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SPACE DOMAIN AWARENESS USING RADIO
TELESCOPE-BASED RADAR SYSTEMS

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To my parents, my greatest blessing and strength.

*"I do not think that the wireless waves I have discovered will have
any practical application."*

— **Heinrich Hertz**

Acknowledgments

A PhD is rarely the work of one person alone, and this thesis is no exception.

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As I said earlier too, it takes more than one person to complete a PhD, and I have been fortunate to have the right ones around me.

Abstract

Resident Space Objects (RSOs) are increasing rapidly in number and must be continuously monitored in order to preserve the safety, reliability, and long-term sustainability of space-based services. This requires reliable surveillance systems capable of detecting, tracking, and characterizing objects across different orbital regimes under increasingly demanding observational conditions. Although radar systems remain among the most reliable sensors for these tasks, current architectures still face important limitations in terms of coverage, measurement diversity, tracking robustness, and cost, particularly for weakly observed or manoeuvring targets.

This dissertation investigates radar-based sensor network architectures for space surveillance and tracking, with particular emphasis on the use of radio telescope receivers in bistatic, multi-bistatic, and passive radar configurations, examining both geometries that exploit dedicated transmitters and those that rely on signals of opportunity. The unifying motivation is to demonstrate that existing radio astronomy assets, when integrated with advanced signal processing, orbit determination, and data-driven prediction techniques, can meaningfully extend the observational capability of current space domain awareness systems across both Low Earth Orbit (LEO) and Geostationary Earth Orbit (GEO) regimes, without the prohibitive cost of deploying new dedicated radar infrastructure.

The observational analysis begins in the GEO regime, where monostatic, bistatic, and multi-bistatic long-baseline radar configurations employing TIRA as the transmitter and e-Merlin and WSRT as bistatic radio telescope receivers are systematically studied to assess how measurement geometry influences tracking performance and observability. The results demonstrate that the inclusion of bistatic measurements from radio telescope receivers improves state estimation accuracy, while multi-bistatic configurations yield the most favourable performance through increased geometric diversity and measurement complementarity.

The analysis then extends to objects undergoing constant thrust manoeuvres, where sustained non-gravitational accelerations make conventional orbit determination frameworks inadequate. A simulation-based study is carried out using three Italian radio telescopes, Medicina, Noto, and SRT, modelling a LEO-to-GEO transfer scenario. A trilateration-based initial orbit determination approach is extended to retrieve thrust acceleration components from multi-bistatic measurements. An

unscented Kalman filter operating on the augmented state vector is then employed to accurately estimate the evolving state of the manoeuvring object throughout the transfer.

The scope then shifts to passive radar, where InterFeX, a radio astronomy-inspired array-based space domain awareness facility located in South Australia, is presented. Designed specifically for space surveillance and exploiting signals of opportunity from non-cooperative transmitters, the facility avoids dependence on both dedicated radar infrastructure and astronomical observing schedules. A coherent signal processing pipeline is developed and experimentally validated using real data, confirming the feasibility of passive array architectures for LEO space surveillance.

The thesis further addresses the problem of long-term satellite trajectory prediction, where purely data-driven approaches struggle to maintain physical consistency over extended prediction horizons. A hybrid LSTM–PINN framework is formulated that embeds orbital mechanics constraints directly into the learning process, showing that the incorporation of physical knowledge into neural network training yields more reliable and consistent trajectory estimates than learning from data alone.

Overall, the thesis demonstrates that improved radar-based sensor networks for space object monitoring can be achieved through the joint development of innovative observation architectures, advanced estimation methods, and modern signal processing techniques. The results support the use of radio telescope receivers and array-based sensing concepts as efficient and potentially cost-effective components of future radar systems for space surveillance and tracking.

List of Publications

International Journal Articles

- [J1] **Bhaskar Ahuja**, L. Gentile, A. Kumar, and M. Martorella, “Role of radio telescopes in space debris monitoring: Current insights and future directions,” *Sensors*, vol. 25, no. 9, p. 2900, 2025. [[View publication](#)]
- [J2] **Bhaskar Ahuja**, L. Gentile, and M. Martorella, “Physics-Aware Neural Networks for Satellite Tracking,” *URSI Radio Science Letters*, vol. 7, p. 33, 2025. [[View publication](#)]
- [J3] **Bhaskar Ahuja**, T. Crowther, S. Tingay, A. Guidi, L. Gentile, and M. Martorella, “First Experimental Results of Space Object Detection using the InterFeX Array,” *IEEE Transactions on Radar Systems*, [under review](#).

International Conferences with Peer Review

- [C1] **Bhaskar Ahuja**, L. Gentile, and M. Martorella, “Improving Satellite Position and Velocity Estimation During Low-Thrust Maneuvers Using Multi-Bistatic Radar and the Unscented Kalman Filter,” *4th IAA Space Situational Awareness Conference*, Florida, USA, 2024. ([Awarded Best Student Paper Award](#)). [[View publication](#)]
- [C2] **Bhaskar Ahuja**, L. Gentile, and M. Martorella, “Advancements in Space Object State Estimation During Constant Thrust Maneuver Using Distributed Sensor Networks: A Radar-Based Approach,” *2024 International Radar Conference*, Rennes, France, IEEE, pp. 1–5, 2024. [[View publication](#)]
- [C3] **Bhaskar Ahuja**, L. Gentile, and M. Martorella, “Performance Evaluation of Radar Architectures with Radio Telescopes as Bistatic Receivers for GEO Tracking,” *5th IAA Space Situational Awareness Conference*, Madrid, Spain, 2026. [[View publication](#)]

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Acronyms

ANNs Artificial Neural Networks 94

BIRALES BI-static RAdar for LEO Survey 13, 16, 20–22, 26, 32, 33, 79

BIRALET BI-static RAdar for LEO Tracking 20, 22, 32, 33

CAF Cross Ambiguity Function 29, 76, 77, 85, 87, 88

COBEAM COoperative BEAM-park 18, 19

CPI Coherent Processing Interval 64, 75–77, 79, 85, 89–91

CW Continuous Wave 21

DAB Digital Audio Broadcasting 28, 29, 73

DoA direction-of-arrival 26, 79, 81, 83, 84, 87

DPI Direct Path Interference 29, 75

DVB-T Digital Video Broadcasting-Terrestrial 17, 29, 69

e-Merlin enhanced Multi-Element Radio Linked Interferometer Network iii, 10, 23, 37–40, 43, 103, 105

ECEF Earth-Centered, Earth-Fixed 40

ECI Earth-Centered Inertial 40, 43, 46, 55, 57–59, 62

EIRP effective isotropic radiated power 73

EKF Extended Kalman Filter 59

ESA European Space Agency 2–5, 115

EUSST European Space Surveillance and Tracking 32

FHR Fraunhofer Institute for High-Frequency Physics and Radar Techniques 18, 37

FM Frequency Modulation 17, 26, 33, 69, 70, 73, 75, 77, 91, 92, 104, 106

GEO Geostationary Earth Orbit 4, 5, 8, 10, 22–25, 31–33, 35–38, 40, 41, 43, 49, 51, 53, 54, 103, 105, 106

GESTRA German Experimental Space Surveillance and Tracking Radar 19

GMAT General Mission Analysis Tool 95, 98–101

GPs Gaussian Processes 94

GRUs Gate Recurrent Unit 95

HBA high-band antennas 28, 29

HPBW Half Power Beam Width 38, 72

IADC Inter-Agency Space Debris Coordination Committee 5

IDAO International Data Analytics Olympiad 95

IOD Initial Orbit Determination 21, 27, 33, 54, 60, 64

IoO Illuminators of Opportunity 17, 69, 70, 77

ISAR Inverse Synthetic Aperture Radar 29

ISS International Space Station 3, 26, 27, 29, 70, 77–80, 85, 88

LBA low-band antennas 28, 29

LEO Low-Earth Orbit 4–7, 10–12, 19, 22, 25, 26, 29, 31, 33, 53, 54, 69, 70, 76, 85, 91, 92, 104

LIDAR Light Detection and Ranging 7

LOFAR Low Frequency Array 13, 28–30, 33, 69

LSTM Long Short-Term Memory iv, 11, 34, 93, 95–101, 104

MAE Mean Absolute Error 45–49, 100, 103

MD Mahalanobis Distance 49, 50

MeerKAT Meer Karro Array Telescope 13, 25, 26, 48

MHR Millstone Hill Radar 23, 24

MIMO multiple-input–multiple-output 25

ML Machine Learning 94, 95

MPT Mission Planning Tool 25

MSE Mean Square Error 100

MUSIC Multiple Signal Classification 79, 80, 92, 104

MVDR Minimum Variance Distortionless Response 79

MW megawatt 23

MWA Murchison Widefield Array 13, 17, 26–28, 30, 33, 69, 71

NN Neural Network 96, 98

ODBD Orbit Determination Before Detect 27

PINN Physics-Informed Neural Network iv, 11, 34, 93, 95, 96, 98–101, 104, 106

RCS radar cross-section 14, 19, 23, 37, 39, 40, 105

RD range–Doppler 23, 24

RMSE Root Mean Square Error 54, 65, 90, 104

RNNs Recurrent Neural Networks 94, 95

RRSG Radar Remote Sensing Group 25

RSOs Resident Space Objects 4, 6, 35, 93, 94

RTG Research Task Group 22, 23, 25

SAR Synthetic Aperture Radar 29

SDA Space Domain Awareness 9–11, 14, 32–34, 69–71, 103, 104

SDRs software defined radios 72

SEZ South-East-Zenith 41, 63

SGP4 Simplified General Perturbation 6, 40, 76, 79, 94, 99

SIMO single-input–multiple-output 25

SKA Square Kilometer Array 15, 25, 26

SNR Signal-to-Noise Ratio 8, 14, 15, 36, 39, 44, 45, 87, 104

SRT Sardinia Radio Telescope 20, 22, 23, 63

SSA Space Situational Awareness 6, 9, 13, 15, 22, 25, 32, 33, 36, 70, 105

SSN Space Surveillance Network 6

SST Space Surveillance and Tracking 6–8, 22, 36, 93, 94, 103

STO Science and Technology Organization 22

SVM Support Vector Machine 94

TIRA Tracking and Imaging Radar iii, 10, 13, 16, 18, 19, 23, 37–41, 43, 48, 103, 105

