false alarm is given by

$$\mathbf{P}_F = \int_{\eta}^{\infty} \mathcal{P}_{R|\mathcal{H}_0}(r|\mathcal{H}_0) dr = \int_{\eta}^{\infty} \frac{e^{-\frac{r}{2\sigma_0^2}}}{2\sigma_0^2} dr = e^{-\frac{\eta}{2\sigma_0^2}} \quad (3.9)$$

where η is the decision threshold, which is derived in subsection 4.5.2. The decision threshold, therefore, can be expressed as a function of $\mathbf{P}_F$ as

$$\eta = -2\sigma_0^2 \ln \mathbf{P}_F \quad (3.10)$$

where $\ln(\cdot)$ denotes the natural logarithm. Furthermore, the probability of detection under NLoS conditions, following similar derivations in (3.9) and substituting σ_0^2 and σ_1^2

yields

$$\mathbf{P}_{DN} = \exp \left(\ln \mathbf{P}_F / \left(1 + \frac{2P\beta}{N_0 d^\rho} \right) \right). \quad (3.11)$$

The expression of the probability of detection under LoS scenarios, according to [54], is defined as

$$\begin{aligned} \mathbf{P}_{DL} &= \int_{\frac{\sqrt{\eta}}{\sigma_1}}^{\infty} r e^{-\frac{(\frac{\mu}{\sigma_1})^2 + r^2}{2}} I_0 \left(\frac{\mu}{\sigma_1} r \right) dr \\ &= Q_1 \left(\frac{\mu}{\sigma_1}, \frac{\sqrt{\eta}}{\sigma_1} \right) \end{aligned} \quad (3.12)$$

where $Q_1(\cdot, \cdot)$ denotes the the first order Marcum Q-function. After substituting the threshold in (4.14), μ , and σ_1 in (3.12), we have

$$\mathbf{P}_{DL} = Q_1 \left(\sqrt{\frac{4kP\beta}{2P\beta + N_0 d^\rho}}, \sqrt{\frac{-\ln \mathbf{P}_F}{0.5 + \frac{P\beta}{N_0 d^\rho}}} \right). \quad (3.13)$$

Note that for a fixed $\mathbf{P}_F$, the probability of detection in (4.15) and (4.16) will degrade as noise variance, distance or path loss exponent increases. However, for larger UAV transmission power or Rician k factor, the detection performance will improve. Considering both LoS and NLoS, and environmental conditions at the sensing node, the average probability of detection for a fixed probability of false alarm, given UAV coordinates³, can be expressed as

$$\begin{aligned} \mathbf{P}_D &= P_{\text{LoS}} Q_1 \left(\sqrt{\frac{4kP\beta}{2P\beta + N_0 d^\rho}}, \sqrt{\frac{-\ln \mathbf{P}_F}{0.5 + \frac{P\beta}{N_0 d^\rho}}} \right) \\ &\quad + (1 - P_{\text{LoS}}) \exp \left(\ln \mathbf{P}_F / \left(1 + \frac{2P\beta}{N_0 d^\rho} \right) \right). \end{aligned} \quad (3.14)$$

³Similar to the earlier works in [6, 20], we assume an acquisition of the UAV coordinates and channel exist for the probability of detection derivations.

3.4.2 Optimum Detector

In this section, we utilize a statistical LLR test to optimize the choice of the decision threshold at the sensing node. The LLR expression under the NLoS channel condition is expressed as

$$\ln(\Lambda|_N \mathcal{R}) \triangleq \ln \left(\frac{\mathcal{P}_{R|\mathcal{H}_{1N}}(r|\mathcal{H}_{1N})}{\mathcal{P}_{R|\mathcal{H}_0}(r|\mathcal{H}_0)} \right) \geq \ln \zeta \quad (3.15)$$

where $\ln(\Lambda|_N \mathcal{R})$ represents the LLR under NLoS state and ζ depends on the a priori probabilities and the error cost under each hypothesis [55]. In our analysis, we assume equal a priori probabilities; hence, $\zeta = 1$ and $\ln \zeta = 0$. The detection decision depends on the received and observed values of r , representing the sufficient statistics to make the optimal decision. By solving (3.15) for r under equal probable hypotheses, we obtain

$$\begin{aligned} \ln \left(\frac{\sigma_0^2}{\sigma_1^2} \right) - r \left[\frac{1}{2\sigma_1^2} - \frac{1}{2\sigma_0^2} \right] &\geq 0 \\ r &\geq \frac{2\sigma_1^2\sigma_0^2}{\sigma_0^2 - \sigma_1^2} \ln \left(\frac{\sigma_0^2}{\sigma_1^2} \right). \end{aligned} \quad (3.16)$$

Substituting σ_0^2 and σ_1^2 in (3.16) to evaluate the NLoS optimum threshold η_N results in

$$\eta_N = \left(\frac{N_0^2 d^\rho}{2P\beta} + N_0 \right) \ln \left(1 + \frac{2P\beta}{N_0 d^\rho} \right). \quad (3.17)$$

Following the same approach for calculating the optimum threshold under LoS, we represent the LLR as

$$\ln(\Lambda|_L \mathcal{R}) \triangleq \ln \left(\frac{\mathcal{P}_{R|\mathcal{H}_{1L}}(r|\mathcal{H}_{1L})}{\mathcal{P}_{R|\mathcal{H}_0}(r|\mathcal{H}_0)} \right) \geq \ln \zeta, \quad (3.18)$$

and after solving for the sufficient statistic r considering equal probable hypotheses, this

leads to

$$\ln \left(\frac{\sigma_0^2 e^{-\frac{\mu^2+r}{2\sigma_1^2}} I_0 \left(\frac{\mu\sqrt{r}}{\sigma_1^2} \right)}{\sigma_1^2 e^{-\frac{r}{2\sigma_0^2}}} \right) \geq 0$$

$$r - \frac{2\sigma_1^2\sigma_0^2}{\sigma_0^2 - \sigma_1^2} \ln \left(I_0 \left(\frac{\mu\sqrt{r}}{\sigma_1^2} \right) \right) \geq \frac{2\sigma_1^2\sigma_0^2}{\sigma_0^2 - \sigma_1^2} \left(\ln \left(\frac{\sigma_0^2}{\sigma_1^2} \right) - \frac{\mu^2}{2\sigma_1^2} \right) \quad (3.19)$$

where $\ln(\Lambda|_{\mathcal{L}}\mathcal{R})$ is the derived LLR assuming LoS conditions. The cumbersome expression in (3.19) can not be simplified in terms of the sufficient statistic r , which leads to high complexity in the design of an optimum detector. We propose in the following subsection a simplified low-complexity detector to overcome this point with reasonable performance.

3.4.3 Proposed Low-Complexity Detector

Due to the sensitivity of the threshold-based detection technique, a slight change in such threshold can considerably increase the error probability, i.e. the probabilities of false alarm and miss detection. Therefore, it is crucial for the sensing node to decide on an appropriate threshold. We first define Ψ to be the weighted average of the RSS, R , under both hypotheses which is given by

$$\begin{aligned} \Psi &= \epsilon \mathbb{E}[R|\mathcal{H}_1] + (1 - \epsilon) \mathbb{E}[R|\mathcal{H}_0] \\ &= 2\epsilon\sigma_1^2 + \epsilon\mu^2 + 2\sigma_0^2 - 2\epsilon\sigma_0^2 \end{aligned} \quad (3.20)$$

where ϵ is the weighting factor that represent the contribution of $\mathcal{H}_1$ on Ψ such that $0 < \epsilon < 1$. Therefore, the expression of the suboptimal threshold under the LoS channel

state, η_L , can be expressed using (3.20) as

$$\eta_L = - \left(\frac{N_0^2 d^\rho}{2P\beta} + N_0 \right) \left(\ln \left(\frac{1}{1 + \frac{2P\beta}{N_0 d^\rho}} I_0 \left(\frac{\sqrt{2kP\beta d^{-\rho} \Psi}}{\frac{N_0}{2} + P\beta d^{-\rho}} \right) \right) - \frac{k}{1 + \frac{N_0 d^\rho}{2P\beta}} \right). \quad (3.21)$$

It can be seen that increasing Ψ results in smoothing the decision threshold with higher detection probabilities at the cost of increasing the false alarm probability. Thus, the selection of ϵ depends on the channel state at the sensing node where higher values are usually chosen at low SNRs. To tackle this problem, we introduce the average overall error probability at the sensing node, ϕ , as

$$\phi = \frac{1 - \mathbf{P}_{DL} + \mathbf{P}_F}{2}, \quad (3.22)$$

which is the average of the miss detection probability and the probability of false alarm. Hence, we can formulate the objective function to optimize the parameter ϵ as

$$\hat{\epsilon} = \arg \min_{0 \leq \epsilon \leq 1} \phi(\Psi) \quad (3.23)$$

where $\hat{\epsilon}$ is the optimized ϵ value. To solve the problem in (3.23), we propose an iterative algorithm to obtain ϵ that minimizes the average overall error probability, ϕ , as shown in Algorithm 1.

Further, under the assumption that the LoS/NLoS channel state is well estimated at the sensing node, the average probability of detection in low-complexity suboptimal receiver using the derived thresholds is

$$\mathbf{P}_D = \mathbf{P}_{\text{LoS}} \times Q_1 \left(\sqrt{\frac{2k}{1 + \frac{N_0 d^\rho}{2P\beta}}}, \sqrt{\frac{\eta_L}{N_0/2 + P\beta d^{-\rho}}} \right) + (1 - \mathbf{P}_{\text{LoS}}) e^{-\frac{\eta_N}{N_0 + 2P\beta d^{-\rho}}}. \quad (3.24)$$

However, if no prior information at the sensing node about the conditions whether

Algorithm 1 Proposed algorithm to solve (3.23)

- 1: define a vector $\boldsymbol{\epsilon} = [0, \frac{1}{\kappa}, \frac{2}{\kappa} \dots 1]$ with a proper κ value.
 - 2: define $\hat{\phi} = 0.5$, $\hat{\epsilon} = 0$ and $i = 1$ as initial values
 - 3: evaluate Ψ at $\boldsymbol{\epsilon}(i)$ from (3.20)
 - 4: evaluate η_L and ϕ from (3.21) and (3.22)
 - 5: **while** $\phi < \hat{\phi}$ **do**
 - 6: $\hat{\phi} \leftarrow \phi$
 - 7: $\hat{\epsilon} \leftarrow \boldsymbol{\epsilon}(i)$
 - 8: $i \leftarrow i + 1$
 - 9: update Ψ at $\boldsymbol{\epsilon}(i)$
 - 10: update η_L and ϕ
 - 11: **end while**
 - 12: **return** $\hat{\epsilon}$
-

Table 3: System and Environment Parameters for Monte-Carlo Simulations

Parameter	Value	Parameter	Value
P	27 dBm	ρ	3.5
k	5 dB	N_0	-90 dBm
β	-30 dB	d	290.2 m
(x_d, y_d, z_d)	(0, 0, 25)	(x_u, y_u, z_u)	(200, 200, 90)
Urban (a, b)	(9.6117, 0.1581)	Suburban (a, b)	(4.88, 0.429)

LoS or NLoS, then an average threshold, η_{avg} , can be used such that $\eta_{\text{avg}} = 0.5\eta_L + 0.5\eta_N$.

3.5 Numerical Results

For our numerical analysis, we set the parameters as in Table 3 where the values of a and b are chosen according to [52], which is based on the International Telecommunication Union (ITU) model. This model considers the density ratio of built-up land area to the total land area, mean number of buildings per unit area, and the buildings' height distribution.

In Figure 4, we present the receiver operating characteristic (ROC), where detec-

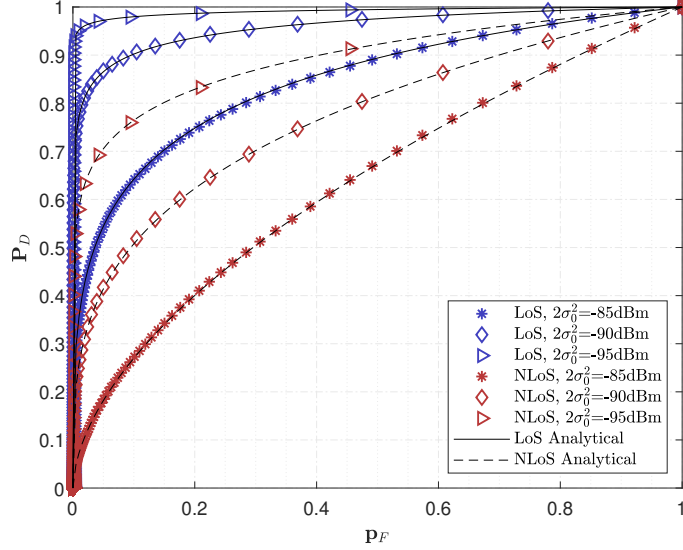


Figure 4: ROCs for LoS/NLoS scenarios and various noise variance $2\sigma_0^2$. The black solid lines represent the analytical results under LoS, while the dashed lines for NLoS.

tion performance is depicted as a function of $\mathbf{P}_F$ at the sensing node. This is obtained using (4.15) and (4.16) under both NLoS and LoS scenarios, respectively, with $2\sigma_0^2 \in \{-95, -90, -85\}$ in dBm. Moreover, 5×10^4 Monte Carlo simulation trials have been performed to validate the derived mathematical expressions. The ROC curves through numerical simulation, shown in Figure 4, match well the derived expressions. ROC curves show that even for a lower variance of noise under NLoS cases, the LoS channel condition will result in better performance due to the existence of the direct path component. Nevertheless, this could change based on the choice of the Rician factor k that may alter the performance under the LoS scenarios.

In Figure 5, the performance of the UAV detection is illustrated under various SNR values for both LoS and NLoS environments. It is noticed that even under the same SNR and fixed $\mathbf{P}_F$, there is higher probability of detection when a direct LoS link exists. This is due to the existence of the non zero mean and the skewed shape of the non-central Chi-squared distribution. In such case, the area under the alternative hypothesis conditional

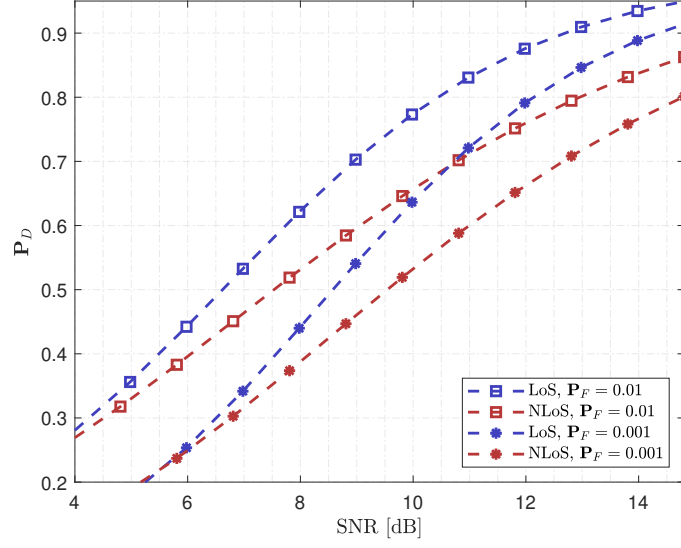


Figure 5: Probability of UAV detection with $\mathbf{P}_F = 0.01$ and 0.001 under LoS/NLoS conditions.

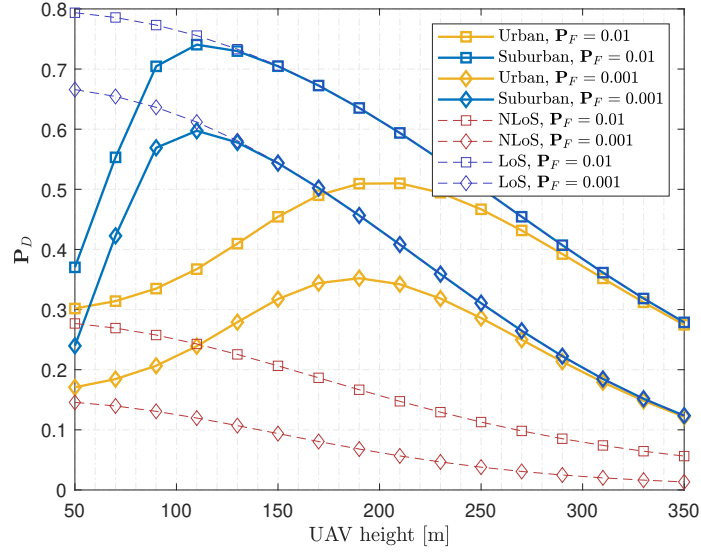


Figure 6: Probability of UAV detection as a function of its altitude in urban and suburban environments.