TLE Two-Line Element 6, 24, 28, 43, 75–81, 83, 85, 88–90, 94, 99, 104

TRF Radio Frequency Transmitter 20, 21

UKF Unscented Kalman Filter 10, 33, 35, 36, 43–45, 49, 50, 53, 54, 59, 60, 63, 65, 67, 104

UT Unscented Transform 59

VLBI Very Long Baseline Interferometry 8, 15

WSRT Westerbork Synthesis Radio Telescope iii, 10, 23, 24, 37–41, 43, 103, 105

Chapter 1

Introduction

Chapter Overview

This chapter establishes the scientific and operational context of the thesis. It opens with a discussion of the growing space debris environment, covering collision risk, debris re-entry, and the mitigation strategies currently adopted by the international community. The limitations of traditional space surveillance and tracking systems are then identified, motivating the need for cost-effective and scalable approaches, particularly the integration of radio telescopes as bistatic receivers, alongside advancements in tracking techniques and data-driven orbit propagation. The chapter concludes by stating the research objectives, the four main contributions of the thesis, and the overall structure of the dissertation.

1.1 The Growing Challenge of Space Debris

The story of human activity in space begins in October 1957, when the Soviet Union placed Sputnik-1 into orbit. It was a single object launched to demonstrate, for the first time, that an artificial object could be placed into sustained orbit around the Earth. In the decades that followed, governments and agencies launched satellites for communication, navigation, Earth observation, and scientific research. Today, space serves as critical infrastructure covering global navigation, defence applications, climate monitoring, and broadband communication. Each mission added something to the orbital inventory: payloads, rocket stages, and hardware that had served its purpose, yet very little thought was given to what would happen to these objects once their operational life ended.

By the late 20th century, the consequences of that oversight were becoming visible. Defunct satellites, spent rocket upper stages, and fragments from in-orbit collisions had begun accumulating in orbital regions critical for active missions. As shown in Figure 1.1, the number of tracked objects in Earth orbit has grown steadily since the early space age, with a particularly sharp rise in recent decades driven by

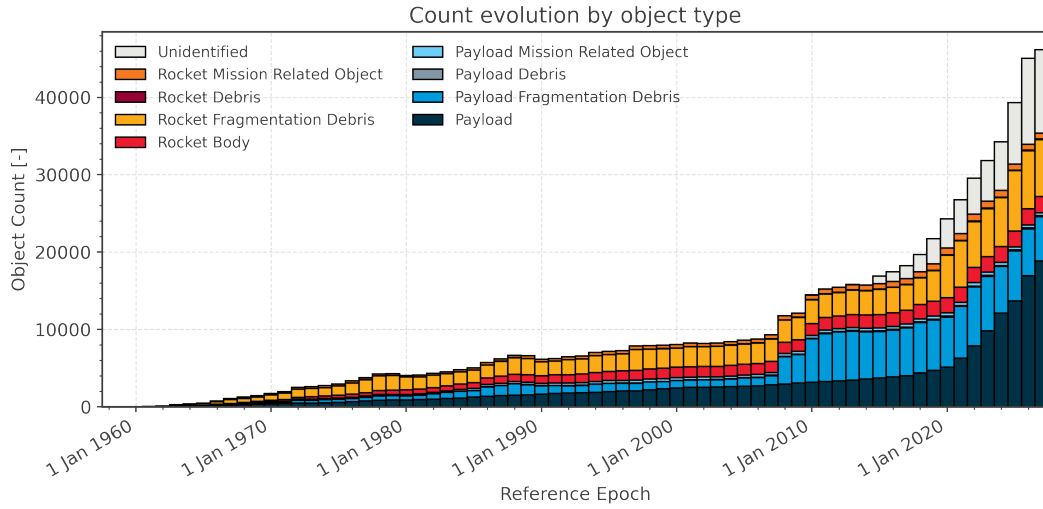


Figure 1.1: Number of tracked objects in Earth orbit over time, including active payloads, inactive payloads, rocket bodies, and fragmentation debris. Source: ESA Space Environment Report 2025 [1].

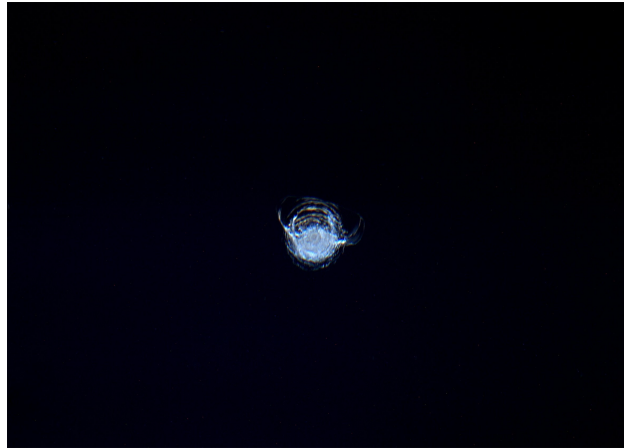


Figure 1.2: Impact damage on a window of the International Space Station (ISS) Cupola module caused by a tiny piece of orbital debris. Image credit: European Space Agency (ESA).

the proliferation of commercial satellite constellations and a series of fragmentation events. According to latest European Space Agency (ESA) annual report (2025), approximately 40,000 objects are tracked by ground-based surveillance networks, of which around 11,000 are active payloads [1]. The rest serve no operational purpose. What makes the situation more serious is that tracked objects represent only a fraction of what is actually out there. Debris with a size larger than one centimeter which are sufficient to cause catastrophic damage to a spacecraft on impact, is estimated to exceed 1.2 million objects. Objects larger than ten centimeters, which



Figure 1.3: Titanium motor casing from a Delta II rocket upper stage that survived atmospheric re-entry and landed in the Saudi Arabian desert in 2001, demonstrating that large debris objects can reach the Earth’s surface after uncontrolled re-entry. Image credit: European Space Agency (ESA).

ground radar can reliably detect, number over 50,000. Between these extremes lies a particularly dangerous class of objects that operators cannot track with sufficient accuracy to avoid.

The concern underlying all of this is the Kessler syndrome [2]. Once enough debris accumulates in a given orbital region, collisions begin generating more debris than the environment can naturally remove, and the process feeds itself. A clear real-world example of this risk can be seen on the International Space Station (ISS), where a very small debris particle travelling at orbital speed left a visible damage on one of the Cupola windows (Refer to Figure 1.2), despite the protective shielding [3]. In addition to the hazards posed by debris remaining in orbit, some objects eventually re-enter the atmosphere and reach the Earth’s surface. Earlier incidents include the recovery of a titanium rocket motor casing from a Delta II upper stage that landed in the Saudi Arabian desert in 2001 [4], as can be seen in the Figure 1.3. These events demonstrate that space debris can pose risks not only to operational spacecraft but also to people and infrastructure on the ground. Moreover, ESA projections indicate that, even if no additional objects are launched into orbit, the number of catastrophic collisions will continue to increase due to the debris already present in space.

1.1.1 Collision Risk and Debris Re-entry

Since the start of the space age, 656 confirmed on-orbit fragmentation events have been recorded, occurring at an average rate of 10.5 non-deliberate events per year over the last two decades. The consequences of this accumulation became visible on 11 January 2007, when China conducted an anti-satellite test against its own

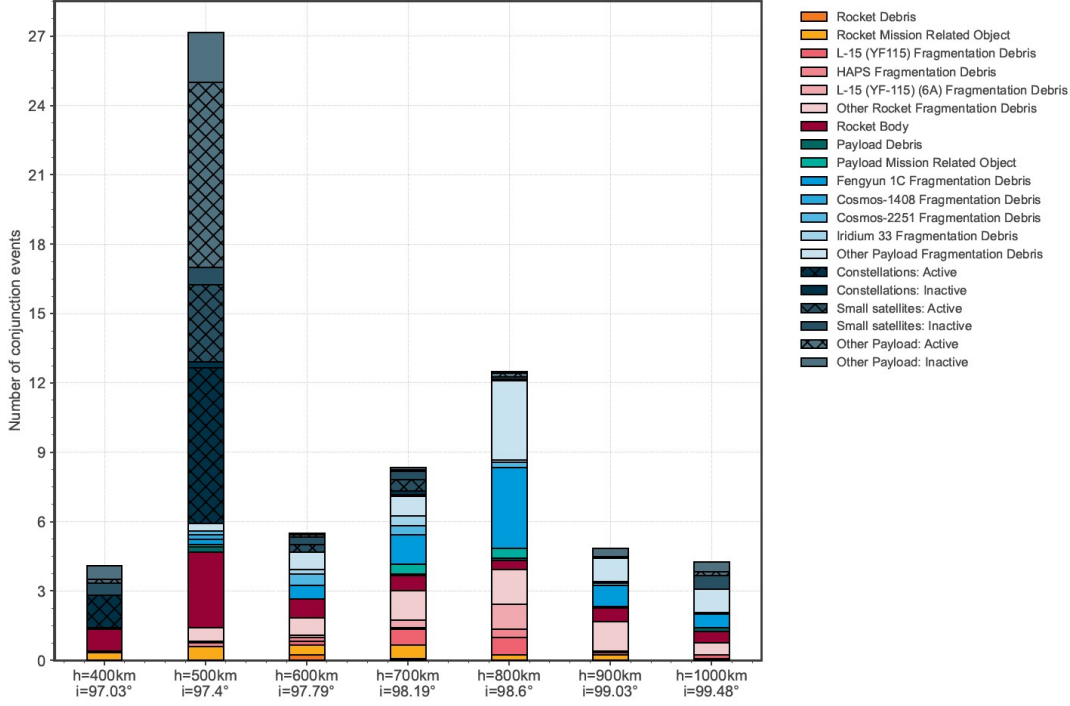


Figure 1.4: Number of conjunction events with collision probability above 10^{-6} for representative target orbits in LEO, broken down by secondary object type, for the year 2024. Source: ESA Space Environment Report 2025 [1].

weather satellite Fengyun-1C at around 850 km altitude, producing one of the largest single debris-generating events in spaceflight history [5]. Two years later, on 10 February 2009, the first accidental collision between two satellites occurred, when the defunct Cosmos-2251 and the operational Iridium-33 collided at approximately 780 km. Their debris fields remain a source of conjunction events for active operators to this day.

Low-Earth Orbit (LEO) is the most densely populated orbital region in terms of Resident Space Objects (RSOs).. Around the 550 km altitude band, the spatial density of debris is now comparable to that of active satellites, and the number of conjunction events has increased steadily since 2015. As shown in Figure 1.4, the 550 km and 800 km altitude bands have the highest collision risk. This is due to the presence of both active constellation satellites and debris fragments from past breakup events.

Geostationary Earth Orbit (GEO) is the second most populated orbital region in space, hosting about 35% of all operational satellites, while LEO remains the most populated with approximately 55%. However, the debris problem in GEO carries a fundamentally different character. Without atmospheric drag, any non-compliant object remains in the geostationary belt for thousands of years. The

total mass currently intersecting the GEO protected region stands at approximately 3,594 tonnes, shared between active payloads, defunct satellites, and rocket bodies. Compliance with disposal guidelines has improved over the past decade, reaching between 70% and 95% of payloads. Nevertheless, two fragmentation events were recorded in GEO in 2024 alone, one of unknown origin and one linked to propulsion failure, adding further uncontrolled objects to an orbital region where debris can persist for extremely long durations. Across both regimes, the orbital environment is becoming more challenging due to increasing traffic, fragmentation, and incomplete mitigation compliance. This motivates the need for robust surveillance, accurate orbit determination, and reliable tracking, which are the focus of this thesis.

1.1.2 Mitigation Strategies

Recognizing the growing threat posed by orbital debris, the international space community began formalizing mitigation measures as early as 2002, when the Inter-Agency Space Debris Coordination Committee (IADC) published its first Space Debris Mitigation Guidelines. The primary purposes of the IADC are to share information on space debris research activities between member space agencies, to support coordinated efforts in space debris research across global space community, to review the progress of ongoing cooperative activities, and to identify debris mitigation options [6]. The core principle of passive mitigation is to reduce the amount of material left in orbit after a mission concludes. For objects in LEO, this translates to a requirement that spacecraft and rocket bodies vacate the protected region within a set time after end-of-life, a standard that ESA reduced from 25 years to 5 years in 2023 as part of its tightened debris mitigation guidelines.

Beyond passive measures, there is growing recognition that active debris removal is now a necessity rather than an option. ESA’s ClearSpace-1 mission, developed in partnership with the Swiss company ClearSpace, aims to remove ESA’s own PROBA-1 satellite from its low-Earth orbit, marking the first ever attempt to capture and de-orbit an uncooperative object [7]. This effort is no longer limited to space agencies alone, as a new generation of commercial companies such as Astroscale¹ and Cosmoserve² actively developing robotic capture systems for debris removal, reflecting a broader shift in how the industry approaches the problem. Despite these efforts, the overall debris population grew in net terms in 2024. ESA projections show that even under current mitigation practices, the risk index associated with the LEO environment is expected to reach four times the acceptable threshold for long-term sustainability. This makes clear that mitigation strategies, however essential, must be supported by equally robust capabilities in surveillance, tracking, and orbit determination to be effective in practice.

¹<https://www.astroscale.com/en>

²<https://cosmoserve.space/>

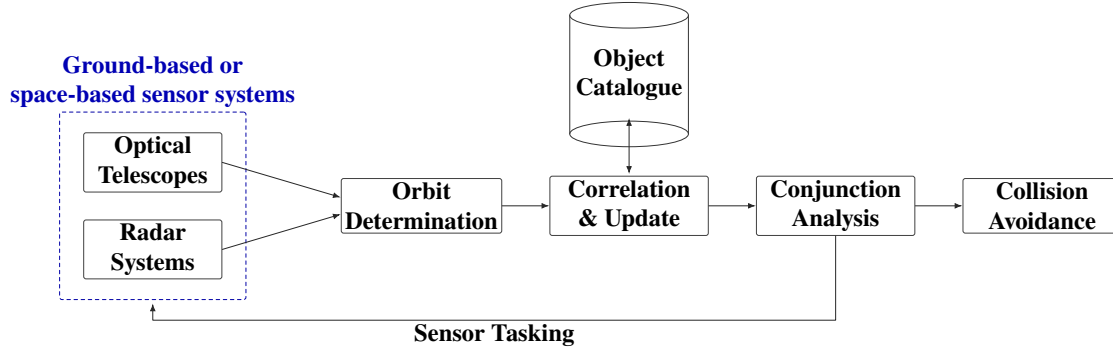


Figure 1.5: Overview of the Space Surveillance and Tracking (SST) process from observation to collision risk assessment.

1.2 Space Surveillance and Tracking

Space Surveillance and Tracking (SST) refers to the systematic detection, tracking, identification, and orbit determination of artificial objects in Earth orbit, including active satellites and space debris, using sensor systems such as radar, optical telescopes, and associated data processing techniques [8]. Measurements collected by these sensors are used to estimate orbital parameters, maintain object catalogues, and assess potential collision risks through conjunction analysis. Figure 1.5 illustrates the sequence of tasks involved in SST framework. SST constitutes a core component of Space Situational Awareness (SSA), which encompasses a broader understanding of the space environment, including not only RSOs but also natural hazards such as near-Earth objects and space weather phenomenon [9]. Within this framework, the present thesis focuses on ground-based radar systems and the orbit determination stage of the SST process.

1.2.1 Ground Based Sensors for Space Debris Studies

A global network of surveillance sites is continuously being developed to ensure uninterrupted space monitoring. The United States maintains a comprehensive catalogue through its Space Surveillance Network (SSN), utilizing both optical and radar sensors [10], [11]. Based on the data collected by these sensors, Two-Line Element (TLE) sets are generated and made freely available to promote international cooperation, enabling orbit propagation using the standard Simplified General Perturbation (SGP4) algorithm [12]. Radar has been a cornerstone of space surveillance since the early years of the space age, operating by transmitting electromagnetic pulses and measuring the reflected signals from objects in orbit. Its primary advantage lies in its ability to operate under all weather conditions and without sunlight, making it well suited for continuous monitoring of LEO where object density is highest [13]. Optical telescopes, by contrast, rely on reflected sunlight

to detect objects, making them most effective during twilight conditions and particularly well suited for surveillance of higher orbital regimes. Complementing these sensors, Laser ranging systems, including Light Detection and Ranging (LIDAR), offer a complementary approach by emitting short pulses of light and measuring the return time to determine precise range and velocity, providing higher accuracy than conventional radar for selected targets [14].

1.2.2 Limitations of Traditional Ground Based Sensors

Despite the variety of available sensor technologies, current SST capabilities still face major limitations in addressing the debris problem on a global scale. Optical sensors inherently depend on favourable lighting and atmospheric conditions, which creates coverage gaps, particularly in LEO, where fast orbital motion requires near-continuous observation. Ground based radar systems are robust and largely unaffected by weather, but they struggle to detect objects smaller than about 10 cm in LEO, and their effectiveness decreases at higher altitudes as distance and signal losses increase. Furthermore, active radar installations, in particular, require substantial financial and technical resources, placing them within reach of only a few nations. The cost of building and operating dedicated surveillance infrastructure further restricts expansion of these systems. Consequently, large portions of the orbital environment remain insufficiently monitored, and existing surveillance assets are increasingly required to operate beyond their intended capacity.

Collectively, these technical, financial, and measurement-related limitations prevent current SST infrastructure from fully characterizing the orbital environment with the scale and accuracy required by the growing debris problem. Addressing these shortcomings calls for approaches that go beyond conventional dedicated systems by extending the utility of existing facilities, improving measurement quality, and expanding surveillance coverage in a cost-effective way. Radio telescopes, developed primarily for astronomical observation, share fundamental characteristics with what dedicated SST radar systems require at scale. Their large collecting apertures, high receiver sensitivity, and geographic distribution across multiple continents make them well-suited for passive reception. These instruments are designed to detect extremely faint signals from distant cosmic sources, and this sensitivity makes them naturally capable of receiving radar echoes from orbiting objects. Integrating them into bistatic radar networks therefore represents a natural and cost-effective extension of existing observational infrastructure. The research presented in this thesis is directed toward such approaches, as introduced in the following Section 1.2.3.

1.2.3 Radio Telescope as a Complementary Asset

Radio telescopes are large antenna systems originally designed to observe faint electromagnetic signals from astronomical sources [15]. Unlike dedicated radar systems, they operate as passive receivers, meaning they detect incoming signals without

transmitting any themselves. Their key strengths lie in their large collecting areas, high sensitivity, and the ability to operate across a wide range of radio frequencies. When a cooperative or non-cooperative transmitter illuminates a space object, the reflected signals can be captured by a radio telescope acting as a bistatic receiver, making them well suited for space surveillance applications [16]. Radio telescopes can be integrated into space surveillance networks in several ways. A large single-dish telescope can be paired with a high-power cooperative and dedicated radar, or a distributed arrays can exploit signals of opportunity such as broadcast transmitters [17]. These configurations and their characteristics are discussed in detail in Section 2.3.