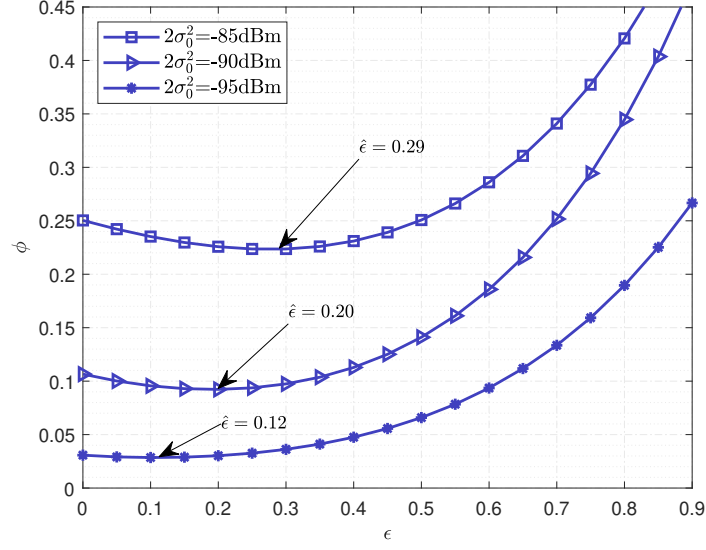
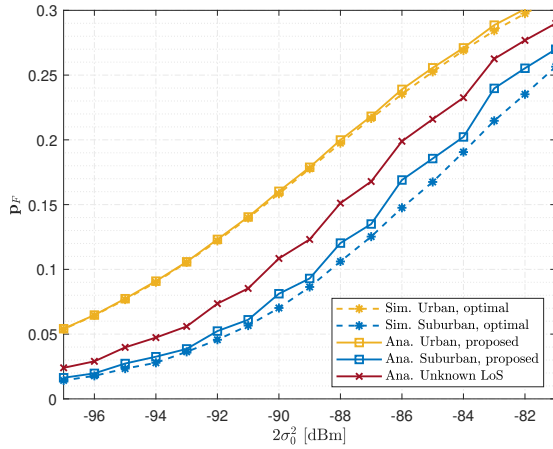
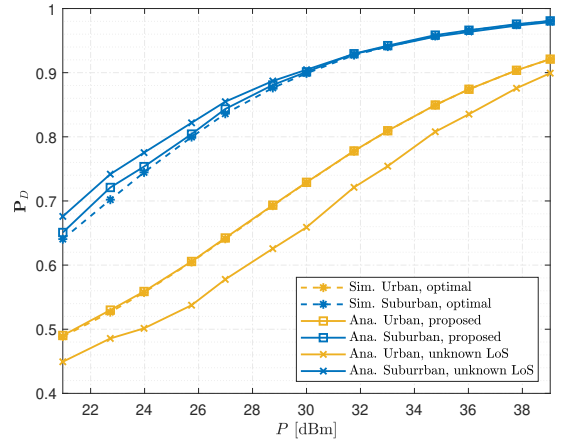


Figure 7: Average overall error probability and optimized parameter $\hat{\epsilon}$ in proposed detector.



(a)



(b)

Figure 8: Performance evaluation of the proposed suboptimal low-complexity detector.

PDF will be larger than the NLoS case where it is exponentially distributed for both $\mathcal{H}_0$ and $\mathcal{H}_{1N}$.

On the other hand, Figure 6 demonstrates the effect of the UAV height on $\mathbf{P}_D$ using (3.14) for both urban and suburban environments compared to the conditionally known LoS or NLoS cases. Due to averaging, it is shown that the conditionally known LoS and NLoS are in fact the upper and lower bounds for the probability of detection, where both environmental expressions will almost match the NLoS state at very low altitudes and will perfectly match the LoS at high altitudes. Note that although the distance between the UAV and the sensing node increases with the UAV height, the probability of detection will continue to increase until reaching its maximum $\mathbf{P}_D$ of about 0.75 at around $z_u = 190\text{m}$ (urban) and about 0.5 at around $z_u = 120\text{m}$ (suburban). This is due to the fact that UAVs at relatively higher altitudes, to some extent, will have larger P_{LoS} . Such improved LoS conditions will enhance the detection probability, $\mathbf{P}_D$, even though the degradation due to free-space path loss increases with increased range between the UAV and sensing node. On the other hand, once $P_{\text{LoS}} \approx 1$, then $\mathbf{P}_D$ decreases as the UAV is flying away from the sensing node. There is around 0.15 increase in $\mathbf{P}_D$ when $\mathbf{P}_F$ rises from 0.001 to 0.01 at LoS conditions, where $\mathbf{P}_D \approx 0.8$ at low UAV altitudes. In NLoS cases, however, a quite weaker performance and lower gains are achieved when rising $\mathbf{P}_F$.

Figure 7 illustrates the average overall error probability for different choices of ϵ with $2\sigma_0^2 \in \{-95, -90, -85\}$ in dBm, i.e. different SNRs. It is noted that the convexity of the average overall error function ϕ is convex with a global minimum value. Hence, our proposed algorithm will keep updating the value of $\hat{\epsilon}$ in an iterative manner, until it reaches an index where the error of the previous iteration was lower. At this stage, the algorithm will break the loop to avoid unnecessary calculations. Besides, the optimum value for ϵ will decrease with lower noise and higher SNRs, leading to stricter decision

criteria and lower probabilities of false alarm.

Figure 8 illustrates the detection performance for the proposed suboptimal low-complexity detector at $\kappa = 25$ and under different environmental scenarios while increasing the noise variance, $2\sigma_0^2$, and the UAV transmitted power, P , in Figs. 8a and 8b, respectively.

In Figure 8a, we evaluate $\mathbf{P}_F$ numerically under the optimum threshold of LoS using (3.19) and compare it to our proposed suboptimal threshold in (3.21). The results show that the proposed suboptimal threshold has comparable performance to the optimal curves. Furthermore, since $\hat{\epsilon}$ is optimized for the considered noise variance, it is notable that the slope of the suboptimal threshold, $\hat{\epsilon}$, is updated, every 2-4 dBm to maintain lower error probability and get closer to the optimal one. Besides, as we increase κ , the slope of the suboptimal curves will be smoother and will eventually get closer the optimal threshold as the algorithm will run more iterations and will reach to an accurate selection of $\hat{\epsilon}$. In urban areas, the probability of LoS existence is small compared to suburban environment, i.e. P_{LoS} is 0.15 and 0.86 for urban and suburban environments, respectively, which affects the LoS component contribution. Furthermore, if the LoS/NLoS status is unknown, $\mathbf{P}_F$ will be the same irrespective of the environment condition because we use η_{avg} where both LoS/NLoS have the same RSS distribution under $\mathcal{H}_0$.

In Figure 8b, the average probability of detection is shown with varying UAV transmit power. It can be seen that the probability of detection under our proposed threshold has a higher detection probability at some instants than the optimum one. However, the overall accuracy of the optimum threshold is better, which is compensated by the probability of false alarm. It is also worth mentioning that the performance under unknown LoS condition will vary across the different environments as the mathematical expression for $\mathbf{P}_D$ depends on LoS and NLoS conditions. It can be seen that due to averaging, the smoothed threshold under suburban environment will have higher $\mathbf{P}_D$, while the restricted

Table 4: Confusion Matrices for LoS Thresholds

(a) Optimal			(b) Suboptimal		
Actual \ Pred.	$\mathcal{H}_0$	$\mathcal{H}_1$	Actual \ Pred.	$\mathcal{H}_0$	$\mathcal{H}_1$
	$\mathcal{H}_0$	47,311 2,689		$\mathcal{H}_0$	46,612 3,388
	$\mathcal{H}_1$	6,504 43,496		$\mathcal{H}_1$	6,029 43,917

threshold in urban environments will have a much lower $\mathbf{P}_D$.

Finally, Table 5 presents the confusion matrices of the optimal criteria under LoS channel and the proposed one at $\kappa = 25$, which are computed using 5×10^4 Monte Carlo simulation trials. Although the proposed threshold has slightly lower probability of miss detection, $P_{\mathcal{H}_0|\mathcal{H}_1}$, than the optimal threshold, the probability of false alarm, $P_{\mathcal{H}_1|\mathcal{H}_0}$, is higher in the suboptimal case. However, the overall accuracy rate is 0.905 for the suboptimal threshold, which is close to the optimal case having an accuracy of 0.908. It is important to note that the performance of the proposed threshold is highly dependant on the choice of the value of κ , where the accuracy will get closer to the optimal threshold as κ increases. However, this comes at the cost of computational complexity.

3.6 Summary

In this chapter, we investigated an RSS-based passive detection approach under a realistic Rician fading channel model and considered the air-to-ground channel conditions. Furthermore, we demonstrated the use of the optimum threshold criteria at the sensing node under NLoS state and proposed a low-complexity sub-optimum threshold under LoS channel conditions based on the LLR. Our performance analysis and closed-form derived analytical expressions have been verified using extensive Monte Carlo simulations. The analytical and simulation results showed that an overall accuracy rate of above 0.9 is achieved under LoS cases and a high probability of detection for a fixed false alarm probability can be attained as well. However, the detection accuracy at sensing node under NLoS conditions is lower but can be improved with the deployment of multiple sensing nodes.

4 Detection Performance using RIS-Aided Systems with Optimum Phase Designs

4.1 Chapter Outline

In Chapter 3, we presented the performance analysis of our sensing under realistic channel conditions. However, the main disadvantage of the proposed model was its weak performance under NLoS channel conditions. Reconfigurable Intelligent Surfaces (RISs) technology has been widely used to overcome the LoS blockage, especially for communication purposes. Nevertheless, in this chapter, we propose a novel RIS-assisted detector to boost the performance of the sensing node in NLoS scenarios, in addition to the massive performance enhancement achieved when a LoS link is also available.

4.2 RIS-Assisted System Model

We consider the system model shown in Figure 9, which illustrates a malicious/unauthorized UAV, a sensing node (D), and J RISs. The sensing node, as in the previous chapter, can be placed at a rooftop in an urban or suburban environment, and it is equipped with a single omni-directional antenna, which is also assumed for the intruding UAV. Moreover, each of the J assisting RISs has M reflecting elements, where they can provide additional array gains for the signal sensed from the target UAV, especially if the direct link to the sensing node is blocked. The sensing node, RISs and the UAV are placed in the 3D cartesian coordinate system where the sensing node is located at (x_d, y_d, z_d) as mentioned in the last chapter, and the j th RIS location is (x_{rj}, y_{rj}, z_{rj}) . On the other hand, the UAV can fly over higher altitudes, $z_u[n]$, where $z_u[n] > z_{rj} > z_d$ is the UAV altitude at the n th time slot. The UAV location, therefore, is denoted by $(x_u[n], y_u[n], z_u[n])$.

The received bandpass waveform at the sensing node, D, is given by

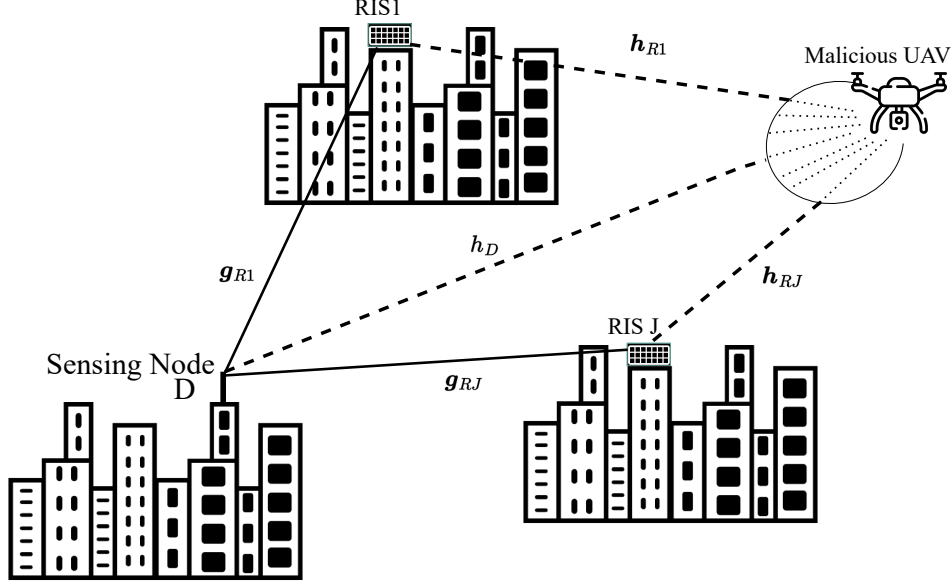


Figure 9: RIS-assisted system model

$$y(t) = \Re \left\{ \left[\int_{-\infty}^{\infty} h_D(\tau, t) s(t - \tau) d\tau + \sum_{j=1}^J \int_{-\infty}^{\infty} f_{R_j}(\tau, t) s(t - \tau) d\tau + w(t) \right] e^{j2\pi f_c t} \right\} \quad (4.1)$$

where $h_D(\tau, t)$, $D \in \{N, L\}$ is the time-varying channel impulse response of direct path representing the NLoS or LoS conditions of the channel, respectively, and $f_{R_j}(\tau, t)$, $j \in \{1, 2, \dots, J\}$ denotes the time-varying channel impulse responses of the j th RIS cascaded channel at the sensing node considering the phase shifts induced by the RISs. The signal sensed from target UAV is denoted by $s(t)$, and $w(t)$ is the complex additive white Gaussian noise (AWGN) with zero mean and variance $\sigma_0^2 = N_0/2$ for each of the in-phase and quadrature components.

Hence, the discrete-time baseband equivalent of the received signal $y(t)$ in the n th time slot is

$$y[n] = \left(h_D[n] + \sum_{j=1}^J \mathbf{h}_{R_j}^H[n] \mathbf{\Phi}_j[n] \mathbf{g}_{R_j} \right) \sqrt{P} s[n] + w[n] \quad (4.2)$$

where P is the transmitted UAV power, $\mathbf{h}_{R_j}[n] \in \mathbb{C}^{M+1}$ and $\mathbf{g}_{R_j} \in \mathbb{C}^{M+1}$ are the channel gains between the UAV and the j th RIS, and from the j th RIS to the sensing node, respectively. $s[n]$ is the UAV unit-energy signal, i.e. $\mathbb{E}[|s[n]|^2] = 1$. Furthermore, the RISs are equipped with a Uniform Linear Array (ULA), where the channel gain of the RIS assisted path, U-R-D, is the product of the two channel gains U-R and R-D [56]. All RISs consist of M reflecting elements that are continuously controllable by the diagonal phase-shift matrix $\mathbf{\Phi}_j[n]$. For each RIS, the diagonal phase-shift matrix $\mathbf{\Phi}_j[n] = \text{diag} \{ \delta e^{j\theta_{j1}[n]}, \delta e^{j\theta_{j2}[n]}, \dots, \delta e^{j\theta_{jM}[n]} \}$ where $\theta_{jm}[n] \in [0, 2\pi)$, $m \in \{1, \dots, M\}$, is the phase shift of the m th reflecting element at the j th RIS and $\delta \geq 1$ is the amplification factor such that the RIS is passive if $\delta = 1$. It is assumed that δ is equal for all RIS elements and for all the RISs utilized. It is also assumed that the channel state information (CSI) is available using proper channel estimation techniques for RIS assisted systems as in [57].

4.2.1 Air-to-Ground Direct Channel

The time-variant Air-to-Ground (A2G) link is described as

$$P_{\text{LoS}}[n] = \frac{1}{1 + a \exp \left\{ -b \left[\frac{180}{\pi} \psi_d[n] - a \right] \right\}} \quad (4.3)$$

where $\psi_d[n] = \tan^{-1} \left(\frac{z_u[n] - z_d}{r_d[n]} \right)$ is the UAV elevation angle of arrival (AoA) of the LoS link for sensing node at the n th time instant, and $r_d[n] = ((x_u[n] - x_d)^2 + (y_u[n] - y_d)^2)^{1/2}$ is the horizontal distance from the UAV to the sensing node. The probability of a channel having NLoS components is $1 - P_{\text{LoS}}[n]$.