Moreover, radio astronomy instruments are designed to operate with very low system noise temperatures, which directly improves the Signal-to-Noise Ratio (SNR) and enables detection of extremely faint signals. Building on this sensitivity, techniques such as interferometry and Very Long Baseline Interferometry (VLBI) further enhance angular resolution and spatial discrimination across wide frequency bands. These capabilities are directly applicable to space surveillance, where detecting weak radar returns from small or distant objects demands precisely this level of receiver performance. Combining radio astronomy principles with radar sensing therefore offers a conceptually coherent and cost-effective pathway toward expanding SST coverage, and it is this combination that forms the technical foundation of the research presented in this thesis.

1.3 Research Motivation and Thesis Contributions

The limitations outlined in Section 1.2.2 point to clear need for surveillance approaches that go beyond conventional dedicated systems. Current SST infrastructure struggles to provide continuous, global coverage across all orbital regimes. Compounding this further, the received signal power in a radar system follows an inverse fourth power dependence on range, a constraint whose effects become most pronounced at large distances, and are particularly severe at the ranges characteristic of GEO orbit. Moreover, building new dedicated radar infrastructure at the scale required remains feasible only for a handful of nations with established space programmes.

Ground-based bistatic radar configurations that employ radio telescopes as receivers offer a practical response to these challenges. Their sensitivity, wide frequency coverage, and geographic distribution make them well-suited for space object detection. However, exploiting these systems for SST operations brings its own set of challenges. Measurement availability is inherently limited, as radio telescopes are primarily scheduled for astronomical campaigns, leaving only opportunistic or dedicated time windows for resident space objects surveillance. Moreover, a single bistatic receiver captures scattering information from only one aspect angle, limiting the ability to fully characterise the object’s bistatic radar-cross-section (RCS). Fur-

thermore, single dish bistatic radio telescope receivers typically operate in beam park mode [18], where the fixed beam yields only a brief observational window as the debris transits through it. As a result, measurements are limited to range and Doppler, which alone are insufficient to fully characterise the object’s position and velocity. Within a bistatic radio telescope network, the presence of manoeuvring objects adds further complexity. Orbital manoeuvres introduce sudden trajectory changes that make orbit determination unreliable, and conventional estimation frameworks are not designed to accommodate such dynamic variations, requiring methods that can accommodate sudden changes in the object’s motion.

Beyond measurement acquisition and tracking, accurate long-term trajectory prediction remains an open challenge in SSA, motivating the exploration of data-driven approaches to orbit propagation as a complement to conventional analytical and numerical methods. Analytical models rely on simplifying assumptions that accumulate error over long propagation intervals, while high-fidelity numerical integration carries significant computational cost that limits operational scalability. Data-driven approaches offer a viable path forward by learning directly from observational data while embedding physical consistency into the prediction process.

This thesis addresses these challenges by investigating the integration of radio telescopes into Space Domain Awareness (SDA) networks. Both single-dish and array-based configurations are considered, operating with cooperative and non-cooperative transmitters. Alongside this, estimation, signal processing, and physics-informed predictive modelling techniques are developed, contributing toward a more capable and scalable SDA framework. The research objectives that follow are defined to target each of these gaps directly.

1.3.1 Research Objectives

- To examine the role of radio telescope receivers within monostatic, bistatic, and multi-bistatic radar configurations for resident space object tracking, assessing their influence on tracking accuracy, measurement observability, and surveillance coverage, with particular focus on the demanding observational challenges posed by Geostationary Earth orbit.
- To examine the feasibility of thrust-aware orbit determination for manoeuvring space objects within a multi-bistatic radio telescope network, assessing the capacity of an adaptive filtering approach to estimate non-Keplerian accelerations and characterise motion during orbital transfer manoeuvres.
- To validate the use of a radio telescope array as a passive radar for Space Domain Awareness, exploiting signals from non-cooperative transmitters, through the development and experimental demonstration of a dedicated coherent signal processing pipeline for space object detection.
- To formulate a physics-informed data-driven framework for satellite trajectory

prediction that embeds orbital dynamics constraints into the learning process, improving long-term prediction accuracy while maintaining physical consistency.

1.3.2 Main Thesis Contributions

This thesis advances SDA capabilities through four main contributions, spanning the evaluation of radio telescope based radar configurations, the development of orbit determination and tracking techniques, the experimental validation of a signal processing pipeline for a radio telescope array based passive radar system, and the formulation of a physics-informed framework for satellite trajectory prediction. The main research contributions of the thesis are summarized as follows:

- **Radar Configurations for GEO Tracking** A systematic study of how monostatic, bistatic, and multi-bistatic radar configurations employing radio telescopes as passive receivers affect the tracking accuracy and observability of objects in GEO orbit [[C3]]. The analysis is conducted using the TIRA radar as the transmitter, with e-Merlin and WSRT serving as bistatic radio telescope receivers, enabling a comparative investigation across monostatic, single-bistatic, and multi-bistatic geometries. The study assesses how incorporating bistatic measurements from these radio telescopes, individually or in combination, improves the accuracy of target state estimation, and evaluates whether these configurations offer a favourable trade-off between tracking performance, system complexity, and cost-effectiveness. The extensive analysis of this contribution is detailed in Chapter 3.
- **Thrust-Aware Orbit Determination with Multi-bistatic Radio Telescope Receivers** Moving to a more complex tracking scenario, this contribution addresses the case of manoeuvring objects observed by a multi-bistatic radio telescope network, where sudden trajectory changes make conventional estimation frameworks insufficient. The analysis is conducted using three Italian radio telescopes, namely Medicina, Noto, and SRT, through a simulation-based study that models a LEO-to-GEO transfer scenario. A trilateration-based initial orbit determination approach is employed and extended to retrieve non-Keplerian thrust acceleration components from multi-bistatic measurements. This extension constitutes the key novelty of this work, where the state vector is augmented to incorporate thrust acceleration components alongside the kinematic states, enabling an adaptive Unscented Kalman Filter (UKF) to accurately estimate the state of manoeuvring objects during orbital transfer [[C1],[C2]]. This contribution is detailed in Chapter 4.
- **InterFeX: Passive Radar Array for LEO SSA** Extending the scope beyond dedicated transmitter configurations, this contribution examines a passive array configuration validated through real experimental data [[J3]]. A coherent

signal processing pipeline is developed and experimentally validated for In-terFeX, a radio astronomy-inspired array-based SDA facility located in South Australia, designed specifically for space surveillance so as to avoid dependence on astronomical observing schedules. The facility exploits signals from non-cooperative transmitters, with the cross-ambiguity function employed to retrieve bistatic range and Doppler measurements, while direction-of-arrival estimation provides angular localisation of LEO objects. The dual-polarisation capability of the array is further exploited to enhance passive detection performance. The methodology, experiments, and results supporting this contribution are presented in Chapter 5.

- **Physics-Aware Neural Network for Satellite Trajectory Prediction** Beyond measurement acquisition and tracking, this contribution addresses long-term trajectory prediction through a physics-informed data-driven approach. A hybrid Long Short-Term Memory (LSTM)–Physics-Informed Neural Network (PINN) framework is formulated for satellite trajectory prediction that embeds orbital mechanics constraints directly into the learning process via a physics-informed loss function, improving long-term prediction accuracy over purely data-driven baselines while remaining computationally efficient. The framework is trained and evaluated on real orbital trajectory data spanning one month, drawn from a large multi-satellite dataset [[J2]]. A comprehensive treatment of this contribution is provided in Chapter 6.

1.4 Structure of the Thesis

This thesis is organised as follows.

Chapter 1 establishes the context and motivation for the research. The growing space debris environment, the limitations of traditional surveillance systems, and the potential of radio telescopes as bistatic receivers are discussed, leading to the definition of the research objectives and main contributions.

Chapter 2 provides a comprehensive review of the state of the art in radar-based space surveillance using radio telescope receivers. The advantages of employing radio telescopes in bistatic configurations are discussed, and major international initiatives are reviewed. The chapter concludes by identifying the key research gaps that motivate the work presented in the subsequent chapters.

Chapter 3 investigates the effect of observation geometry on the tracking of geostationary objects by comparing monostatic, bistatic, and multi-bistatic radar configurations. The study considers long-baseline geometries combining a high-power transmitter with radio telescope receivers and evaluates their impact on tracking accuracy and estimation performance.

Chapter 4 develops an orbit determination framework for multi-bistatic observations with radio telescope receivers, covering initial state estimation and subsequent

refinement. The framework is extended to estimate thrust-related acceleration components, enabling the characterisation of manoeuvring motion during orbital transfer.

Chapter 5 presents the development and experimental validation of a coherent signal processing pipeline for a radio telescope array operating in passive radar mode, exploiting illuminators of opportunity. The chapter addresses target detection, bistatic parameter estimation, and angular localisation for passive surveillance of LEO objects.

Chapter 6 investigates data-driven approaches for long-term satellite trajectory prediction that embed the physical constraints of orbital motion into the learning process. A hybrid prediction framework is presented and evaluated against conventional propagation methods.

Finally, **Chapter 7** summarises the main findings of the thesis and outlines directions for future research.

Chapter 2

State-of-the-Art Review

Chapter Overview

This chapter provides a comprehensive review of the state-of-the-art in radar-based space surveillance, with a particular focus on systems that exploit radio telescope infrastructure. The advantages of using radio telescopes in bistatic radar configurations for SSA are discussed, followed by a survey of transmitter-receiver architectural configurations. Six prominent international research efforts and experimental demonstrations are reviewed in detail, including TIRA with the Effelsberg telescope, BIRALES, MeerKAT, MWA, and LOFAR. A comparative discussion of these systems is presented, and the chapter concludes by identifying the research gaps that this thesis addresses.

2.1 Background

Radio telescopes are among the most sensitive electromagnetic sensors available, built to detect extremely weak radio signals arriving from cosmic sources over a broad frequency range [15]. Although they were originally developed for astronomical observation, modern radio telescope facilities combine large collecting apertures, low-noise receiver systems, accurate pointing capability, and advanced digital signal processing, which also make them useful beyond their traditional scientific role. In recent years, these features have made radio telescopes increasingly attractive for space surveillance and tracking applications.

The broad frequency coverage of radio telescopes enables a variety of observation strategies. They can operate in an active radar mode, where transmitted radio waves illuminate a space object and the reflected echoes are received by the telescope, or in a passive mode, where reflections from non-cooperative transmitters are observed. From the receiver perspective, two main radio telescope architectures are commonly considered for these applications: single-dish systems and array-based systems. Since they differ substantially in sensitivity, field of view, and beamform-

ing capability, they are discussed separately in detail in Section 2.3. In addition to these capabilities, radio telescopes offer several further advantages for space surveillance applications, which are discussed in detail in the Section 2.2. Over the past few decades, radio telescopes have been used in several experiments around the world for SDA, especially for detecting and tracking space objects through active and passive radar approaches. These efforts are briefly reviewed in this chapter to provide the necessary background, followed by a discussion of the main gaps and open challenges in the existing literature that motivate the research presented in this thesis.

2.2 Advantages of Radio Telescope

The use of radio telescopes as bistatic receivers is motivated largely by their superior sensitivity to small debris objects that remain undetectable by conventional monostatic radar systems. This capability is best understood through the bistatic radar equation given in (2.1) [19].

$$SNR = \frac{P_t G_t G_r \lambda^2 \sigma}{(4\pi)^2 R_t^2 R_r^2 L k T_{sys} B}, \quad (2.1)$$

where P_t is the transmitted power, G_t and G_r are the gains of the transmitter and receiver respectively, λ is the operating wavelength, σ is the radar cross-section (RCS) of the debris object, R_t and R_r are the ranges from the target to the transmitter and receiver respectively, k is Boltzmann's constant, T_{sys} is the system noise temperature, B is the signal bandwidth, and SNR is the ratio of received signal power to noise power. The advantages of adopting a radio telescope as a bistatic receiver are discussed in what follows:

1. The high sensitivity of radio telescopes arises from their large collecting areas. According to antenna theory, receiver antenna gain, G_r in (2.1) can be expressed as follows:

$$G_r = \frac{4\pi A_{eff}}{\lambda^2}, \quad (2.2)$$

where A_{eff} denotes the effective reception area. The larger the effective area, the larger the SNR. Hence, the large aperture size of the radio telescopes significantly enhances their detection range.

2. The lower system noise temperature (T_{sys}) of radio telescopes is another key factor contributing to their higher SNR, as it is inversely proportional. This improved sensitivity is achieved by cryogenically cooling the receiver front-end, including the low-noise amplifiers, to temperatures as low as 4 Kelvin using liquid helium. Such cryogenic cooling significantly reduces thermal noise and enhances the overall sensitivity of the system [20].
3. In a bistatic configuration, separating the transmitter and receiver enhances angular diversity, minimizing blind spots and improving detection capabilities.

The total bistatic range, given by $R_b = R_t + R_r$, provides greater flexibility in observation geometry. This configuration complements traditional monostatic radar systems by enhancing coverage and redundancy [21].

4. Radio telescopes can also contribute to debris characterization by analyzing radar cross-sections σ at multiple scattering angles, providing detailed information about the size, shape, and material composition of debris, as σ is a function of $f(\theta_{inc}, \theta_{sca}, \phi, \lambda)$, where θ_{inc} is the incident angle, θ_{sca} is the scattering angle, and ϕ is the polarization. This detailed profiling is vital for understanding the physical properties of debris and assessing its potential threats [22].
5. Interferometric capabilities from modern phase array radio telescopes such as the Square Kilometer Array (SKA) enable high-resolution imaging of space debris, allowing precise visualization of debris clouds and their spatial distribution.
6. Using these radio telescopes in a multi-bistatic configuration becomes beneficial, as the systems already work in synchronization for VLBI or similar projects.
7. Another benefit of using a radio telescope is to utilize the existing infrastructure, primarily designed for other purposes, which makes the overall system cost-effective.

This shows that the contribution of radio astronomy to SSA extends beyond infrastructure alone, since its measurement principles and processing methodologies can also be successfully applied to space object detection and tracking.

2.3 Radar Configurations Using Radio Telescopes

When radio telescopes are used as bistatic receivers for radar-based space surveillance, system configurations can be categorized based on the characteristics of the receiver and the illuminating source. Early experiments in this domain were primarily based on configurations employing a cooperative radar transmitter together with a single-dish radio telescope receiver. In such systems, the transmitter illuminates the target with a controlled waveform, while the reflected echo is collected by the receiving dish, as shown in the Figure 2.1. A single-dish radio telescope receiver typically offers high gain and a narrow beamwidth, which makes it well suited for detecting weak echoes from distant space objects with high sensitivity. This concentrated receive beam improves the SNR within the illuminated region and can support the detection of relatively small resident space objects. At the same time, the narrow field of view limits the surveillance volume, so the observable region is largely constrained by the overlap between the transmit and receive beams. As a result, although such configurations are highly sensitive, their sky coverage is limited and they are generally more effective when prior information is available. One

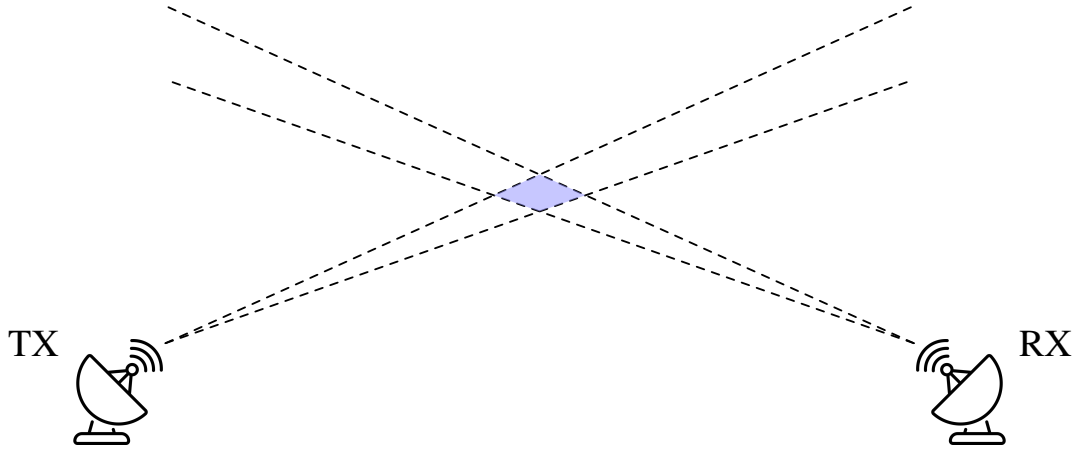


Figure 2.1: Bistatic observation geometry for space surveillance, showing a cooperative transmitting radar and a single-dish receiving telescope. The highlighted region marks the effective sensing volume where both beams overlap.

example of this kind of system is the Effelsberg radio telescope with Tracking and Imaging Radar (TIRA) as the transmitter [23].

Subsequent developments explored configurations employing an array of receiving antennas instead of a single-dish receiver while retaining a narrow-beam cooperative transmitter. Such systems employ interferometric or phased-array receivers capable of forming multiple beams electronically. In this configuration, the transmitter illuminates the target region with a focused beam, while the reflected signals are captured by the receiver array, as illustrated schematically in Figure 2.2. The use of an array enables digital beamforming, allowing the receiver to observe multiple directions simultaneously or to synthesize a wider effective field of view compared to a single-dish telescope. This increases the surveillance volume and improves the probability of detecting uncued objects, while also providing enhanced angular resolution through interferometric processing. A representative example of this approach is the BI-static RAdar for LEO Survey (BIRALES) system in Italy [24], which utilizes a high-power transmitting radar in conjunction with a radio telescope array as the receiving element.

However, the surveillance region remains constrained by the narrow transmit beam, since only objects illuminated by the transmitter can produce detectable echoes. Similar to the single-dish receiver case, this configuration continues to rely on a dedicated high-power transmitter, meaning that the cost of active illumination is not eliminated. This configuration offers a practical balance between sensitivity, coverage, and operational cost.

From the transmitter perspective, radar observations using radio telescopes can be broadly categorized into active and passive configurations. In active radar sys-

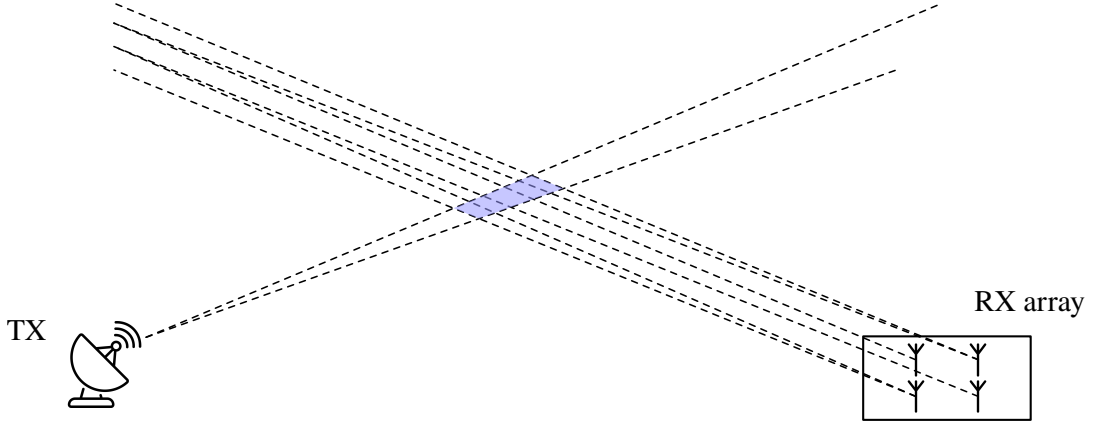


Figure 2.2: Bistatic observation geometry for space surveillance, showing a cooperative transmitting radar and arrays of receivers. The highlighted region marks the effective sensing volume where both beams overlap.

tems, a dedicated high-power cooperative transmitter illuminates the target region, and the reflected signals are received by the radio telescope. Such systems provide well-characterized waveforms, and controlled illumination geometry, enabling accurate estimation of range and Doppler measurements and improving tracking performance. Both the configurations discussed above and illustrated in Figure 2.1 and Figure 2.2 fall into this category.