Furthermore, the time-variant multipath propagation of the direct links $h_N[n]$ and

$h_L[n]$, under NLoS and LoS conditions, are

$$h_N[n] = \sqrt{\beta d_d^{-\rho_d}[n]} \tilde{X} \quad (4.4)$$

$$h_L[n] = \left(\sqrt{k_d \beta d_d^{-\rho_d}[n]} + j \sqrt{k_d \beta d_d^{-\rho_d}[n]} \right) + \sqrt{\beta d_d^{-\rho_d}[n]} \tilde{X} \quad (4.5)$$

where ρ_d is the path loss exponent of the direct link, $d_d[n] = (r_d^2[n] + (z_u[n] - z_d)^2)^{1/2}$ is the Euclidean distance between the UAV and the sensor at n th time instant and k_d is the Rician factor of the direct path.

4.2.2 RIS-Assisted Channels

The channel links from the UAV to the RISs (U-R) are assumed to be in LoS since the UAV is flying at high altitude and the RISs are placed on the facade of the buildings. Hence, the channel gain of the U-R and the R-D links of the j th RIS are given by [49]

$$\mathbf{h}_{Rj}[n] = \sqrt{\beta d_{urj}^{-\rho_{ur}}[n]} \left[1, e^{-j \frac{2\pi}{\lambda} d \cos \psi_{urj}[n]}, \dots, e^{-j \frac{2\pi}{\lambda} (M-1) d \cos \psi_{urj}[n]} \right]^T \quad (4.6)$$

$$\mathbf{g}_{Rj} = \sqrt{\beta d_{rjd}^{-\rho_{rd}}[n]} \left(\sqrt{\frac{k_r}{1+k_r}} \mathbf{g}_{Rj}^L + \sqrt{\frac{1}{1+k_r}} \mathbf{g}_{Rj}^N \right) \quad (4.7)$$

where ρ_{ur} , ρ_{rd} are the corresponding path loss exponents of the links between the UAV to the RISs, and between the RISs to the sensing node, respectively. $\psi_{urj}[n]$ is the time varying AoA from the UAV at the j th RIS with $\cos \psi_{urj}[n] = \left(\frac{x_u[n] - x_{rj}}{d_{urj}[n]} \right)$ where $d_{urj}[n] = ((x_u[n] - x_{rj})^2 + (y_u[n] - y_{rj})^2 + (z_u[n] - z_{rj})^2)^{1/2}$ is the Euclidean distance from the UAV to the j th RIS at the n th time instant. k_r is the Rician factor of the link between the RIS and the sensing node. $d_{rjd} = ((x_{rj} - x_d)^2 + (y_{rj} - y_d)^2 + (z_{rj} - z_d)^2)^{1/2}$ is the Euclidean distance between the j th RIS and the sensing node. Further, λ is the carrier wavelength, d is the separation between antenna elements separation such that

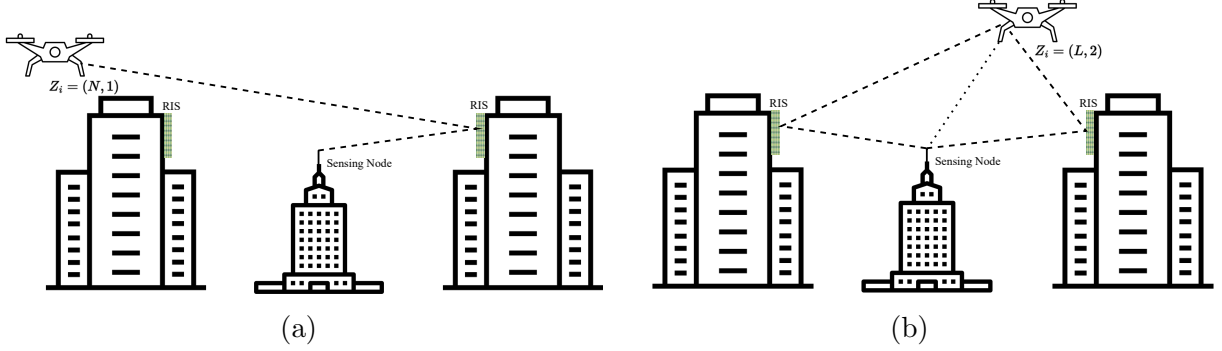


Figure 10: Possible scenarios for the target UAV location in the zones (a) $Z_i = (N, 1)$ for direct in NLoS and 1 RIS, (b) $Z_i = (L, 2)$ for direct in LoS and 2 RISs

$d = \frac{\lambda}{4}$, $\mathbf{g}_{R_j}^L = \left[1, e^{-j\frac{2\pi}{\lambda}d \cos \psi_{rjd}}, \dots, e^{-j\frac{2\pi}{\lambda}(M-1)d \cos \psi_{rjd}}\right]^T$ is the deterministic LoS component where ψ_{rjd} is the angle of departure (AoD) of the link from the j th RIS to the sensing node, $\cos \psi_{rjd} = \left(\frac{x_{rj} - x_d}{d_{rjd}}\right)$ and $\mathbf{g}_{R_j}^N \in \mathbb{C}^{M+1}$ is the NLoS components from CSCG random vector of zero mean and covariance matrix $\mathbf{I}_M$ where it denotes the identity matrix of size M . Moreover, the SNR at the sensing node can be defined as

$$\gamma[n] = \frac{P \left| h_D[n] + \sum_{j=1}^J \mathbf{h}_{R_j}^H[n] \mathbf{\Phi}_j[n] \mathbf{g}_{R_j} \right|^2}{2\sigma_0^2}. \quad (4.8)$$

4.3 Detection Approach

For the UAV detection, we will consider all possible scenarios depending on the location of the UAV with respect to the RISs and the LoS condition between the UAV and the sensing node. First, if more than one RIS is utilized, the horizontal coordinates of each two RISs locations will be set in opposite directions where each will reflect to the sensing node from one side. Hence, the choice of the RISs locations in our model is made to guarantee that, when using more than one RIS, at least one RIS will be utilized all the time regardless of the UAV location. Further, as shown in Figure 10, the UAV is assumed to be in one of possible zones based on the existence of direct path, its LoS/NLoS condition, and number

of available RISs which can reflect the signal from the target UAV. We form ordered 2-tuples to indicate such scenarios where $(D, .)$ and $(B, .)$ denote the case of direct path existence and in case it is blocked, respectively. If the direct path is not blocked, then $D \in \{N, L\}$ represents the NLoS or LoS conditions, respectively, for the channel between the UAV and the sensing node. If the UAV is in the zone where its signal can be reflected by j RISs, then it is indicated by $(., j)$ where $j \in \{0, \dots, J\}$. Therefore, the possible zones $Z_i \in \{(D, 0), (D, 1), \dots, (D, J), (B, 1), \dots, (B, J)\}$, $i \in \{1, 2, \dots, 3J + 2\}$. The special case of $(D, 0)$ represents the situation when no RIS is used, which was presented and investigated in Chapter 3. Despite that scenarios with $(B, .)$ are uncommon in real-life due to multipath propagation and NLoS reflections, we assume dominant paths from the RISs. The performance analysis will be investigated for optimization of RIS placement and to analyze the impact of the RISs on the probability of detection.

Moreover, we use the binary hypothesis testing approach for the detection of the UAV presence based on the RSS at the sensing node. Based on the location of the target UAV in the i th zone, Z_i , and assuming quasi-static fading with channel gains remain constant over the time duration of interest, we have the following conditional hypotheses at the sensing node,

$$\begin{aligned} \mathcal{H}_0 : y &= w \\ \mathcal{H}_{1i} : y &= \left(h_D + \sum_{j=1}^J \mathbf{h}_{R_j}^H \mathbf{\Phi}_j \mathbf{g}_{R_j} \right) \sqrt{P} s + w \end{aligned} \quad (4.9)$$

where $\mathcal{H}_{1i}$ represents the alternative hypothesis for UAV at zone i . Further, as defined in (4.2), the received signal $y = y_I + jy_Q$ consists of both the in-phase and quadrature components at the sensing node, and the RSS can be expressed as a function of the signal decomposition given in (3.6).

4.4 Optimal Phase Shift Design

The gain achieved by incorporating RISs in the scene can be enhanced further with the optimization of the phase shifts for each element. We will propose an optimal phase shift design and investigate in this section the detection performance. Due to the channel dynamics and time-varying location of the intruding UAV, the diagonal phase-shift matrix $\Phi_j[n]$ has to be continuously optimized. Another important factor in our model is to minimize the reflections from other interfering sources at the sensing node by considering the signal received from higher altitudes where the UAV with high probability will be located.

4.4.1 Proposed Algorithm

We will base our optimization approach on maximizing the received SNR at sensing node for received signals from the UAV through the direct path and the RIS-assisted paths as well [17]. Hence, we mathematically formulate our optimization problem to maximize the received SNR for a specific $\Phi_j[n]$ as

$$\max_{0 \leq \theta_{jm}[n] \leq 2\pi} \gamma(\Phi_j[n]) \quad (4.10)$$

where, by using the Cauchy-Schwarz inequality, the SNR at the sensing node is

$$\begin{aligned} \gamma(\Phi_j[n]) &= \frac{P \left| h_D[n] + \sum_{j=1}^J \mathbf{h}_{R_j}^H[n] \Phi_j[n] \mathbf{g}_{R_j} \right|^2}{2\sigma_0^2} \\ &\leq \frac{P}{2\sigma_0^2} |h_D[n]|^2 + \frac{P}{2\sigma_0^2} \left| \sum_{j=1}^J \mathbf{h}_{R_j}^H[n] \Phi_j[n] \mathbf{g}_{R_j} \right|^2. \end{aligned} \quad (4.11)$$

By solving the aforementioned problem, we develop and reach the following theorem.

Theorem 1. *The optimal phase shift of m th reflecting element at j th RIS, considering*

multiple M -element RISs that maximize the received SNR, given any UAV location at n th time instant, is

$$\theta_{jm}[n] = \frac{2\pi d(m-1)(\cos \psi_{urj}[n] + \cos \psi_{rjd})}{\lambda} + \frac{\pi}{4} \quad (4.12)$$

Proof. See Appendix A. □

Furthermore, in order to minimize the effect of other interfering sources at the sensing node from the RISs reflections, we propose Algorithm 2 on the diagonal phase-shift matrix $\Phi_j[n]$.

Algorithm 2 Proposed algorithm for solving (4.10)

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1: Input:  $\psi_{urj}[n]$ 
2: Initialisation: Set feasible initial value for  $\theta_{jm}[n]$ 
3: if  $\psi_{urj}[n] \in [0, \frac{\pi}{2})$  then
4:    $\theta_{jm}[n] = \frac{2\pi d(m-1)(\cos \psi_{urj}[n] + \cos \psi_{rjd})}{\lambda} + \frac{\pi}{4}$ 
5: else
6:    $\theta_{jm}[n] = \theta_{jm}[n-1]$ 
7: end if
8: return  $\theta_{jm}[n]$ 

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Applying Algorithm 2 will ensure that the reflecting surfaces will only tune the diagonal phase-shift matrix if and only if AoA of the received signal, $\cos^{-1}(\psi_{urj}[n])$, is coming from a higher altitude source.

4.5 Performance Analysis

4.5.1 Probability of Detection Analysis

In this subsection, we go through all possible channel conditions and derive the probability of detection, P_d , the probability of false alarm, P_f , and the probability of detection in terms of the probability of false alarm. We will again rely on the conditional probability density function of the RSS depending on the detection zone as

$$P_f = \int_{\eta_i}^{\infty} \mathcal{P}_{R|\mathcal{H}_0}(r|\mathcal{H}_0) dr \quad P_d = \int_{\eta_i}^{\infty} \mathcal{P}_{R|\mathcal{H}_{1i}}(r|\mathcal{H}_{1i}) dr \quad (4.13)$$

Since the null hypothesis does not depend on the presence of RISs into the model, the expression of the probability of false alarm is the same as the one derived in Chapter 3, which is expressed as $\exp(-\frac{\eta_i}{2\sigma_0^2})$ where η_i is the decision threshold at zone i , which will be derived in subsection 4.5.2. The decision threshold, again, is

$$\eta_i = -2\sigma_0^2 \ln P_f. \quad (4.14)$$

For the probability of detection analysis and derivations, we will consider all possible scenarios of $\mathcal{H}_{1i}$. We first assume the case of no reflections from RISs for the zones $(L, 0)$ and $(N, 0)$, followed by the scenarios with multiple RISs, i.e. $\{(D, 1), \dots, (D, J)\}$, then we consider the blocked direct path case for the zones $\{(B, 1), \dots, (B, J)\}$.

• No Reflections from RISs

If the UAV is flying in the zones where there are no reflections from the RISs, that is, $(L, 0)$ and $(N, 0)$, then more details are covered in Chapter 3. Let $\sigma_{1D}^2 = N_0/2 + P\beta d_d^{-\rho_d}$ be the variance of the in-phase and the quadrature components of the direct path. The received signal $y_N \sim \mathcal{N}_{\mathbb{C}}(0, 2\sigma_{1D}^2)$ and $y_L \sim \mathcal{N}_{\mathbb{C}}(\frac{\mu_D}{\sqrt{2}}, 2\sigma_{1D}^2)$ for NLoS and LoS conditions, respectively, where $\mu_D = \sqrt{2k_d P\beta d_d^{-\rho_d}}$ is the non-centrality parameter of the direct path and equals zero for $(N, 0)$. With that, the expressions of the probability of detection, under each zone condition, are given by

$$P_{d(N,0)} = \exp\left(\ln P_f / \left(1 + \frac{2P\beta}{N_0 d_d^{\rho_d}}\right)\right), \quad (4.15)$$

and

$$P_{d,(L,0)} = Q_1 \left(\sqrt{\frac{4k_d P \beta}{2P\beta + N_0 d_d^{\rho_d}}}, \sqrt{\frac{-\ln P_f}{0.5 + \frac{P\beta}{N_0 d_d^{\rho_d}}}} \right). \quad (4.16)$$

which coincides with the obtained results in Chapter 3.

• Including Reflections from RISs

The conditional probability density function of the RSS where one or more RIS are utilized will follow a non-central Chi-square distribution with two degrees of freedom due to the presence of a fixed mean from the RIS reflected paths. With that in mind, we obtain and prove the following theorem of a generalized closed-form expression for the probability of detection using multiple RISs.

Theorem 2. *For an optimized RIS's phase-shift matrix and a sufficiently large k_r such that $k_r \gg 1$, and using multiple RISs with $J \geq 1$ assuming the direct path exists, the generalized probability of detection is*

$$P_{d,(D,J)} = Q_1 \left(a_D + \sum_{j=1}^J a_{rj}, \sqrt{\frac{-\ln P_f}{0.5 + \frac{P\beta}{N_0 d_d^{\rho_d}}}} \right) \quad (4.17)$$

where

$$a_D = \begin{cases} \sqrt{\frac{4k_d P \beta}{2P\beta + N_0 d_d^{\rho_d}}}, & \text{for } D = L \\ 0, & \text{for } D = N \end{cases} \quad (4.18)$$

$$a_{rj} = \sqrt{\frac{m^2 \delta^2 \beta^2 P d_{urj}^{-\rho_{ur}} d_{rjd}^{-\rho_{rd}} k_r}{(1 + k_r) \left(\frac{N_0}{2} + P \beta d_d^{-\rho_d} \right)}} \quad (4.19)$$

Proof. The mean of each RIS's path over the optimized phases is the product of $\mathbf{h}_{Rj}^H$, the large-scale fading factor $\mathbf{g}_{Rj}$, and constant $\frac{\sqrt{2}}{2}$, which results from the phase shift of $\frac{\pi}{4}$.

The non-centrality parameter, μ , is defined as [54] $\mu = \sqrt{Z_I^2 + Z_Q^2} = \sqrt{2}Z$ where Z_I , Z_Q are the means of the in-phase and quadrature components, respectively, which are equal in our analysis. Therefore, we may express $\mu_{(D,J)}$ as

$$\mu_{(D,J)} = \mu_D + \sum_{j=1}^J m \delta \sqrt{P} \beta \sqrt{d_{urj}^{-\rho_{ur}} d_{rjd}^{-\rho_{rd}}} \sqrt{\frac{k_r}{1 + k_r}} \quad (4.20)$$

where the multiplication of m is resulting from the optimization of the diagonal phase-shift matrix. Further, since coherent addition among the RISs assisted paths with the LoS link is achieved, the overall mean of all paths is the sum of the individual means. Moreover, the variance of the RIS assisted paths is the multiplication squared of $\mathbf{h}_{Rj}^H$ with the small-scale fading part in $\mathbf{g}_{Rj}$, which will be added up to the direct path variance from the properties of independent Gaussian random variables. Hence, the total variance, $\sigma_{1(D,J)}^2$, is

$$\sigma_{1(D,J)}^2 = \sigma_{1D}^2 + \sum_{j=1}^J \sum_{m=1}^M \frac{\delta^2 \beta^2 d_{urj}^{-\rho_{ur}} d_{rjd}^{-\rho_{rd}}}{1 + k_r} \exp \left(\frac{-j4\pi d(m-1) \cos \psi_{urj}}{\lambda} \right) \quad (4.21)$$

where the right hand side of (4.21) can be neglected due to the fact that this terms represents the portion of the signal without phase shift optimization, the effect of double path loss in the RIS paths, the significant difference of its value compared to σ_{1D}^2 and the fact that $k_r \gg 1$. Therefore, we may claim that $\sigma_{1(D,J)}^2 \approx \sigma_{1D}^2$. Finally, substituting the expressions of $\mu_{(D,J)}$ and $\sigma_{1(D,J)}$ in (3.12) proves the proposed probability of detection formula. $\square$

With that, the average probability of detection for a fixed probability of false alarm and a given UAV coordinates at n th time instant, using multiple RISs with $J \geq 1$ can be

expressed as

$$P_{d,(D,J)} = P_{\text{LoS}} P_{d,(L,J)} + (1 - P_{\text{LoS}}) P_{d,(N,J)}. \quad (4.22)$$

• Blocked Direct Path

We will finally consider the scenarios where the direct path from the UAV to the sensing node is totally neglected. For such cases, the RSS conditional probability density function will also follow non-central Chi-squared distribution with two degrees of freedom. The following lemma is obtained to represent the detection probability.

Lemma 1. *For an optimized RIS's phase-shift matrix and a sufficiently large k_r such that $k_r \gg 1$, and using multiple RISs with $J \geq 1$ assuming the direct path is blocked/neglected, the generalized probability of detection is*

$$P_{d,(B,J)} = Q_1 \left(\sum_{j=1}^J \sqrt{\frac{2m^2\delta^2\beta^2 P d_{urj}^{-\rho_{ur}} d_{rjd}^{-\rho_{rd}} k_r}{N_0(1+k_r)}}, \sqrt{-2 \ln P_f} \right). \quad (4.23)$$

Proof. Following the same argument in proof of Theorem 2, the non-centrality parameter in this case, $\mu_{(B,J)} = \mu_{(D,J)} - \mu_D$. Further, since the direct path is blocked completely, the variance of the received complex Gaussian signal $\sigma_{1(B,J)}^2 = \sigma_0^2 = N_0/2$. Substituting $\mu_{(B,J)}$ and $\sigma_{1(B,J)}$ in (3.12) proves the obtained results. $\square$

4.5.2 Optimal and Suboptimal Thresholds

In order to obtain the optimal threshold for detection of intruding UAV under the considered system model with multiple RISs, we use again the LLR test which is defined as

$$\ln(\Lambda|_i(\mathcal{R})) \triangleq \ln \left(\frac{\mathcal{P}_{R|\mathcal{H}_{1i}}(r|\mathcal{H}_{1i})}{\mathcal{P}_{R|\mathcal{H}_0}(r|\mathcal{H}_0)} \right) \geq \ln \zeta. \quad (4.24)$$

Similar to the earlier detection probability analysis, the detection thresholds for the zone $(D, 0), D \in \{N, L\}$ has been presented in details in Chapter 3. However, in this chapter we generalize the detection threshold expression to span multiple zones and scenarios, and cover the special case of blocked direct path. RSS distribution is crucial to obtain the optimum threshold.

- **Exponentially Distributed RSS**

This case occurs only for the zone $(N, 0)$, and the detection threshold is already presented in (3.17).

- **Non-Central Chi-squared Distributed RSS**

For all zones apart from $(N, 0)$, the RSS distribution will be non-central Chi-squared due to the existence of a fixed non-zero mean component from the direct channel or the RISs reflections. Hence, we express the LLR for such cases as

$$\ln \left(\frac{\frac{1}{2\sigma_{1D}^2} e^{-\frac{\mu_i^2 + r}{2\sigma_{1D}^2}} I_0 \left(\frac{\mu_i}{\sigma_{1D}} \sqrt{r} \right)}{\frac{1}{2\sigma_0^2} e^{-\frac{r}{2\sigma_0^2}}} \right) \geq 0$$

$$r - \frac{2\sigma_{1D}^2 \sigma_0^2}{\sigma_0^2 - \sigma_{1D}^2} \ln \left(I_0 \left(\frac{\mu_i}{\sigma_{1D}} \sqrt{r} \right) \right) \geq \frac{2\sigma_{1D}^2 \sigma_0^2}{\sigma_0^2 - \sigma_{1D}^2} \left(\ln \left(\frac{\sigma_0^2}{\sigma_{1D}^2} \right) - \frac{\mu_i^2}{2\sigma_{1D}^2} \right). \quad (4.25)$$

The expression in (4.25) can not be simplified further and lead to a cumbersome expression of the sufficient statistic r as stated in the case of $(L, 0)$ in Chapter 3. However, the same case is now applied to all other zones of non-central Chi-squared distributed RSS. Motivated by this, we propose a generalized threshold in the following theorem.

Theorem 3. *For an optimized RIS's phase-shift matrix and a sufficiently large k_r such that $k_r \gg 1$, and using multiple RISs with $J \geq 1$ assuming the direct path exists with*

$\sigma_{1D}^2 \neq \sigma_0^2$ and equal a priori probabilities, the proposed sub-optimal threshold at zone i where $i \neq (N, 0), i \neq (B, J)$ at n th time instant is

$$\eta_{i \neq (N,0), i \neq (B,J)} = - \left(\frac{N_0^2 d_d^{\rho_d}}{2P\beta} + N_0 \right) \left(\ln \left(\frac{1}{1 + \frac{2P\beta}{N_0 d_d^{\rho_d}}} I_0 \left(\frac{\mu_i \sqrt{\Psi_i}}{\frac{N_0}{2} + P\beta d_d^{\rho_d}} \right) \right) - \frac{a_i^2}{2} \right). \quad (4.26)$$

where $a_i = a_D + \sum_{j=1}^J a_{rj}$, $\mu_i = a_i \sigma_D$ and Ψ_i is defined in (3.20), which can be optimized using Algorithm 1.

Proof. The expression in (4.26) is obtained by replacing r in the Bessel function in (3.19) with Ψ_i and solve for r . $\square$

Remark 1. It can be observed that the expression in (3.21) is a special case of the generalized threshold mentioned in (4.26) when $i = (L, 0)$.

The average probability of detection based on the optimal/suboptimal threshold can be expressed as done in (3.14) and (4.22) by substituting the value of η_i in (4.14). Furthermore, due to the fact that $\sigma_{1(B,J)}^2 = \sigma_0^2$ for the zones where the direct path is neglected, i.e. $i = (B, J)$, the expression in (3.19) will reduce to

$$\ln \left(I_0 \left(\frac{\mu_{(B,J)} \sqrt{r}}{\sigma_{1(B,J)}^2} \right) \right) \geq \frac{\mu_{(B,J)}^2}{2\sigma_{1(B,J)}^2} \quad (4.27)$$

By approximating the Bessel function in (4.27), we can rewrite $I_0 \left(\frac{\mu_{(B,J)} \sqrt{r}}{\sigma_{1(B,J)}^2} \right)$ under certain conditions as follows [54]

$$I_0 \left(\frac{\mu_{(B,J)} \sqrt{r}}{\sigma_{1(B,J)}^2} \right) = \frac{e^{\left(\frac{\mu_{(B,J)} \sqrt{r}}{\sigma_{1(B,J)}^2} \right)}}{\sqrt{\frac{2\pi \mu_{(B,J)} \sqrt{r}}{\sigma_{1(B,J)}^2}}}, \quad \text{for } \frac{\mu_{(B,J)} \sqrt{r}}{\sigma_{1(B,J)}^2} \gg 1 \quad (4.28)$$

Lemma 2. *For an optimized RIS's phase-shift matrix and a sufficiently large k_r such that $k_r \gg 1$, and using multiple RISs with $J \geq 1$ assuming the direct path is blocked where $\sigma_{1(B,J)}^2 = \sigma_0^2$ and equal a priori probabilities, the proposed sub-optimal threshold at zone $i = (B, J)$ at n th time instant for the cases where $\frac{\mu_{(B,J)}\sqrt{r}}{\sigma_{1(B,J)}^2} \gg 1$ is*

$$\eta_{(B,J)} = \frac{N_0^2}{4\mu_{(B,J)}^2} \left(\frac{\mu_{(B,J)}^2}{N_0} + \ln \left(\sqrt{\frac{4\pi\mu_{(B,J)}\sqrt{\Psi_{(B,J)}}}{N_0}} \right) \right)^2. \quad (4.29)$$

Proof. The expression in (4.29) is obtained by replacing r at the denominator in (4.28) with $\Psi_{(B,J)}$ and solving for r . $\square$

Remark 2. *The weighted average of the RSS, $\Psi_{(B,J)}$ was substituted for r in the denominator of the expression in (4.28), since the error impact will be less significant compared to replacing r at the power of the exponential. Further, the expression in Lemma 2 is valid when the condition in (4.28) is satisfied, and the threshold is undefined elsewhere, which will be shown in the results section.*

4.5.3 RISs Deployment and Placement

We have many possible locations of RISs with respect to the UAV and sensing node, the significance of the RIS's placements is investigated in this subsection. First, we define d_{sj} to be the total distance for j th RIS-assisted path such that $d_{sj} = d_{urj} + d_{rjd}$. For a fixed d_{sj} , there are infinite possibilities of where the RIS can be placed, and the detection performance will be significantly altered according to different placements options. With this, we define Δ_j to be the ratio of each distance in dB for j th RIS such that

$$\Delta_j = 10 \log \frac{d_{urj}}{d_{rjd}}. \quad (4.30)$$

Furthermore, since the direct path link is irrelevant of RIS location optimization, we may express the first input of the Marcum Q-function for zone $i = (B, J)$ and for j th RIS in (4.23) as

$$\hat{a}_{rj} = \sqrt{\frac{2m^2\delta^2\beta^2P(d_{sj} - d_{rjd})^{-\rho_{ur}}d_{rjd}^{-\rho_{rd}}k_r}{N_0(1+k_r)}}. \quad (4.31)$$

It can be seen that the expression in (4.31) is convex for d_{rjd} , and there is a fixed value of d_{rjd} which will lead to the weakest detection performance. Hence, we may re-write the problem as

$$\min_{d_{rjd}} \hat{a}_{rj}(d_{rjd}) \quad (4.32)$$

which can be solved using straightforward derivative method.

Theorem 4. *For an optimized RIS's phase-shift matrix and a sufficiently large k_r such that $k_r \gg 1$, and using multiple RISs with $J \geq 1$ and for a fixed total RIS's path distanced d_{sj} , the distance ratio for j th RIS, Δ_j , that will lead to the worst detection performance, is*

$$\Delta_j = 10 \log \frac{\rho_{urj}^2 d_{rjd}}{\rho_{rjd}^2 d_{urj}}. \quad (4.33)$$

Proof. Please refer to Appendix B □

From Theorem 4, we can conclude that the detection performance of the RIS's paths will go to the maximum if the RIS is too close to the UAV or to the sensing node, where the result of the multiplication in (4.31) will go to the minimum. However, placing the RIS close to the sensing node will come at the cost of narrowing the coverage zone of the RIS.

4.5.4 Optimal Number of RIS Elements

In this subsection, we aim to study the minimum required number of elements per RIS such that the detection performance of intruding UAV in the zones (N, J) will outperform

the case of $(L, 0)$, i.e. $\frac{P_d}{(N,J)} \geq \frac{P_d}{(L,0)}$. Since the second argument in the Marcum Q-function is equal under both scenarios, we may express the inequality as

$$\sum_{j=1}^J \sqrt{\frac{m^2 \delta^2 \beta^2 P d_{urj}^{-\rho_{ur}} d_{rjd}^{-\rho_{rd}} k_r}{(1+k_r)(\frac{N_0}{2} + P\beta d_d^{-\rho_d})}} \geq \sqrt{\frac{4k_d P \beta}{2P\beta + N_0 d_d^{\rho_d}}}. \quad (4.34)$$

A special case when $J = 1$ and by squaring both sides and solving for m will result in

$$\mathcal{M}(r_1) = \sqrt{\frac{(2k_d)(1+k_r)(\frac{N_0}{2} + P\beta d_d^{-\rho_d})}{\left(1 + \frac{N_0 d_d^{\rho_d}}{2P\beta}\right) (\delta^2 \beta^2 P d_{urj}^{-\rho_{ur}} d_{rjd}^{-\rho_{rd}} k_r)}} \quad (4.35)$$

where $\mathcal{M}(r_1)$ stands for the minimum required number of elements, m , when r_1 is utilized. However, for a generalized number of RISs with $J \geq 1$, we propose and prove the following theorem.

Theorem 5. *For an optimized RIS's phase-shift matrix and a sufficiently large k_r such that $k_r \gg 1$, the minimum number of elements per RIS for multiple RISs with $J \geq 1$, $\mathcal{M}(r_1, r_2, \dots, r_J)$, that is needed at zone $i = (N, J)$ to have an equal probability of detection with zone $i = (L, 0)$ can be expressed as*

$$\mathcal{M}(r_1, r_2, \dots, r_J) = \sqrt{\frac{2k_d}{\left(1 + \frac{N_0 d_d^{\rho_d}}{2P\beta}\right) \left(\sum_{j=1}^J \frac{\delta^2 \beta^2 P d_{urj}^{-\rho_{ur}} d_{rjd}^{-\rho_{rd}} k_r}{(1+k_r)(\frac{N_0}{2} + P\beta d_d^{-\rho_d})} + \Gamma\right)}} \quad (4.36)$$

where

$$\Gamma = \sum_{j=1}^J \sum_{\substack{z=1 \\ z \neq j}}^J \frac{\delta^2 \beta^2 P k_r \sqrt{d_{urj}^{-\rho_{ur}} d_{rjd}^{-\rho_{rd}} d_{urz}^{-\rho_{ur}} d_{rzd}^{-\rho_{rd}}}}{(1+k_r)(\frac{N_0}{2} + P\beta d_d^{-\rho_d})} \quad (4.37)$$

Proof. Please refer to Appendix C. □

Furthermore, we use Algorithm 3 to determine the number of required elements m

and to calculate the detection performance for each UAV location coordinates at the n th time instant.