In contrast, passive radar configurations utilize non-cooperative transmitters, commonly referred to as Illuminators of Opportunity (IoO), such as commercial Frequency Modulation (FM) radio and Digital Video Broadcasting-Terrestrial (DVB-T) signals. A representative geometry of this approach is shown in Figure 2.3. Passive systems offer several advantages, including wide-area illumination due to the broad coverage of broadcast transmitters, the possibility of exploiting multiple transmitters simultaneously, and significantly reduced operational cost since no high-power radar transmitter is needed. These characteristics enable large surveillance volumes and continuous monitoring capabilities. An example of such a passive system is the Murchison Widefield Array (MWA) in Australia [25], which has demonstrated the feasibility of detecting space objects using FM signals.

The overall performance of a radio telescope-based radar system therefore depends on the combined characteristics of the receiver architecture and the illumination source. Narrow-beam cooperative systems maximize sensitivity within a confined region, enabling detection of small objects but limiting surveillance coverage. Array-based or passive configurations provide broader coverage and increased flexibility, though often with reduced signal-to-noise ratio. The selection of a particular configuration thus represents a trade-off between sensitivity, coverage, operational complexity, and availability of transmitting resources.

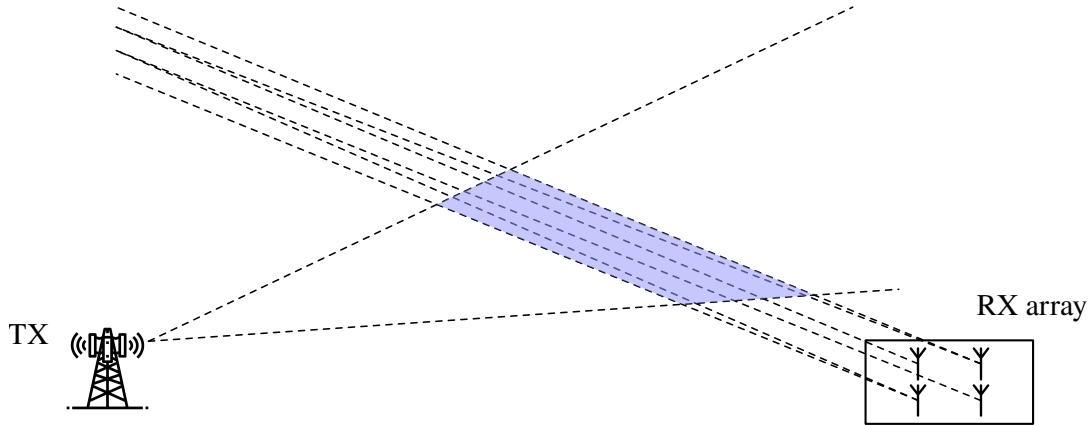


Figure 2.3: Bistatic observation geometry for space surveillance, showing a non-cooperative transmitter and arrays of receivers. The highlighted region marks the effective sensing volume where both beams overlap.

2.4 Global Initiatives

Previous investigations have shown that several facilities around the globe have participated in collaborative space debris monitoring based on the architectures discussed in Section 2.3 [16]. This section reviews several systems reported in the literature that are relevant to this study.

2.4.1 TIRA with the Effelsberg Telescope

The Fraunhofer Institute for High-Frequency Physics and Radar Techniques (FHR), Germany, operates one of the largest radars in Europe, the TIRA. It is capable of operating in both the L-band at 1.33 GHz as a narrow-band mono-pulse tracking radar and the Ku-band at 16.7 GHz as a high-range-resolution imaging radar [26]. In 1996, a space debris observation experiment was conducted using a bistatic radar formed with the TIRA system as the radar transmitter and the Effelsberg radio telescope as the radar receiver [13]. The Effelsberg radio telescope has a 100 m dish antenna and is operated by the Max Planck Institute for Radio Astronomy in Germany. Several experiments using TIRA as the transmitter/receiver and the Effelsberg radio telescope as a secondary receiver to lower the detection threshold have been performed since 1996 [27], [28], [29]. Figure 2.4 illustrates the geometry of the experiment, showing the TIRA transmitter and the Effelsberg radio telescope as the receiver.

The initial COoperative BEAM-park (COBEAM) experiment was conducted over a 24-h period and successfully collected observational data on objects as small as 0.9 cm at a range of 1000 km [27]. Figure 2.5a illustrates the detection rate (detections per hour) against altitude (at 30 km intervals) for the TIRA L-band radar

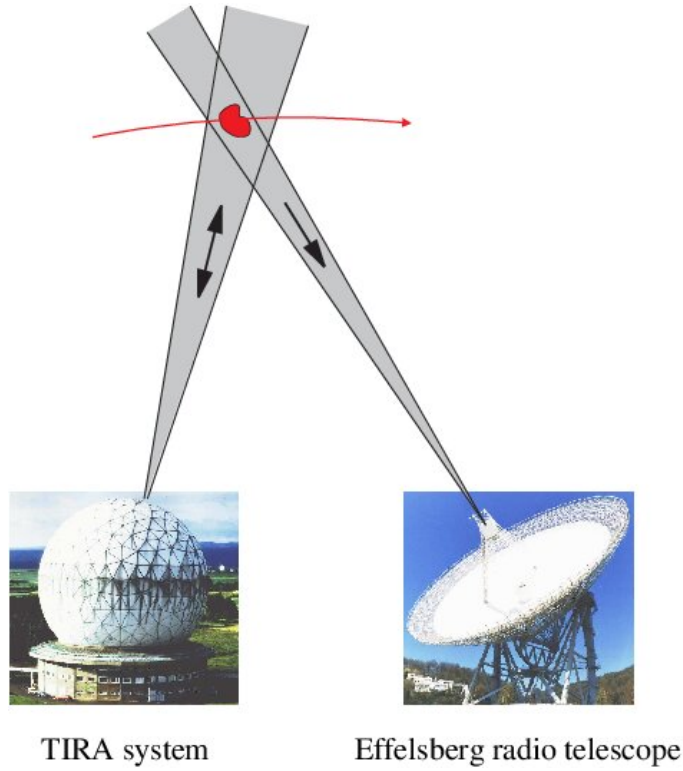


Figure 2.4: Tracking and Imaging Radar (TIRA) used as the transmitter and Effelsberg radio telescope as the receiver, reproduced from [23].

and Effelsberg. Effelsberg achieved a notably higher detection rate owing to its higher sensitivity, even though its beam width was only one-third that of the TIRA L-band beam. Figure 2.5b displays the detection rates compared with range rates over the -1 to 1.8 km/s limits, segmented into 100 m/s increments. The distribution peaks at 0.1 km/s for data from TIRA, whereas the Effelsberg data predominate around 1 km/s. Following the first promising results of the COBEAM experiment, researchers have refined estimation and calibration procedures to further enhance system performance [30]. The authors in [31] showed a moderate improvement in the detection capability after revising the multidimensional maximum likelihood estimation for determining object trajectories and RCS between beam park campaigns in 2008 and 2009. Expanding on the successful bistatic radar experiments involving TIRA-Effelsberg, which improved the detection of space debris in LEO, the German Experimental Space Surveillance and Tracking Radar (GESTRA) is set to further enhance these capabilities. Its phased-array design inherently supports bistatic and multistatic configurations, leading to an improved detection accuracy and estimation performance [32].

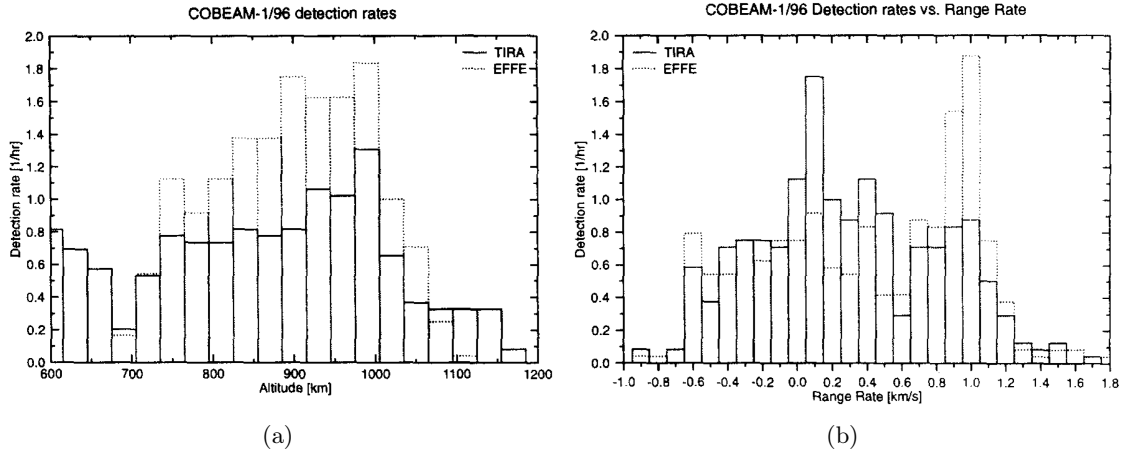


Figure 2.5: Results from the first COBEAM experiment performed in 1996: (a) Detection rate versus altitude, shown in 30 km bins, comparing performance of the TIRA L-band radar and the Effelsberg radio telescope. Effelsberg demonstrates significantly higher detection rates across all altitude ranges due to its superior sensitivity, and (b) Detection rate versus range rate in 100 m/s bins over the interval -1 to 1.8 km/s. The TIRA detections peak around 0.1 km/s, indicating more detections of near-stationary or slowly moving objects, while Effelsberg shows a dominant detection rate near 1 km/s, corresponding to faster-moving targets in its field of view [27].