Algorithm 3 Proposed algorithm to determine $\mathcal{M}$, a_{rj} and $\hat{a}_{rj}$

```

1: Input:  $(x_{r1}, y_{r1}, z_{r1})(x_{r2}, y_{r2}, z_{r2})$  in Table 3
2: Initialisation: set  $\mathcal{M} = \mathcal{M}(r_1, r_2)$  using (4.36),
3: evaluate  $a_{r1}, a_{r2}$  using (4.19), evaluate  $\hat{a}_{r1}, \hat{a}_{r2}$  using (4.31)
4: if  $x_u \geq x_{r1}$  then
5:    $a_{r1} = 0$ ,  $\hat{a}_{r1} = 0$ ,  $\mathcal{M} = \mathcal{M}(r_2)$ 
6: end if
7: if  $x_u \leq x_{r2}$  then
8:    $a_{r2} = 0$ ,  $\hat{a}_{r2} = 0$ ,  $\mathcal{M} = \mathcal{M}(r_1)$ 
9: end if
10:  $a_{rj} = a_D + a_{r1} + a_{r2}$ 
11:  $\hat{a}_{rj} = \hat{a}_{r1} + \hat{a}_{r2}$ 
12: return  $a_{rj}$ ,  $\hat{a}_{rj}$ ,  $\mathcal{M}$ 

```

Remark 3. *The case presented in algorithm 3 is an example that depends on the proposed locations of the RISs in our model. However, the same approach can be extended for higher number of RISs to calculate a_{rj} , $\hat{a}_{rj}$, and $\mathcal{M}$.*

4.6 Results and Discussion

For our numerical analysis, we set the parameters as in Table 5 where the values of a and b are again chosen based on the International Telecommunication Union (ITU) model [52]. Figure 11 illustrates the receiver operating characteristic (ROC) for all type of zones, where detection performance is depicted for a specific P_f at the sensing node. 11a present the ROCs under passive RIS assumption where 11b is for $\delta = 2$. The results presented was obtained using the expressions in (4.15), (4.16), (4.17) and (4.23) for NLoS, LoS, RIS assisted paths and only RIS case, respectively. Moreover, 5×10^4 Monte Carlo simulation trials have been performed to validate the derived mathematical expressions where the analytical results have match well the derived expressions. It is also observed that the

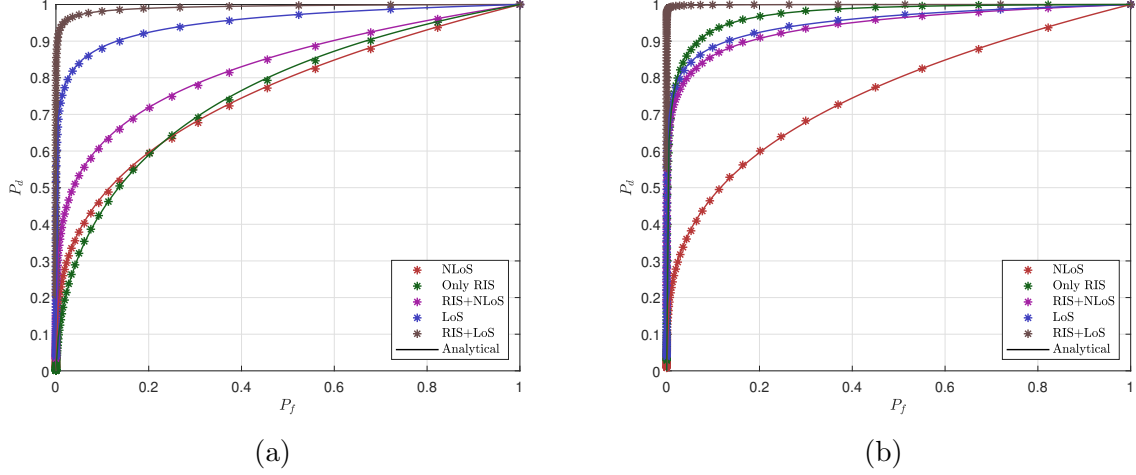


Figure 11: ROC for all channel scenraios (a) $\delta = 1$, (b) $\delta = 2$

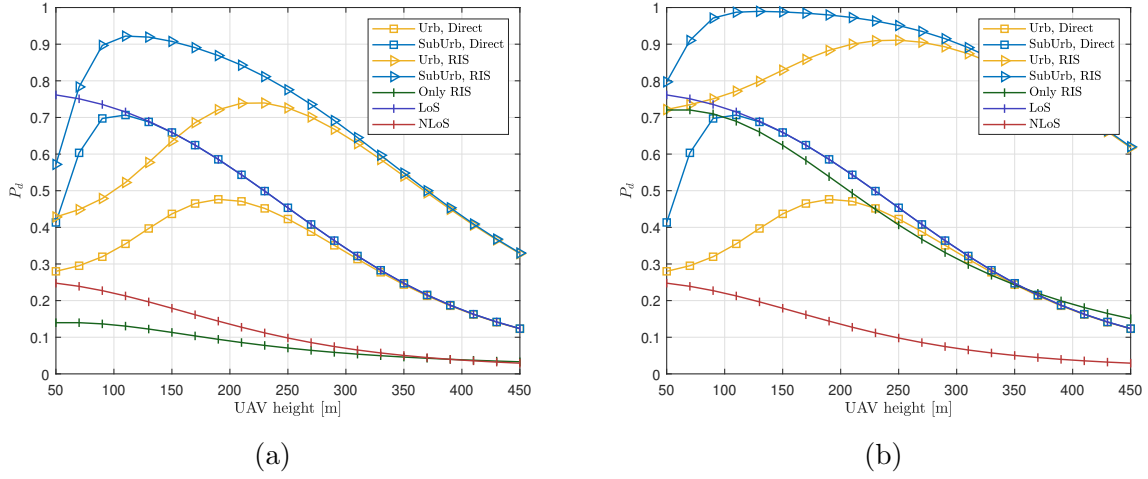


Figure 12: The impact of the UAV altitude on P_d (a) $\delta = 1$, (b) $\delta = 2$

detection performance of the RISs paths under active RIS assumption will be closed to the scenario where only a direct LoS link exists. Additionally, when supported by a direct LoS link, the RIS assisted path will have a $P_d = 0.99$ at $P_f = 0.01$. It is important to note that the overall power consumption is not reserved for both active and passive RISs cases. Hence, the active RISs scenario consumes more power, which is reflecting the performance gain.

Table 5: Simulation Parameters

Parameter	Value	Parameter	Value
P	27 dBm	ρ_d	3.5
ρ_{urj}	2	ρ_{rjd}	2.5
k_d	5 dB	k_r	10 dB
d_d	301 m	N_0	-90 dBm
β	-30 dB	δ	1
(x_d, y_d, z_d)	(0, 0, 15)	(x_u, y_u, z_u)	(150, 250, 90)
(x_{r1}, y_{r1}, z_{r1})	(250, 100, 60)	(x_{r2}, y_{r2}, z_{r2})	(-250, 100, 60)
Urban (a, b)	(9.6117, 0.1581)	Suburban (a, b)	(4.88, 0.429)

Furthermore, Figure 12 demonstrates the impact of the UAV height on P_d using (3.14) and (4.22) for the zones $i = (D, 0)$ and $i = (D, J)$, respectively, for both urban and suburban environments compared to the conditionally known LoS or NLoS cases and the only RIS scenario $i = (B, J)$ at $P_f = 0.01$. This Figure is a re-representation of Figure 6 but with the presence of active/passive RISs in the analysis. It is initially noted that, even at a low false alarm probability, the performance of the sensing node when two RISs are utilized at suburban environments will range between 0.8 to 0.92 when the UAV height is between 70m to 250m for the passive RIS and will remain above 0.9 at all heights lower than 300m with a maximum of around 0.99 at 120m since the probability of LoS will approach 1 at this height for suburban environments. Furthermore, the performance of the only RIS zones was comparable to the direct channel without RIS under suburban environments at almost all UAV heights. The results of both Figures emphasized the performance gain achieved from utilizing the two RISs, with clearer performance comparison between passive and active RISs cases. We note that the curves representing the direct path are not altered when using active or passive RISs, as those curves are a re-representation of Figure 6 results.

Figure 13 demonstrates the average error probability, which is the average over the

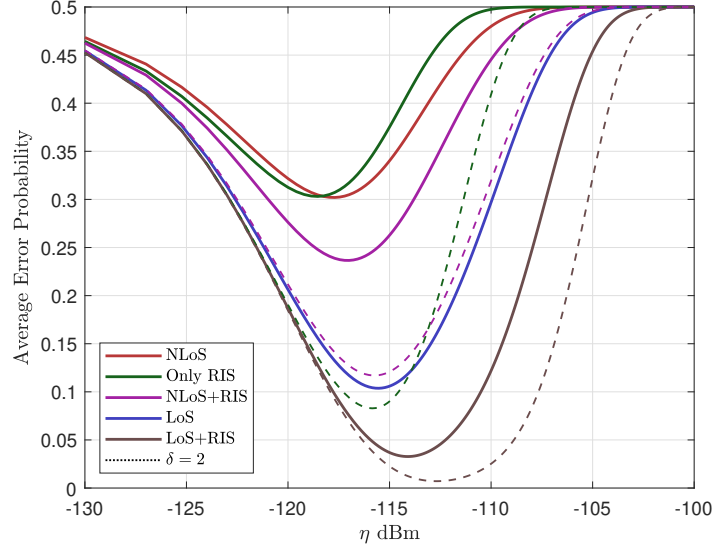


Figure 13: Average error probability at different decision thresholds.

probability of miss detection and the probability of false alarms i.e. $\frac{(1-P_d)+P_f}{2}$ under different decision thresholds to emphasize the importance of optimizing the decision criteria at the sensing node for all zones scenarios. It is noted that the optimum decision threshold will be stricter when the SNR is high. At low decision criteria, the average error probability will increase due to a higher probability of false alarms, where the error probability will increase at higher thresholds due to decreasing the detection probability. Furthermore, it is shown that the overall accuracy of $i = (L, J)$ zone at the optimum decision threshold will be around 0.99 when the RIS is active, which is 0.1 more accurate compared to the LoS case with no RIS assistance. With that, under the assumption that lower false alarms probability is prioritized, this can be achieved by adjusting the weighting factor ϵ of our proposed suboptimal threshold to have a stricter criteria.

Figure 14 illustrates the performance evaluation for the generalized detection thresholds under different environmental scenarios for $\epsilon = 0.5$ while increasing the noise variance σ_0^2 and the UAV transmitted power P in Figure 14a and Figure 14b, respectively, as done

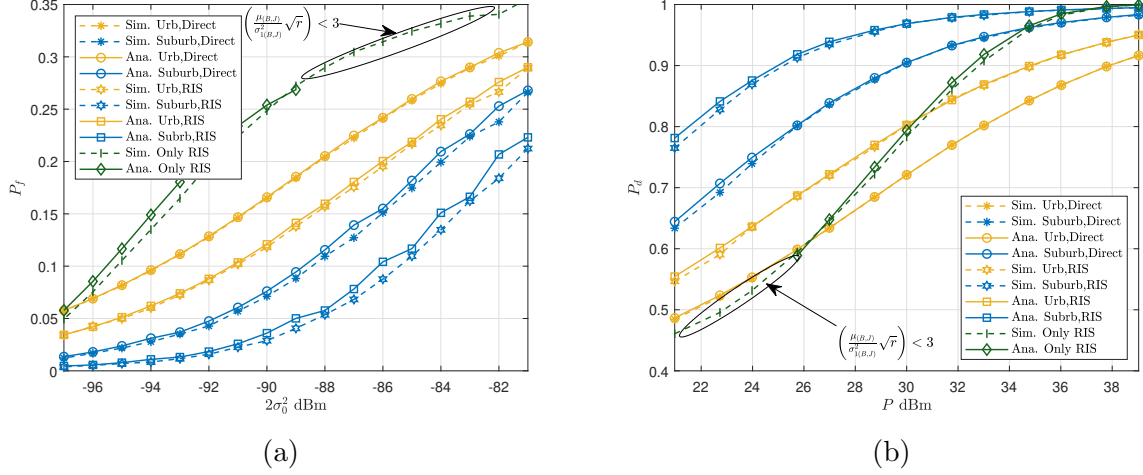


Figure 14: Performance evaluation for the generalized detection thresholds.

in figure 8.

First, in Figure 14a, we calculate P_f numerically under the optimum threshold of all zones using (3.17), (3.19) and (4.27) compared to the suboptimal threshold proposed in (4.26) and (4.29). The results show that even with passive RISs, an around 0.05 reduction of the false alarm probability can be approached at the sensing node using the optimum decision criteria. Furthermore, as expected, the application of Algorithm 1 keeps the performance of the suboptimal criteria as close as possible to the optimum one. Furthermore, in Figure 14b, the average probability of detection is illustrated with varying UAV transmit power. It is again noted that an even larger gain can be approached of on the probability of detection by utilizing RISs, where the probability of detection can reach 0.9 at 26 dBm at suburban environments when the RISs is utilized compared to 30 dBm required at the same environment without RISs. Finally, since the proposed suboptimal threshold under the zone $i = (B, J)$ is only valid when the condition mentioned in Lemma 2 is satisfied, where we have $\left(\frac{\mu_{(B,J)}}{\sigma_{1(B,J)}^2}\sqrt{r}\right) > 3$ to be our assumed condition, there exists some cases, typically at low SNRs, where our proposed threshold is undefined as shown in both figures.

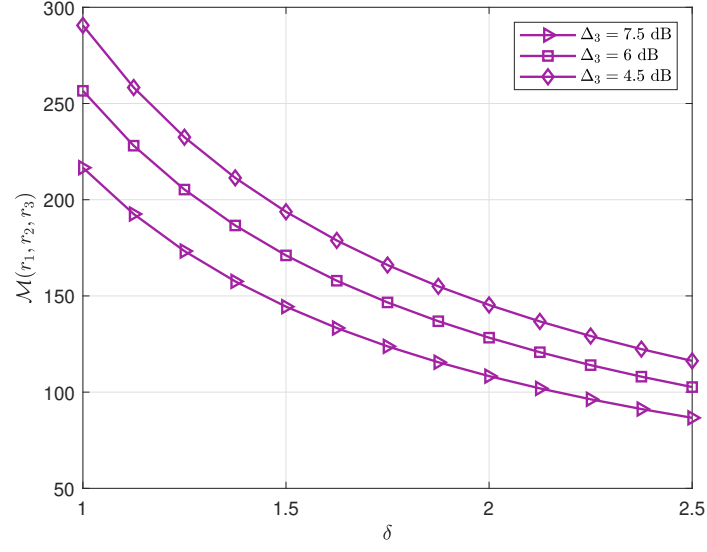


Figure 15: The impact of Δ_3 and δ on $\mathcal{M}(r_1, r_2, r_3)$.

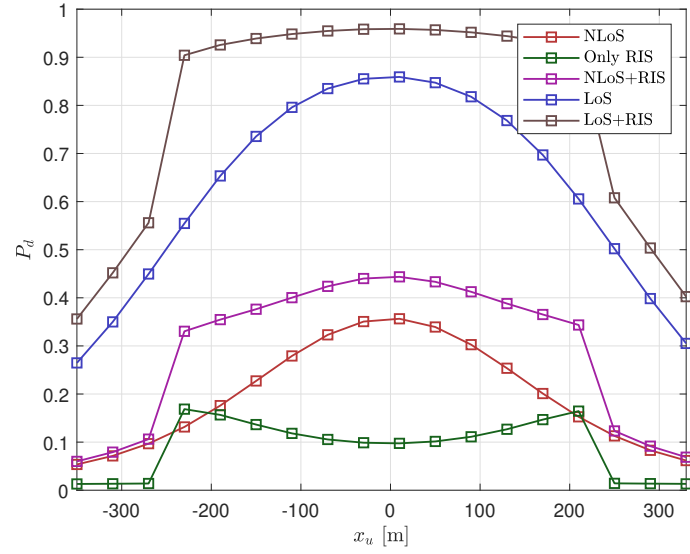


Figure 16: Effect of X_u on the probability of detection.

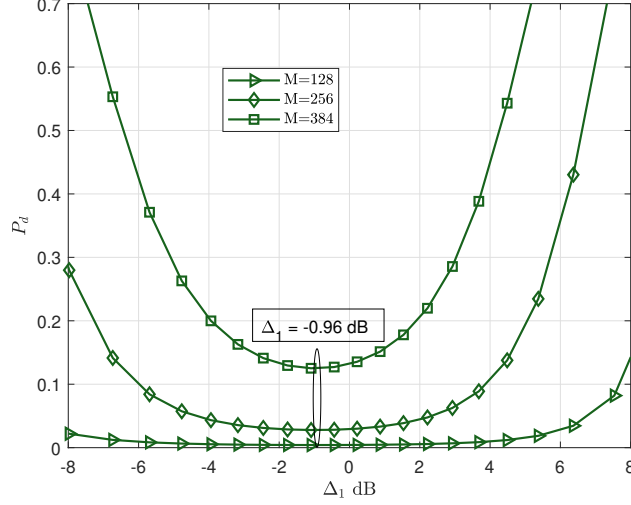


Figure 17: Effect of Δ_1 on the probability of detection for various M at $i = (B, J)$.

In Figure 15, we add a new RIS in our model and fix the total distances $d_{s3} = 500$ m. With that, we present the impact of the amplification factor of the 3 used RISs and the placement of the new RIS on the optimal number of elements per RIS at zone $i = (N, J)$ presented in (4.36) with varying $\Delta_3 \in \{4.5, 6, 7.5\}$ in dB. It is shown that we can save up to 50 elements per RIS when $\Delta_3 = 7.5$ dB as compared to the case of $\Delta_3 = 4.5$ dB. Furthermore, increasing the amplification factor to 2 will save half of the required elements.