2.4.2 BIRALES and BIRALET

Italy is home to two operational bistatic radar systems based on radio telescope infrastructure, namely BI-static Radar for LEO Survey (BIRALES) and BI-static Radar for LEO Tracking (BIRALET). The BIRALES system, located at the Medicina Radio Observatory near Bologna, is one of the two Italian bistatic radar systems based on radio telescope infrastructure and has been developed for space debris detection and tracking [24]. The other system, BIRALET, employs the Sardinia Radio Telescope (SRT) in Sardinia as its receiver and constitutes a second major Italian effort in radio telescope-based space surveillance [33]. Both systems utilize a common transmitter, the Radio Frequency Transmitter (TRF) which consists of a 7 m dish wheel-and-track steerable parabolic antenna. The transmitter is situated in the Italian Joint Test Range within the region of Cagliari, Sardinia, Italy. TRF is capable of generating a peak power of 10 kW and operates with a 410–415 MHz bandwidth [34].

BIRALES

BIRALES receiving antenna is part of the Northern Cross radio telescope, which is currently one of the largest UHF-capable antennas worldwide [35], as shown in Figure 2.6. The components of the BIRALES receiver include eight parabolic cylindrical antennas located along the north–south (N-S) arm with a combined collection area of approximately 1400 square meters, enabling the detection of objects as small

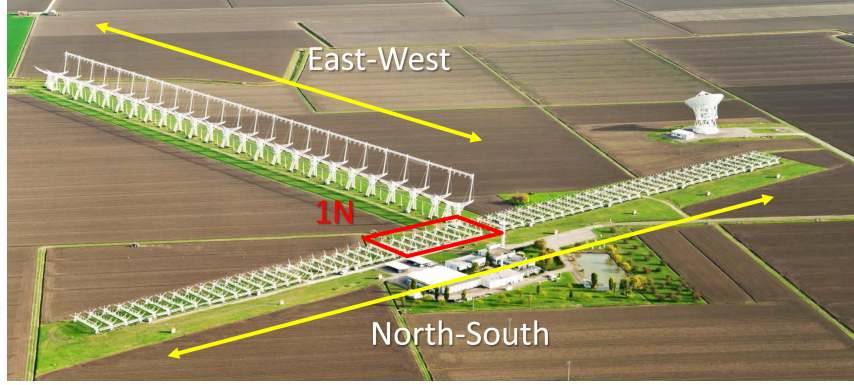


Figure 2.6: BIRALEES receiving antenna, part of the Northern Cross radio telescope located at the Medicina Observatory in Bologna, Italy. It consists of eight parabolic cylindrical antennas arranged along the north-south arm depicted in red box, with a total collection area of approximately 1400 m^2 [35]

as 10 cm at a slant range of 2000 km [36]. BIRALEES has achieved notable success in tracking debris owing to its higher sensitivity and strategic location in central Italy. The current 32-receiver multibeam configuration of BIRALEES allows the angular track of the space object to be calculated to complement the bistatic range and Doppler measurements [37], [38]. This innovative technique outperforms conventional single-dish radar because when an object passes through the field of view of the radar, it is illuminated by radio waves, and the beam illumination sequence helps define the angular trajectory of the target, as explained in [37]. BIRALEES began its measurement campaigns with initial trials in 2014, during which the bistatic radar successfully detected around 20 objects at altitudes between 300 and 850 km. A comprehensive summary of the experimental measurements performed by BIRALEES in 2014, is reported in the comprehensive analysis by Muntoni et al. [39].

Moreover, BIRALEES is designed to simultaneously receive Continuous Wave (CW) and chirp signals from the TRF for Doppler and range measurements, respectively [40]. With the help of the multi-beam approach, the time profiles of the range, Doppler, and angular position can be used to perform Initial Orbit Determination (IOD) for unknown objects and reconstruct the track [41]. Researchers have reported a range accuracy of 50 m and an angular accuracy of 10^{-3} deg, which were utilized by the orbit determination block to perform statistical orbit determination using measurement data from BIRALEES during single- or multipass observations [42].

Overall, BIRALEES demonstrates notable efficiency in detecting small objects owing to its large receiving area and real-time radar data processing backends [43]. This enables it to identify items just a few centimeters in size while significantly conserving energy. Future plans include upgrading 64 parabolic cylindrical reflectors on the N-S arm, totaling 256 receivers and over $10,000 \text{ m}^2$ of the collecting area, and

a new transmitting antenna for observation flexibility of any kind [44]. Maximum sensitivity is achieved when all reflectors are aligned in the same direction, enabling BIRALES to detect debris a few centimeters in size in LEO. This configuration reduces the field of view from $90^\circ \times 6.6^\circ$ to $5.7^\circ \times 6.6^\circ$ compared with independent cylinder pointing. This mode will be effective in specific cases, such as monitoring fragment clouds after satellite explosions and to prevent collisions with operational satellites.

BIRALET

On the other hand, BIRALET operates in the P-band at 410–415 MHz, has a bistatic configuration composed of the same transmitting antenna used in BIRALES and SRT as the receiver, with a baseline of approximately 20 km [45]. The SRT is a 64-meter fully steerable wheel-and-track antenna located near San Basilio (Cagliari, Sardinia, Italy). In the initial phase, SRT participated in the debris monitoring campaign in 2014 jointly with the Northern Cross radio telescope and was able to detect six objects [45]. Moreover, researchers described three possible hardware configurations of the system to perform Doppler shift and range measurements [24]. The first configuration utilizes the spectrum analyzer as a back end that permits Doppler shift measurements, whereas the second configuration is based on the electronic Red Pitaya board. The final configuration uses the National Instruments USRP board as a back end. The hardware has been constantly upgraded to perform space debris monitoring, including the re-entry of the Chinese space station Tiangong-1 together with other Italian SST sensors in 2018 [46], [47]. Between 13 December 2018, and 10 October 2019, the BIRALET system was able to observe a total of 33 objects in the beam-parking mode using the dedicated back-end. The estimated and measured Doppler shifts for the detected debris between 13 December 2018, and 8 October 2019, can be found in the following literature [24], [33]. Beyond the P-band measurement campaigns, a feasibility analysis has examined the potential of upgrading BIRALET to S-band operation, with the SRT as the bistatic receiver [48]. The results indicate that such a configuration could detect smaller debris at extended ranges, significantly improving system sensitivity and further demonstrating the potential of large radio astronomy facilities as high-sensitivity bistatic receivers for SSA.

2.4.3 Long Baseline Bistatic Radar

In the last few years, experiments have been conducted by NATO Science and Technology Organization (STO) members for GEO monitoring [49]. Research Task Group (RTG) assigned for this study investigated the use of existing monostatic radars as transmitters in combination with large-aperture radio telescopes as bistatic receivers for GEO monitoring [49], [50]. This approach aimed to enhance the sensitivity of object detection at GEO distances. Monitoring geostationary satellites

Table 2.1: List of high-power radar transmitters with the capability to detect GEO targets. The table includes radar systems that are either currently used for GEO monitoring or are suitable for such applications.

Name	Country of Origin	Peak Power	Operating Frequency
TIRA	Germany	1.6 MW	1.33 GHz
Millstone Hill Radar	USA	3 MW	1.295 GHz
Haystack Radar	USA	400 kW	10 GHz
Goldstone Radar	USA	440 kW	8.56 GHz
EISCAT * UHF Radar	Sweden	2 MW	930 MHz
EISCAT Svalbard Radar (ESR)	Norway	1 MW	500 MHz

* European Incoherent Scatter Scientific Association.

poses significant challenges due to their considerable distance of approximately 36,000 km from Earth. Addressing these challenges requires high-power radars, typically in the megawatt (MW) range, as well as international collaboration to establish the necessary bistatic configuration for effective detection and tracking of objects at GEO altitudes. Table 2.1 lists high-power radars that are either currently used for GEO monitoring or have the capability to track GEO targets due to their substantial transmission power. Only radars that can be configured in a bistatic setup with radio telescopes are included. Other high-power phased array radars, such as the Cobra Dane phased array radar with a peak power of 15.4 MW, are not listed here. However, the full list can be found in [39].

The experiments conducted by RTG involved two transmitting radars: the Millstone Hill Radar (MHR) in the USA and TIRA in Germany. These transmitters were paired with multiple receiving radio telescopes in Europe, including SRT in Italy, Westerbork Synthesis Radio Telescope (WSRT) in the Netherlands, and multiple antennas of the enhanced Multi-Element Radio Linked Interferometer Network (e-Merlin) array in Manchester, United Kingdom. The research team conducted several experiments between 2020 and 2021, targeting known geostationary satellites, to test the feasibility and performance of the bistatic radar setup. In such scenarios, a large-aperture radio telescope is the best option to increase the sensitivity of the system, especially when dealing with large-distance detection. Consequently, the results demonstrate successful continental baseline coherent bistatic radar collections of GEO targets. It should be noted that there was no synchronization between the transmitters and receivers, and the only available time synchronization was provided by GPS, which was presumed sufficient for these experiments.