On the other hand, we present the probability of detection with $P_f = 0.01$ for different UAV horizontal locations in Figure 16. It is noted that the impact of having assistance from RISs is higher on the LoS case as compared to the NLoS. This is due to the fact that the optimal phase shift design is calculated to guarantee coherent addition with the LoS components. However, since coherent addition with the small scale fading components of NLoS case is not possible, the performance enhancement from using RISs is lower. Further, it is also worth mentioning that the sudden increase of the probability of detection at the edges of $x_u = -250$ and $x_u = 250$ comes from having an additional RIS into the

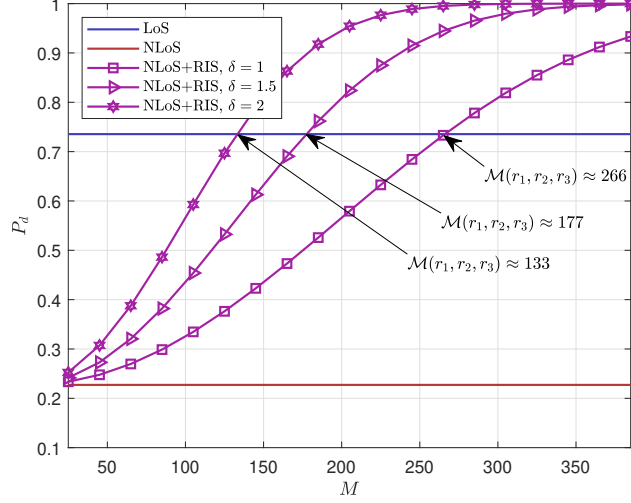


Figure 18: Comparison between the direct path zones and the zone $i = (N, J)$ for different M and δ

UAV detection zone, where Δ_1 and Δ_2 will usually be as far as possible from the worst case scenario when the RIS is too close to the UAV, as in this case, or to the sensing node. Finally, the behavior of the probability of detection of the zone $i = (B, J)$ clearly shows the significance of the RIS placement, where the detection performance will get lower as the UAV moves away from the RIS, this is not clearly shown in $i = (D, J)$ scenarios due to the affect of the direct path links on P_d .

Figure17 illustrates the probability of detection performance at $P_f = 0.001$ under $i = (B, J)$ with varying Δ_1 with $d_{s1} = 400$ m after removing RIS2 from the model and for $M \in \{128, 256, 384\}$. It can be seen that, there exist a value of Δ_1 where the detection performance is at the weakest, where this value will go to 0 dB if the path loss exponents ρ_{urj} , ρ_{rjd} are equal. However, since in our model they are not equal, this value comes at $d_{r1d} = \frac{\rho_{r1d}}{\rho_{ur1}} d_{ur1}$ as explained in Appendix B, where $\Delta_1 = -0.96$ dB.

Finally, in Figure 18, we add RIS3 at $(0, -100, 60)$ and present the probability of detection performance at $P_f = 0.01$ with various number of elements per RIS, M , to

compare the performance of the direct path zones with the zone $i = (N, J)$ for both passive and active RIS scenarios. It is observed that the minimum required number of elements, $\mathcal{M}(r_1, r_2, r_3)$ will go down from 266 to 177 by only having an amplification factor of 1.5 compared to the passive case, where the gain after moving from $\delta = 1.5$ to $\delta = 2$ is slightly lower.

4.7 Summary

In this chapter, an RSS-based RIS-assisted passive detection approach was presented. Closed-form expressions for the probability of detection under all zone scenarios were derived in addition to proposing a low-complexity suboptimal detector similar to Chapter 3. The design of the RIS phase shift was optimized to ensure coherent addition with the direct path link. Furthermore, we investigated the impact of the number of elements in RIS on the probability of detection, the needed elements to overcome direct path blockage, and the RIS placement with respect to the sensing node trade-offs. The UAV detection performance was analyzed with various environmental conditions and system parameters. Our findings showed that the performance is highly sensitive to the direct path LoS state, the number of deployed RISs, the amplification factor, the RIS location with respect to sensing node, and the number of elements per RIS. Finally, an overall accuracy of 0.99 was achieved using the optimum detector under the scenarios when active RISs are utilized along with the direct path in LoS condition.

5 Detection Performance in the Presence of RF Interference

5.1 Chapter Outline

Chapter 4 presented a comprehensive performance analysis of UAV detection aided by Reconfigurable Intelligent Surfaces (RISs). Our analysis has shown how the use of RISs can significantly boost the sensing node accuracy, especially when a fixed LoS path is available from the UAV to the sensing node. In this chapter, however, we consider the cases of which the sensing node is placed in an RF interference environment, which will have a negative impact on the detection performance. The random number and locations of the interfering sources will add up to the complexity of the problem. An analytical framework for the performance analysis will be proposed by the end of this chapter taking into consideration all system parameters.

5.2 System Model with Interference

For convenience, we will consider the same system model used in Chapter 4 with the same notations, while adding the new part of the RF interfering nodes. First of all, as the RF interference devices are distributed around the sensing node from all directions, we will assume that the sensing node has a detection range of which the antenna sensitivity can detect the RF signal. For simplicity, the range of detection is assumed to have a circular shape of radius B . Moreover, as shown in Figure 19, we assume a smaller circle of radius A in which no interference devices are in this area, or have weak signals with no potential to cause interference and can be neglected. This is due to the location of the sensing node with respect to any possible interferers in such close proximity. Hence, the area of the detection range, $|G|$ is the shaded area in light blue of Figure 19, which can be expressed

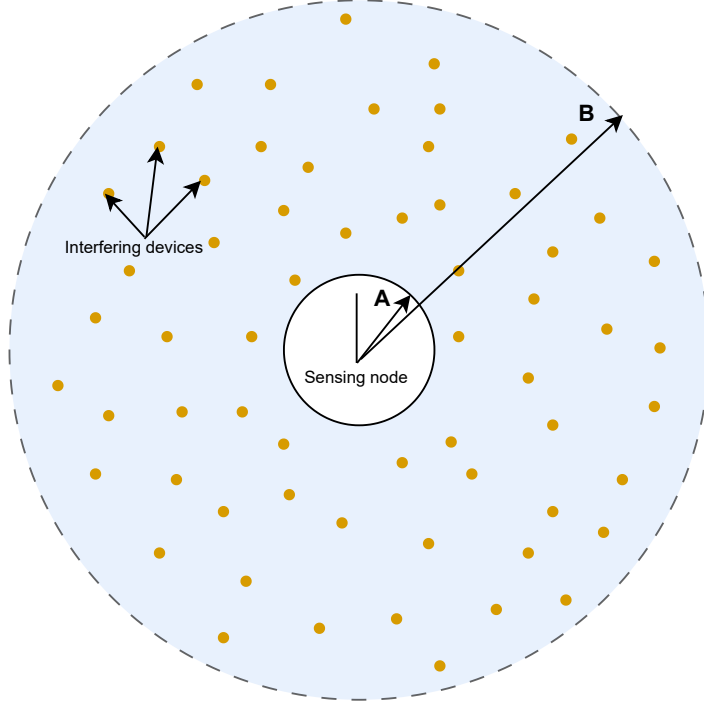


Figure 19: Aerial view of the interfering devices and the sensing node detection range with potential interference

as

$$|G| = \pi B^2 - \pi A^2. \quad (5.1)$$

Furthermore, we assume F terrestrial interfering devices that are distributed according to Homogeneous Poisson Point Process (HPPP) with parameter ϱ , where each interfering node has a time-variant coordinates of $(x_f[n], y_f[n], 0)$ for the f th device. With that, we might claim that the average number of interfering sources in our bounded detection range is $\varrho|G|$ [58]. Furthermore, the bounded area assumption allows us to assume that the interfering sources are uniformly distributed within the detection zone of the sensing node [59]. The minimum and maximum distances from the sensing node to any interfering source are $\hat{A} = \sqrt{A^2 + z_d^2}$ and $\hat{B} = \sqrt{B^2 + z_d^2}$, respectively.

Hence, the updated discrete-time baseband equivalent of the received signal $y(t)$ in

the n th time slot is

$$y[n] = \left(h_D[n] + \sum_{j=1}^J \mathbf{h}_{R_j}^H[n] \mathbf{\Phi}_j[n] \mathbf{g}_{R_j} \right) \sqrt{P} s[n] + \left(\sum_{f=1}^F h_f[n] \right) \sqrt{P_c} s_c[n] + w[n] \quad (5.2)$$

where $h_f[n]$ is the channel gain of the signal from the interfering source f to the sensing node, P_c is the transmitted power from any interfering device and $s_c[n]$ is the unit energy signal of the interfering nodes with zero mean and unit variance.

For each interference node link, we assume that the multipath propagation follows the Rayleigh fading model, and channel gain is defined as

$$h_f[n] = \sqrt{\beta d_f^{-\rho_c}} \tilde{X} \quad (5.3)$$

where d_f is the distance from the node f and the sensing node and ρ_c is the path loss exponent of the link from any interfering device to the sensing node. Furthermore, the Signal to Interference Plus Noise Ratio, SINR, at the sensing node can be defined as

$$\gamma[n] = \frac{P \left| h_D[n] + \sum_{j=1}^J \mathbf{h}_{R_j}^H[n] \mathbf{\Phi}_j[n] \mathbf{g}_{R_j} \right|^2}{P_c \left| \sum_{f=1}^F h_f[n] \right|^2 + 2\sigma_0^2}. \quad (5.4)$$

5.3 Detection Performance Analysis

We start by expressing the updated conditional binary hypothesis assuming slow fading coefficients as mentioned in equation (4.9) as

$$\begin{aligned}
\mathcal{H}_0 : y &= \left(\sum_{f=1}^F h_f \right) \sqrt{P_c} s_c + w \\
\mathcal{H}_{1i} : y &= \left(h_D + \sum_{j=1}^J \mathbf{h}_{R_j}^H \mathbf{\Phi}_j \mathbf{g}_{R_j} \right) \sqrt{P} s + \left(\sum_{f=1}^F h_f \right) \sqrt{P_c} s_c + w
\end{aligned} \tag{5.5}$$

again, it is noted that only the alternative hypothesis, $\mathcal{H}_{1i}$, depends on the detection zone $i = (D, J)$ as mentioned in Chapter 4, while the null hypothesis is the same under all cases. This allows us to start the analysis by evaluating the false alarm probability, in order to use it to get the ROCs for each zone i .

5.3.1 Under Assumption of Known Interference Locations

To simplify our analysis, we will start by assuming that the number of interfering devices in our detection range is known, as well as the location of each interfering node.

- **Probability of False Alarm**

The received signal y under the null hypothesis is a zero mean complex Gaussian random variable with variance $= 2\sigma_0^2$, i.e. $y \sim \mathcal{N}_{\mathbb{C}}(0, 2\sigma_0^2)$ where $\sigma_0^2 = P_c \beta \sum_{f=1}^F d_f^{-\rho_c} + N_0/2$, which comes from the summation of independent Gaussian random variables. Under this hypothesis, the RSS, R , is sum of the squares of two independent and identically distributed (i.i.d) Gaussian random variables and will follow the exponential distribution, i.e. $R|\mathcal{H}_0 \sim \exp\{2\sigma_0^2\}$. Since the number of interfering nodes and their locations is assumed to be known here, the probability of false alarm expression can be now expressed as

$$P_f = \int_{\eta}^{\infty} \mathcal{P}_{R|\mathcal{H}_0}(r|\mathcal{H}_0) dr = \int_{\eta}^{\infty} \frac{e^{-\frac{r}{2\sigma_0^2}}}{2\sigma_0^2} dr = e^{-\frac{\eta}{2\sigma_0^2}} \quad (5.6)$$

and the detection threshold η can be described as

$$\eta = \left(-2P_c\beta \sum_{f=1}^F d_f^{-\rho_c} - N_0 \right) \ln P_f \quad (5.7)$$

• Probability of Detection

In Theorem 2, we proved that the use of RISs does not contribute to the variance of the alternative hypothesis received signal, or more specifically, it can be ignored without sacrificing the accuracy. Hence, we start by updating $\sigma_1^2 = P\beta d_d^{-\rho_d} + P_c\beta \sum_{f=1}^F d_f^{-\rho_c} + N_0/2$ to be the variance of the received signal under the alternative hypothesis and at any zone $i = (D, J)$. Again, this result has been obtained by adding the variances of independent Gaussian random variables of the UAV signal, interfering signals and the white noise.

Since the zone $i = (N, 0)$ has no fixed mean component, the probability of detection will have the same expression in (5.6) with replacing σ_0^2 by σ_1^2 . Hence, we may express the probability of detection after substituting the values of σ_1^2 and η in (5.7) as

$$P_{d(N,0)} = \exp \left(\frac{\ln P_f}{\left(1 + \frac{P\beta d_d^{-\rho_d}}{P_c\beta \sum_{f=1}^F d_f^{-\rho_c} + \frac{N_0}{2}} \right)} \right) \quad (5.8)$$

The rest of the zones will have a fixed mean component in the received signal. Hence, the received signal strength, R , will have a non-central Chi-squared distribution. The probability of detection will again take the form of

$$\begin{aligned}
P_d &= \int_{\frac{\sqrt{\eta}}{\sigma_1}}^{\infty} r e^{-\frac{(\frac{\mu_i}{\sigma_1})^2 + r^2}{2}} I_0\left(\frac{\mu_i}{\sigma_1} r\right) dr \\
&= Q_1\left(\frac{\mu_i}{\sigma_1}, \frac{\sqrt{\eta}}{\sigma_1}\right)
\end{aligned} \tag{5.9}$$

where μ_i is the non centrality parameter of the zone i and σ_1^2 is equal under all zones as already mentioned. Fortunately, the addition of RF interference does not alter the values of the non centrality parameter derived in Chapter 4, since the interfering nodes are assumed to have NLoS link with the sensing node, which have only contributed to the variance of the received signal as shown. Hence, the updated detection probabilities are calculated by substituting σ_1^2 and μ_i for each zone in (5.9) and can be expressed as

$$P_{d(L,0)} = Q_1\left(\sqrt{\frac{2k_d}{1 + \frac{\frac{N_0}{2} + P_c\beta \sum_{f=1}^F d_f^{-\rho_c}}{P\beta d_d^{-\rho_d}}}}, \sqrt{\frac{-\ln P_f}{0.5 + \frac{P\beta d_d^{-\rho_d}}{N_0 + 2P_c\beta \sum_{f=1}^F d_f^{-\rho_c}}}}\right) \tag{5.10}$$

$$P_{d(N,J)} = Q_1\left(\sum_{j=1}^J \sqrt{\frac{m^2 \delta^2 \beta^2 P d_{urj}^{-\rho_{ur}} d_{rjd}^{-\rho_{rd}} k_r}{(1 + k_r)(\frac{N_0}{2} + P_c\beta \sum_{f=1}^F d_f^{-\rho_c} + P\beta d_d^{-\rho_d})}}, \sqrt{\frac{-\ln P_f}{0.5 + \frac{P\beta d_d^{-\rho_d}}{N_0 + 2P_c\beta \sum_{f=1}^F d_f^{-\rho_c}}}}\right) \tag{5.11}$$

The expression of $P_{d(L,J)}$ is obtained by adding the first Marqum-Q input of (5.10) and (5.11) as a first input with the second input unchanged, as done in Theorem 2.

Remark 4. *In this chapter, the analysis of the zones $i = (B, J)$ is not considered. This is explained by the nature of the environment where the sensing node is assumed to be placed. More Specifically, if the sensing node is able to detect NLoS reflections from all interfering sources, this implicitly implies that NLoS reflections from the UAV will be received by the sensing node at all cases.*

$$P_{d(N,0)} = \int_0^\infty \frac{\exp\left(\frac{(x-\varrho|G|\mathbb{E}[V])^2}{2\varrho|G|Var(V)}\right)}{\sqrt{2\pi\varrho|G|Var(V)}} \exp\left(\frac{\ln P_f}{\left(1 + \frac{P\beta d_d^{-\rho_d}}{P_c\beta x + \frac{N_0}{2}}\right)}\right) dx \quad (5.13)$$

5.3.2 Under Assumption of Unknown Interference Locations

Due to the nature of the mobile interfering users, the assumption of having known the number and locations of the interfering nodes is not realistic for real world applications. This takes us to the final step of evaluating the performance analysis. Fortunately, we have shown that the number of interfering nodes follows the Poisson random variable with mean $\varrho|G|$ where the nodes are uniformly distributed with minimum and maximum distances from the sensing node of $\hat{A}$ and $\hat{B}$, respectively. Therefore, by averaging over those random variables, we may express a generalized form of the probability of detection as

$$\sum_{n=0}^{\infty} \int \int \cdots \int_{|G|} \left(\frac{e^{\varrho|G|} (\varrho|G|)^n}{n!} \right) \times \left(\frac{1}{\hat{B} - \hat{A}} \right)^n P_{d(D,J)}(d_1, d_2, \dots, d_n) df_1 df_2 \dots df_n \quad (5.12)$$

The expression in (5.12) takes the average over a Poisson random variable with mean $\varrho|G|$ in addition to averaging over all possible locations of each interfering source by taking the n -fold integral of the probability density function of a Uniform random variable that represents all nodes n of each iteration. In other words, the number of integrals evaluated keeps increasing infinitely with each iteration from the Poisson probability mass function, which makes it tedious to calculate. However, in order to tackle this problem, we present the following Lemma.

$$P_{d(L,0)} = \int_0^\infty \frac{\exp\left(\frac{(x-\varrho|G|\mathbb{E}[V])^2}{2\varrho|G|\text{Var}(V)}\right)}{\sqrt{2\pi\varrho|G|\text{Var}(V)}} Q_1\left(\sqrt{\frac{2k_d}{1+\frac{\frac{N_0}{2}+P_c\beta x}{P\beta d_d^{-\rho_d}}}}, \sqrt{\frac{-\ln P_f}{0.5+\frac{P\beta d_d^{-\rho_d}}{N_0+2P_c\beta x}}}\right) dx \quad (5.14)$$

$$P_{d(N,J)} = \int_0^\infty \frac{\exp\left(\frac{(x-\varrho|G|\mathbb{E}[V])^2}{2\varrho|G|\text{Var}(V)}\right)}{\sqrt{2\pi\varrho|G|\text{Var}(V)}} Q_1\left(\sum_{j=1}^J \sqrt{\frac{m^2\delta^2\beta^2 P d_{urj}^{-\rho_{ur}} d_{rjd}^{-\rho_{rd}} k_r}{(1+k_r)(\frac{N_0}{2}+P_c\beta x+P\beta d_d^{-\rho_d})}}, \sqrt{\frac{-\ln P_f}{0.5+\frac{P\beta d_d^{-\rho_d}}{N_0+2P_c\beta x}}}\right) dx \quad (5.15)$$

Lemma 3. *For a high number of interfering devices ⁴ F in the bounded detection range of area $|G|$, with an average number of interfering devices of $\varrho|G|$, the receiver operating characteristic (ROC) can be obtained for all zones $i = (D, J)$ as (5.13), (5.14), (5.15) and (5.16)*

where

$$\mathbb{E}[V] = \frac{(\hat{B})^{1-\rho_c} - (\hat{A})^{1-\rho_c}}{(1-\rho_c)(\hat{B} - \hat{A})} \quad (5.17)$$

$$\text{Var}(V) = \frac{(\hat{B})^{1-2\rho_c} - (\hat{A})^{1-2\rho_c}}{(1-2\rho_c)(\hat{B} - \hat{A})} - (\mathbb{E}[V])^2 \quad (5.18)$$

Proof. See Appendix D. □

It is worth mentioning that the expressions of Lemma 3 are the most generalized forms of the probability of detection, and substituting $P_c = 0$ will bring us back to the detection formulas derived in Chapter 4. Additionally, Lemma 3 can only be used when the number of interfering nodes are large enough for the Gaussian approximation to converge with an

⁴The derivation of this Lemma is only valid with high number of interfering nodes. For lower number of devices, the assumption of Central Limit Theorem does not converge.

$$P_{d(L,J)} = \int_0^\infty \frac{\exp\left(\frac{(x-\varrho|G|\mathbb{E}[V])^2}{2\varrho|G|\text{Var}(V)}\right)}{\sqrt{2\pi\varrho|G|\text{Var}(V)}} Q_1\left(\sqrt{\frac{2k_d}{1+\frac{\frac{N_0}{2}+P_c\beta x}{P\beta d_d^{-\rho_d}}}} + \sum_{j=1}^J \sqrt{\frac{m^2\delta^2\beta^2 P d_{urj}^{-\rho_{ur}} d_{rjd}^{-\rho_{rd}} k_r}{(1+k_r)(\frac{N_0}{2}+P_c\beta x+P\beta d_d^{-\rho_d})}}, \sqrt{\frac{-\ln P_f}{0.5+\frac{P\beta d_d^{-\rho_d}}{N_0+2P_c\beta x}}}\right) dx \quad (5.16)$$

Table 6: Complete System Parameters

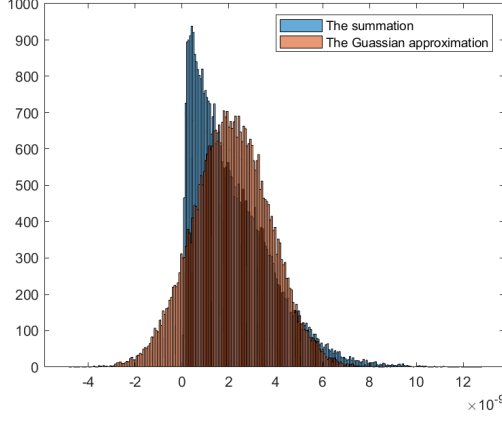
Parameter	Value	Parameter	Value
P	27 dBm	ρ_d	3.5
ρ_{urj}	2	ρ_{rjd}	2.5
k_d	5 dB	k_r	10 dB
d_d	301 m	N_0	-90 dBm
β	-30 dB	δ	1
(x_d, y_d, z_d)	(0, 0, 15)	(x_u, y_u, z_u)	(150, 250, 90)
(x_{r1}, y_{r1}, z_{r1})	(250, 100, 60)	(x_{r2}, y_{r2}, z_{r2})	(-250, 100, 60)
Urban (a, b)	(9.6117, 0.1581)	Suburban (a, b)	(4.88, 0.429)
A	150 m	B	1000 m
$ G $	$3.07 \times 10^6 \text{ m}^2$	ϱ	$\frac{40}{ G }$
P_c	24 dBm	ρ_c	4.25

acceptable accuracy.

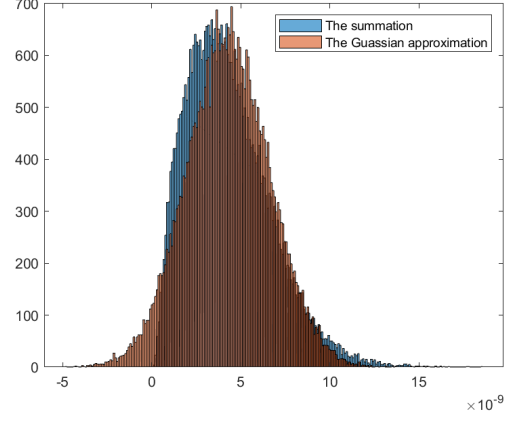
5.4 Numerical Results

For our numerical results, we set the parameters as in Table 6. To better compare the performance, we keep the simulation parameters choices of Chapter 4 unchanged, while adding the new parameters related to the RF interference.

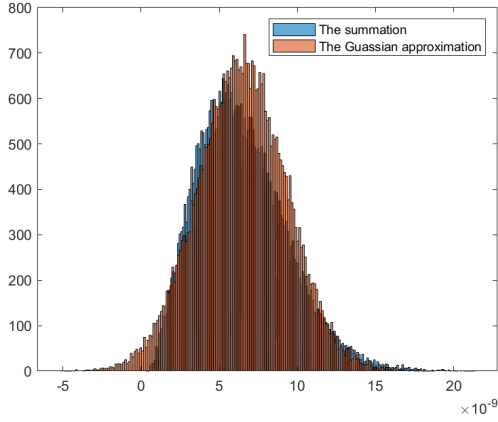
First, Figure 20 presents the histogram analysis to prove the accuracy of the Gaussian approximation proposed in Lemma 3 when adding 20, 40 and 60 random functions, V as compared to the Gaussian approximation. Figure 20a shows that the addition of only 20 functions of V is not enough to consider the Gaussian approximation accurate due to the skewed nature of the function V resulting from raising the uniform random variable to a negative ρ_c power. However, Figures 20b and 20c show that it would require the presence of at least 40 interfering nodes to assume that the Gaussian approximation holds true, while adding 60 will even have a better accuracy. It is worth mentioning that the convergence is highly dependant on the path loss exponent assumed for the link



(a)



(b)



(c)

Figure 20: Histogram comparison between the summation of N functions of V with the Gaussian approximation proposed (a) $N = 20$, (b) $N = 40$, (c) $N = 60$

between the interfering devices and the sensing node, which contribute to the Skewness of the random function V . In our analysis, for example, we assume a path loss exponent of 4.25, since all interfering nodes are ground based and do not have a direct LoS link with the sensing node. However, under the assumption of a smaller ρ_c value, the Gaussian approximation will require a lower number of interfering devices to converge.

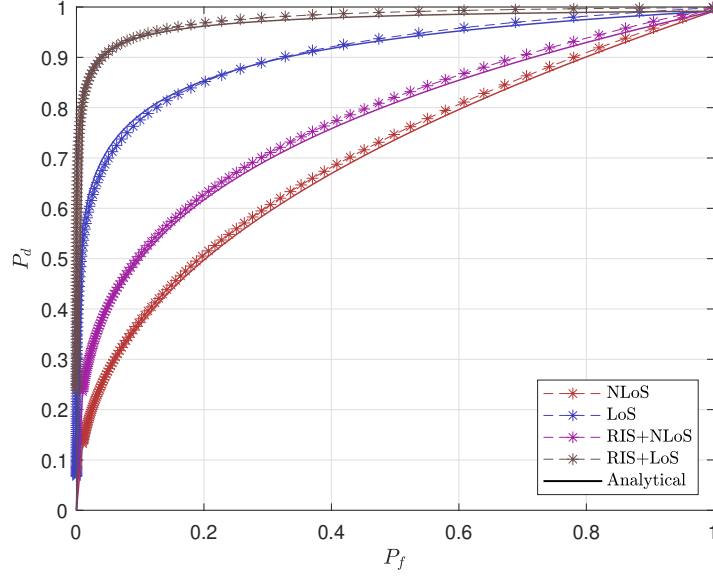


Figure 21: Receiver operating characteristic (ROC). The solid lines represent the analytical results proposed

On the other hand, Figure 21 illustrates the ROCs evaluated from extensive Monte Carlo simulations and by the proposed detection expression for all zones $i = (D, J)$. Those curves can be used for performance comparison with Figure 12a in Chapter 4, which represented the case of similar system parameters but without interference. It is initially observed that adding RF interference does indeed reduce the overall performance accuracy of the sensing node by around 0.1 as compared to the case of no interference. Additionally, the performance of the zones of which the direct channel is NLoS was affected more severely as compared to the zones of $i = (L, J)$. This is due to the fact that the interference signals themselves have NLoS channel links, and having a direct LoS link between the UAV and the sensing node will be dominant in terms of the signal energy level. Furthermore, as shown in Figure 20b, the proposed formulas have matched quite well the simulation trials when the number of interfering node is 40.

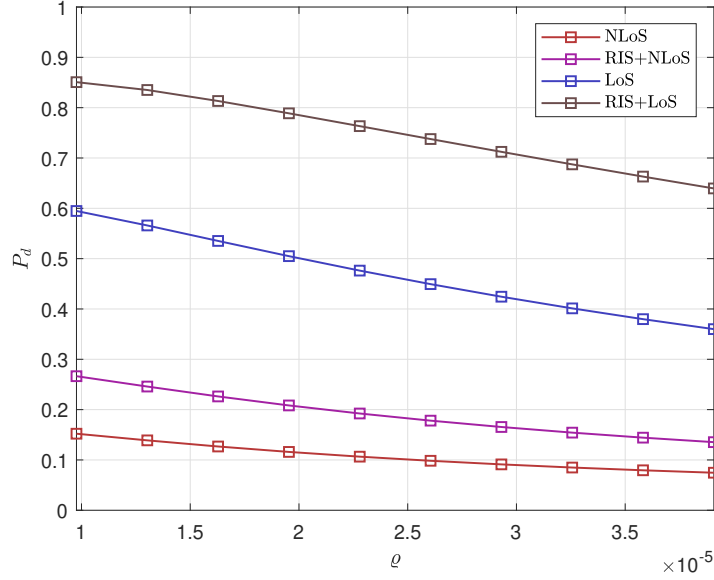


Figure 22: Effect of ρ on the probability of detection for all zones scenarios.

Figure 22 presents the impact of the interference density ρ on the probability of detection given the same area of detection $|G|$ and at a probability of false of $P_f = 0.01$. The range varies from $\rho = 1 \times 10^{-5}$ and $\rho = 4 \times 10^{-5}$, representing a minimum of 30 and maximum of 120 interfering nodes within the detection area. Clearly, the results show that a drop of more than 0.2 on the detection probability for the zones of high detection probabilities, i.e. $i = (L, J)$, and a drop of more than 0.1 for the NLoS direct path zones. This figure can also be used to compare the performance of the sensing node in the presence of interference with the one presented in Figure 12a for the direct path links, i.e. $i = (D, 0)$ since we have fixed the same false alarm probability. The figure shows a drop of 0.17 and 0.1 in the $i = (L, 0)$ and $i = (N, 0)$ zones, respectively.

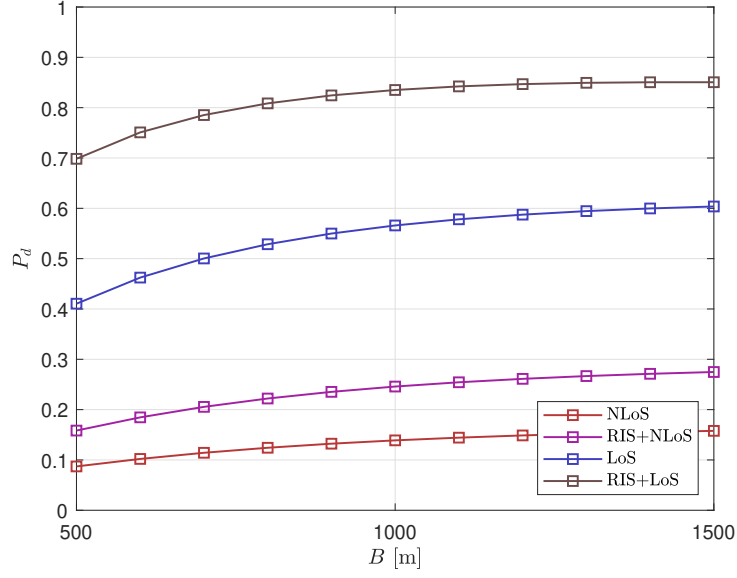


Figure 23: Impact of the outer circle radius, B , on the probability of detection for all zones scenarios.

Finally, Figure 23 illustrates the impact of increasing the detection zone of the sensing node given the same number of interfering nodes. In other words, we fix the multiplication of $\varrho |G| = 40$ under all choices of B . As expected, the probability of detection will improve as we increase the detection zone radius. More importantly, as we increase the area further, the enhancement will start to decay and the performance will saturate. This is due to the fact that having interfering devices placed very close to the sensing node will have a much higher impact than those devices far away. Hence, for the same number of nodes, it is more likely that more devices will be placed close to the sensing node when the detection zone is smaller.

5.5 Summary

In this chapter, we extend our problem of UAV detection by considering RF interference sources surrounding our sensing node. This assumption adds up to the overall complexity of the problem due to the random and mobile nature of the interfering devices around the sensing node. We first started our analysis by deriving closed form expressions for the probability of detection assuming a prior knowledge of the number and locations of the interfering devices. Afterwards, Central Limit Theorem (CLT) has been well utilized to tackle the randomness problem under the assumption of large enough number of interfering nodes distributed in an enclosed detection area of the sensing node. Our proposed analytical expressions have been verified by the use of extensive Monte Carlo simulations and for all detection zones defined. The overall performance decay ranged differently among the zones, where the scenarios of higher detection performance have shown more immunity to the interference as compared to the weaker cases of NLoS direct link between the UAV and the sensing node.

6 Conclusion and Future Directions

6.1 Thesis Summary

In this thesis, the problem of detecting malicious UAVs is investigated using passive Radio Frequency (RF) based detection technique. The importance of UAV detection problem has been rapidly growing due to their ability to cause physical, cyber and social harms if they are used illegally to breach into restricted areas. Our work starts by proposing a simple system model considering a realistic Air to Ground (A2G) channel between the drone and our single antenna sensing node where the received signal strength (RSS) level being the decision criteria of the detector. A derivation of closed form expressions of the detection probabilities was derived using the conventional binary hypothesis testing approach. Additionally, a Log-Likelihood Ratio (LLR) based optimal/suboptimal decision thresholds were derived with an iterative algorithm at the sensing node. The analysis of this model, despite being simple, has shown a promising results, especially under the cases of having a fixed LoS link. However, under NLoS scenarios, it was shown that the detection performance is relatively poor and require enhancement. To tackle this problem, Reconfigurable Intelligent Surfaces (RISs), which have been widely used as a promising technology for the future of wireless communication systems were utilized to support the performance of the sensing node. The updated system model supported by RISs has shown a massive improvement and an overall detection accuracy of above 0.99 was achieved when using active typed RISs. As in all RIS assisted systems, we considered the problem of optimizing the phase shift induced while insuring coherent addition among the RIS assisted path with the direct path form the UAV to the sensing node. Additionally, further insights on the required number of elements and the possible placement of the RISs were investigated to optimize the overall performance of the system. Finally, we

introduced RF interfering nodes at the sensing node, taking into consideration random number and locations of the interfering devices, which was challenging to derive. An analytical framework based on Central Limit Theorem (CLT) was proposed to express the most comprehensive expressions of the probability of detection, which was reassured, as all other results obtained, by the use of extensive Monte Carlo simulations.

6.2 Conclusion

Overall, we have proven that a simple system, that does not require signal decoding and is only based on the received signal level, can be a promising starting point for the detection of UAVs. Moreover, the iterative algorithm proposed to calculate the decision criteria has proven to be accurate and simple to use with a near optimum performance. Additionally, to improve the accuracy of the system, we have shown that Reconfigurable Intelligent Surfaces (RISs) is a promising technology to tackle the problem of UAV detection under NLoS scenarios, especially when using an active typed RISs. Moreover, our analytical and numerical results showed that the use of RIS has to be optimized in order to achieve the maximum possible gain. This optimization includes factors such as phase shift optimization, amplification factor choice, number of elements per RIS and the location of the RIS with respect to the sensing node and the target UAV. The impact of the addition of RF interfering sources was clearly shown in the numerical analysis with a decrease of the detection probability with around $0.1 - 0.15$, leaving the space of possible enhancements to the system capability in the future.

6.3 Future Directions

There are many possible directions to further improve the performance of the sensing node. Below list indicates some potential ideas to be investigated in the future research.

- The use of multiple antennas at the sensing node can potentially enhance the performance of the system. Similarly, a system of multiple sensing nodes can boost the detection accuracy.
- The scenarios where the location of the UAV itself is random can also be investigated, where the performance analysis in such scenarios will require averaging over all possible locations of the target UAV.
- A system that is capable to detect swarms of UAVs together can be considered as well. This is motivated from the fact that the use of UAV swarms is being more popular with time. Hence, it is important to have such scenarios considered.
- The performance analysis of the sensing node in an environment with low number of interfering devices to be investigated.
- Finally, combining the use of radar, acoustic signal or computer vision, along with our proposed sensing node that is based on RF signals, can substantially improve the overall system accuracy.

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$$\sum_{j=1}^J \mathbf{h}_{R_j}^H[n] \mathbf{\Phi}_j[n] \mathbf{g}_{R_j} = \sum_{j=1}^J \sqrt{\beta d_{urj}^{-\rho_{ur}}[n]} \sum_{m=1}^M \exp\left(-j \frac{2\pi d(m-1) \cos \psi_{urj}[n]}{\lambda}\right) \times \begin{bmatrix} \delta e^{j\theta_{j1}[n]} & & \\ & \ddots & \\ & & \delta e^{j\theta_{jM}[n]} \end{bmatrix} \sqrt{\frac{\beta d_{rjd}^{-\rho_{rd}} k_r}{1+k_r}} \sum_{m=1}^M \exp\left(-j \frac{2\pi d(m-1) \cos \psi_{rjd}}{\lambda}\right) \quad (7.1)$$

$$\left| \sqrt{2k_d \beta d_d^{-\rho_d}[n]} \exp\left(j \frac{\pi}{4}\right) + \sum_{j=1}^J \left(\sqrt{\frac{\delta^2 \beta^2 d_{urj}^{-\rho_{ur}}[n] d_{rjd}^{-\rho_{rd}} k_r}{1+k_r}} \sum_{m=1}^M \exp\left(-j \left(\frac{2\pi d(m-1) (\cos \psi_{urj}[n] + \cos \psi_{rjd})}{\lambda} - \theta_{jm}[n] \right)\right) \right) \right| \leq \left| \sqrt{2k_d \beta d_d^{-\rho_d}[n]} \exp\left(j \frac{\pi}{4}\right) \right| + \left| \sum_{j=1}^J \left(\sqrt{\frac{\delta^2 \beta^2 d_{urj}^{-\rho_{ur}}[n] d_{rjd}^{-\rho_{rd}} k_r}{1+k_r}} \sum_{m=1}^M \exp\left(-j \left(\frac{2\pi d(m-1) (\cos \psi_{urj}[n] + \cos \psi_{rjd})}{\lambda} - \theta_{jm}[n] \right)\right) \right) \right| \quad (7.2)$$

7 Appendix

7.1 Appendix A: Proof of Theorem 1

The problem formulated in (4.10) and (4.11) can be smoothed to maximize only the part including the diagonal phase-shift matrix [60] $\left| h_D[n] + \sum_{j=1}^J \mathbf{h}_{R_j}^H[n] (\mathbf{\Phi}_j[n]) \mathbf{g}_{R_j} \right|$. Hence, we may re-write (4.11) as

$$\left| h_D[n] + \sum_{j=1}^J \mathbf{h}_{R_j}^H[n] \mathbf{\Phi}_j[n] \mathbf{g}_{R_j} \right| \leq |h_D[n]| + \left| \sum_{j=1}^J \mathbf{h}_{R_j}^H[n] \mathbf{\Phi}_j[n] \mathbf{g}_{R_j} \right| \quad (7.3)$$

In our analysis, we will only consider the large scale fading of the RIS assisted path, and will assume that the LoS path exists at the direct link. Hence, we may express $h_D[n]$ and $\sum_{j=1}^J \mathbf{h}_{R_j}^H[n] (\mathbf{\Phi}_j[n]) \mathbf{g}_{R_j}$ as (7.1) and (7.4), :

$$h_D[n] = \left| \sqrt{2\sqrt{k_d \beta d_d^{-\rho_d}[n]} \tan\left(\frac{\sqrt{k_d \beta d_d^{-\rho_d}[n]}}{\sqrt{k_d \beta d_d^{-\rho_d}[n]}}\right)}^{-1} \right| \quad (7.4)$$

We may use (7.4) and (7.1) to rewrite the expression in (7.3) as (7.2):

where the equality in (7.2) will hold true if $\frac{\pi}{4} = - \left(\frac{2\pi d(m-1)(\cos \psi_{urj}[n] + \cos \psi_{rjd})}{\lambda} - \theta_{jm}[n] \right)$,
which proves the optimum phase expression mentioned in (4.12) after solving for $\theta_{jm}[n]$.

Remark 5. *The above mentioned optimal phase-shift matrix aims to ensure coherent combination of the direct path link at the sensing node along with the RIS assisted paths. Hence, we assume an existing LoS path from the UAV at the sensing node in our analysis, which resulted in the $\frac{\pi}{4}$ phase shift. However, at the case where the LoS is blocked, the impact of the additional phase will not affect the performance. Further, the small scale fading factors in the RIS assisted paths $\sqrt{\frac{1}{1+k_r}} \mathbf{g}_{Rj}^N$ was not considered due to its insignificant impact and the fact that $k_r \gg 1$.*

7.2 Appendix B: Proof of Theorem 4

In order to solve the problem in (4.32), we start by taking the first derivative of $\hat{a}_j$. First, we define $z = \frac{2m^2\delta^2\beta^2Pk_r}{N_0(1+k_r)}$ as a constant with respect to r_{rjd} . Hence, the problem is simplified to

$$\begin{aligned} \frac{\partial \hat{a}_j}{\partial d_{rjd}} &= \frac{\partial}{\partial d_{rjd}} \sqrt{\frac{z}{(d_{sj} - d_{rjd})^{\rho_{urj}} d_{rjd}^{\rho_{rjd}}}} \\ &\stackrel{a}{=} -\frac{z \frac{\partial}{\partial d_{rjd}} \left[(d_{sj} - d_{rjd})^{\rho_{urj}} d_{rjd}^{\rho_{rjd}} \right]}{2 \sqrt{\frac{z}{(d_{sj} - d_{rjd})^{\rho_{urj}} d_{rjd}^{\rho_{rjd}}}}} \end{aligned} \quad (7.5)$$

$$\stackrel{b}{=} \frac{-z \rho_{rjd} (d_{sj} - d_{rjd})^{\rho_{urj}} d_{rjd}^{\rho_{rjd}-1}}{2 (d_{sj} - d_{rjd})^{2\rho_{urj}} d_{rjd}^{2\rho_{rjd}} \sqrt{\frac{z}{(d_{sj} - d_{rjd})^{\rho_{urj}} d_{rjd}^{\rho_{rjd}}}}} \quad (7.6)$$

$$\begin{aligned} &+ \frac{z \rho_{urj} (d_{sj} - d_{rjd})^{\rho_{urj}-1} d_{rjd}^{\rho_{rjd}}}{2 (d_{sj} - d_{rjd})^{2\rho_{urj}} d_{rjd}^{2\rho_{rjd}} \sqrt{\frac{z}{(d_{sj} - d_{rjd})^{\rho_{urj}} d_{rjd}^{\rho_{rjd}}}}} \\ &\stackrel{c}{=} \frac{\frac{z \rho_{urj}}{(d_{sj} - d_{rjd})} - \frac{z \rho_{rjd}}{d_{rjd}}}{2 (d_{sj} - d_{rjd})^{\rho_{urj}} d_{rjd}^{\rho_{rjd}} \sqrt{\frac{z}{(d_{sj} - d_{rjd})^{\rho_{urj}} d_{rjd}^{\rho_{rjd}}}}} \end{aligned} \quad (7.7)$$

where (a) follows from the power and reciprocal rules, (b) follows from the product and chain rules and (c) follows from taking $d_{rjd}^{\rho_{rjd}} (d_{sj} - d_{rjd})^{\rho_{urj}}$ as a common factor in the nominator. Next, the expression in (7.7) will go to zero if.

$$\begin{aligned} \frac{z \rho_{urj}}{(d_{sj} - d_{rjd})} &= \frac{z \rho_{rjd}}{d_{rjd}} \\ d_{rjd} &= \frac{d_{sj} \rho_{rjd}}{\rho_{urj} + \rho_{rjd}} \end{aligned} \quad (7.8)$$

after substituting the value of $d_{sj} = d_{rjd} + d_{urj}$, we may express d_{rjd} and d_{urj} as

$$d_{rjd} = \frac{\rho_{rjd}}{\rho_{urj}} d_{urj}, \quad d_{urj} = \frac{\rho_{urj}}{\rho_{rjd}} d_{rjd} \quad (7.9)$$

Finally, substituting the values of (7.9) in (4.30) proves the theorem.

7.3 Appendix C: Proof of Theorem 5

We will solve the equation in (4.34) fist by squaring both sides.

$$\left(\sum_{j=1}^J a_{rj} \right)^2 \geq \frac{4k_d P \beta}{2P\beta + N_0 d_d^{\rho_d}} \quad (7.10)$$

Using the algebraic property for the square of the sums that

$$\left(\sum_{j=1}^J a_{rj} \right)^2 = \left(\sum_{j=1}^J a_{rj}^2 \right) + \sum_{j=1}^J \sum_{\substack{z=1 \\ z \neq j}}^J a_{rj} a_{rz} \quad (7.11)$$

Substituting the values of a_{rj} as defined in (4.19) in (7.11)

$$\begin{aligned} \left(\sum_{j=1}^J a_{rj} \right)^2 &= \sum_{j=1}^J \frac{m^2 \delta^2 \beta^2 P d_{urj}^{-\rho_{ur}} d_{rjd}^{-\rho_{rd}} k_r}{(1 + k_r) \left(\frac{N_0}{2} + P \beta d_d^{-\rho_d} \right)} + \\ &\sum_{j=1}^J \sum_{\substack{z=1 \\ z \neq j}}^J \frac{m^2 \delta^2 \beta^2 P k_r \sqrt{d_{urj}^{-\rho_{ur}} d_{rjd}^{-\rho_{rd}} d_{urz}^{-\rho_{ur}} d_{rzd}^{-\rho_{rd}}}}{(1 + k_r) \left(\frac{N_0}{2} + P \beta d_d^{-\rho_d} \right)} \end{aligned} \quad (7.12)$$

and using (7.12) to solve the inequality in (7.10) for m proves the expression in (4.36).

7.4 Appendix D: Proof of Lemma 3

We first observe that the expression in 5.12 contains a large summation of n independent and identically distributed functions of uniform random variables, $(d_1^{-\rho_c} + d_2^{-\rho_c} \dots + d_n^{-\rho_c})$. Despite the fact that each term does not, by itself, represent a valid random variable [61], the use of central limit theorem is still possible to approximate the sum of random functions. Let us define $V = d^{-\rho_c}$, then we may express $\mathbb{E}[V]$ as

$$\mathbb{E}[V] = \frac{1}{\hat{B} - \hat{A}} \int_{\hat{A}}^{\hat{B}} x^{-\rho_c} dx = \frac{\left(\hat{B}\right)^{1-\rho_c} - \left(\hat{A}\right)^{1-\rho_c}}{(1-\rho_c)(\hat{B} - \hat{A})} \quad (7.13)$$

We note that since the function V is not a valid random variable, the mean is calculated using the arithmetic method by integrating over all range and dividing by the range itself; and not by taking the conventional statistical mean. The variance of V , $Var(V)$, can be defined as

$$Var(V) = \frac{1}{\hat{B} - \hat{A}} \int_{\hat{A}}^{\hat{B}} \left(x^{-\rho_c} - \frac{\left(\hat{B}\right)^{1-\rho_c} - \left(\hat{A}\right)^{1-\rho_c}}{(1-\rho_c)(\hat{B} - \hat{A})} \right)^2 dx \quad (7.14)$$

using the linearity property of the integral, the integration above can be expressed as

$$\begin{aligned} Var(V) = & \frac{1}{\hat{B} - \hat{A}} \int_{\hat{A}}^{\hat{B}} x^{-2\rho_c} dx - \frac{2}{\hat{B} - \hat{A}} \int_{\hat{A}}^{\hat{B}} x^{-\rho_c} \frac{\left(\hat{B}\right)^{1-\rho_c} - \left(\hat{A}\right)^{1-\rho_c}}{(1-\rho_c)(\hat{B} - \hat{A})} dx \\ & + \frac{1}{\hat{B} - \hat{A}} \int_{\hat{A}}^{\hat{B}} \frac{\left(\left(\hat{B}\right)^{1-\rho_c} - \left(\hat{A}\right)^{1-\rho_c}\right)^2}{(1-\rho_c)^2 (\hat{B} - \hat{A})^2} dx \end{aligned} \quad (7.15)$$

leading to

$$\begin{aligned}
Var(V) &= \frac{\left(\hat{B}\right)^{1-2\rho_c} - \left(\hat{A}\right)^{1-2\rho_c}}{(1-2\rho_c)\left(\hat{B} - \hat{A}\right)} - 2 \frac{\left(\left(\hat{B}\right)^{1-\rho_c} - \left(\hat{A}\right)^{1-\rho_c}\right)^2}{(1-\rho_c)^2\left(\hat{B} - \hat{A}\right)^2} + \frac{\left(\left(\hat{B}\right)^{1-\rho_c} - \left(\hat{A}\right)^{1-\rho_c}\right)^2}{(1-\rho_c)^2\left(\hat{B} - \hat{A}\right)^2} \\
&= \frac{\left(\hat{B}\right)^{1-2\rho_c} - \left(\hat{A}\right)^{1-2\rho_c}}{(1-2\rho_c)\left(\hat{B} - \hat{A}\right)} - \frac{\left(\left(\hat{B}\right)^{1-\rho_c} - \left(\hat{A}\right)^{1-\rho_c}\right)^2}{(1-\rho_c)^2\left(\hat{B} - \hat{A}\right)^2} \\
&= \frac{\left(\hat{B}\right)^{1-2\rho_c} - \left(\hat{A}\right)^{1-2\rho_c}}{(1-2\rho_c)\left(\hat{B} - \hat{A}\right)} - (\mathbb{E}[V])^2
\end{aligned} \tag{7.16}$$

With that, and using central limit theorem, the summation of multiple random functions V can be represented by Gaussian random variable of mean $\varrho |G| \mathbb{E}[V]$ and variance $\varrho |G| Var(V)$, i.e. $\sum_{f=1}^{\varrho |G|} d_f^{-\rho_c} \sim \mathcal{N}_{\mathbb{C}}(\varrho |G| \mathbb{E}[V], \varrho |G| Var(V))$.

We note that we assumed that the number of interfering devices is approximated by the mean of the HPPP random variable, which allowed us to cancel out the averaging over the Poisson random variable in (5.12). Replacing the averaging over the Poisson random variable and all Uniform random variables by averaging over one Gaussian random variable proves the proposed Lemma.

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