The team performed range-Doppler (RD) processing after long-duration coherent integration and subsequently estimated the target RCS. The experimental out-

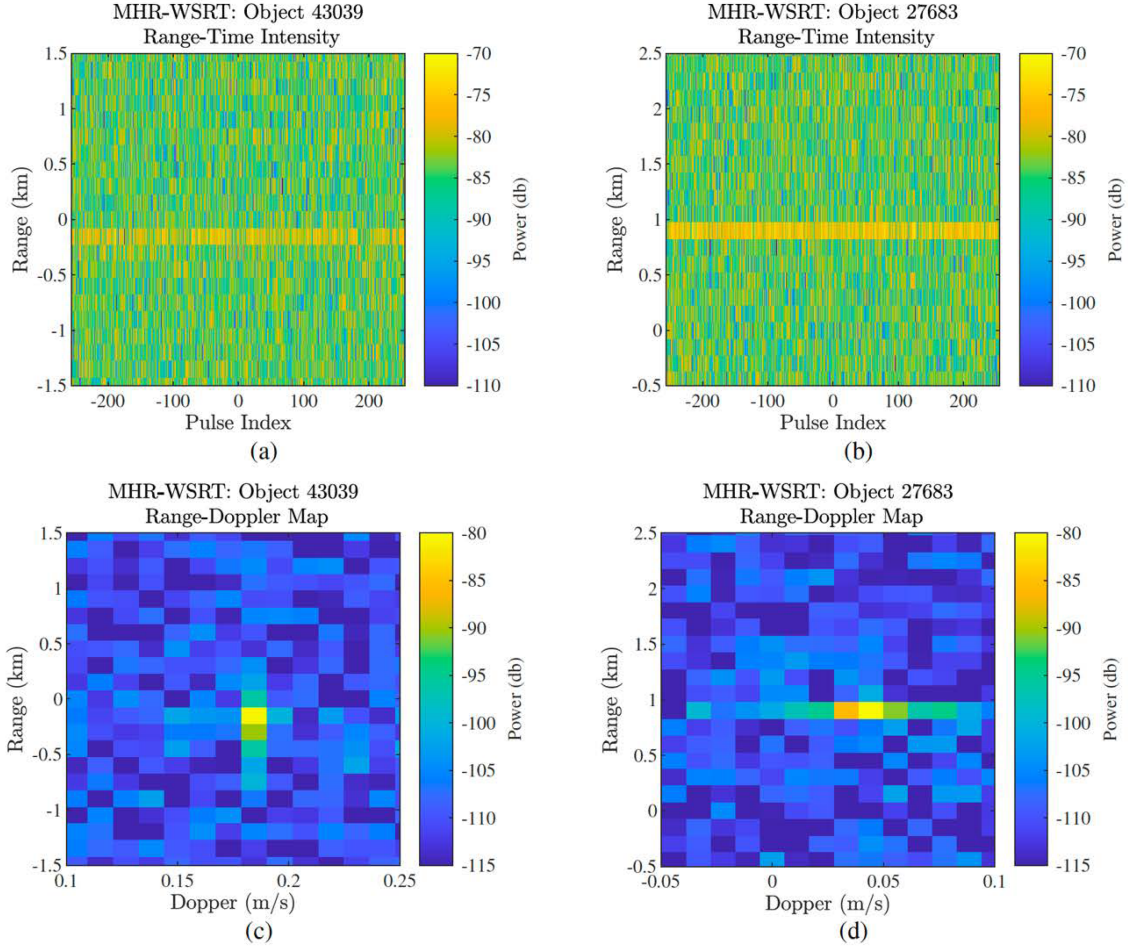


Figure 2.7: (a,b) Range-time intensity plots for objects 43039 and 27683, recorded during a single CPI in January 2020 using the MHR transmitter and WSRT receiver. These plots show signal strength variations over time and range, and (c,d) Corresponding range-Doppler maps for the same targets. The origin (0,0) in each map is aligned with the expected range and Doppler shift of the respective object, aiding in accurate target identification and motion characterization [49].

comes for two targets (ID 43039 and 27683) in January 2020 using the MHR-WSRT combination are displayed in Figure 2.7. Specifically, Figure 2.7(a,b) present the range-time intensity plot, whereas Figure 2.7(c,d) show the RD maps for the same targets. It is important to note that the origin (0, 0) of the RD maps aligns with the expected target range and Doppler measurements. The bias in the range value plots could be a result of the timing difference between the transmit and receive site clocks and the TLE error, which can reach up to 25 km in the along-track direction and 10 km in the cross-track direction for GEO objects [51]. The observed Doppler offset may have resulted from an unmatched bistatic Doppler during pulse compression, leading to a residual phase ramp across the pulses. The study also highlighted

the challenges and complexities of long-baseline bistatic radar, including timing synchronization, phase coherence, and the need for an accurate target ephemeris. To the best of our knowledge, orbit determination results are not included in the study.

The same RTG performed monostatic and bistatic radar imaging experiments on real on-orbit tumbling rocket bodies by utilizing the same network of transmitters and receivers [52], [53], [54], [55]. These studies demonstrated advanced bistatic Doppler characterization across diverse imaging geometries and highlighted the successful implementation of specialized Doppler processing techniques, such as the Doppler superpulse algorithm. The study in [54] also outlines the methodology for accurately determining the rotation periods and maximum observed length extent of tumbling objects in space. In another study, Riofrío et al. [56] discussed the performance analysis of ground-based long baseline radar for SSA by examining targets at different altitudes. The study examines the performance of a multistatic system considering one transmitter in three scenarios: a cluster of receivers, receivers spread throughout the world, and a combination of both. The authors used the multiple-input–multiple-output (MIMO) ambiguity function to analyse the system’s performance, and simulations were performed for targets in LEO and GEO to check the feasibility of the proposed radar systems.

2.4.4 MeerKAT

The Meer Karro Array Telescope (MeerKAT), located in the Northern Cape of South Africa, is part of the SKA network. It comprises 64 dishes intended for radio astronomy and serves as proof of technological advancement toward constructing a SKA, as shown in Figure 2.8. The MeerKAT radar is designed to operate at 1350 MHz (L- Band) frequency with a bandwidth of 10 MHz. The Radar Remote Sensing Group (RRSG) at the University of Cape Town, South Africa, laid the essential groundwork with simulations for the Mission Planning Tool (MPT), which will be used at the MeerKAT radar to perform sensor scheduling and orbit determination analysis [57], [58]. Agaba’s PhD thesis [57] primarily concentrates on designing the comprehensive system operation and the radar signal processing for the proposed MeerKAT radar with the RRSG’s Flexible Extensible Radar Simulator [59]. In addition, different radar configurations, such as monostatic, quasi-monostatic, and single-input–multiple-output (SIMO), were analyzed to determine the best performance with MeerKAT. The results indicate that the multistatic radar configuration is the most appropriate and computationally efficient option compared with the bistatic and SIMO configurations.

Moreover, in another study, a bistatic system was proposed with a transmitter located at Denel Dynamics’ Overberg Test Range in Arniston, Bredasdorp (Western Cape, South Africa) and a receiver at MeerKAT, separated by a baseline of approximately 450 km. A preliminary case study was conducted to demonstrate the operation of a bistatic passive radar system to observe an International Space Station [60]. The authors compared the capabilities of the MeerKAT radar to the

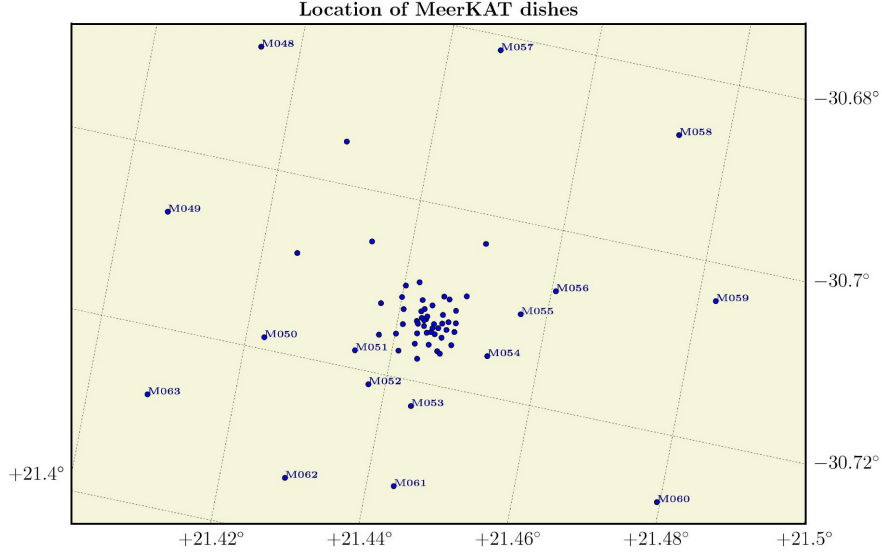


Figure 2.8: Map showing the layout of the MeerKAT radio telescope array. The receptors, labeled M000 to M063, are distributed across the site based on Gaussian configuration [58].

BIRALES system, as described in Section 2.4.2, with estimate azimuth and elevation angles [58]. This comparison was necessary because the current design of MeerKAT does not include an direction-of-arrival (DoA) estimation scheme. Nonetheless, the simulation results demonstrate the potential effectiveness of the MeerKAT radar in tracking LEO space debris. However, this must be validated through real-world measurement campaigns.

2.4.5 Murchison Widefield Array

Murchison Widefield Array, a member of the trio of SKA Precursor telescopes, is situated at the Murchison Radio-astronomy Observatory in the Murchison Shire, located in the mid-west of Western Australia. This site was specifically chosen because of its exceptionally low radio-frequency interference. Operating in the low radio frequency range of 80–300 MHz, the MWA features a processed bandwidth of 30.72 MHz per linear polarization. It comprises 128 aperture arrays or tiles spread across an area with a diameter of approximately 3 km, as illustrated in Figure 2.9 [25], [61]. The primary objectives of MWA include detecting neutral hydrogen from the epoch of re-ionization, investigating Earth’s ionosphere, and creating maps of both galactic and extragalactic radio sources. Earlier demonstrations used MWA to detect ISS and the moon using reflected FM radio emissions, but observations were limited to angular domain (i.e., right ascension and declination) only [62], [63].

The experimental campaign conducted in April 2015 used both the MWA and a Defense Science and Technology group line-of-sight receiver in Adelaide. The pri-

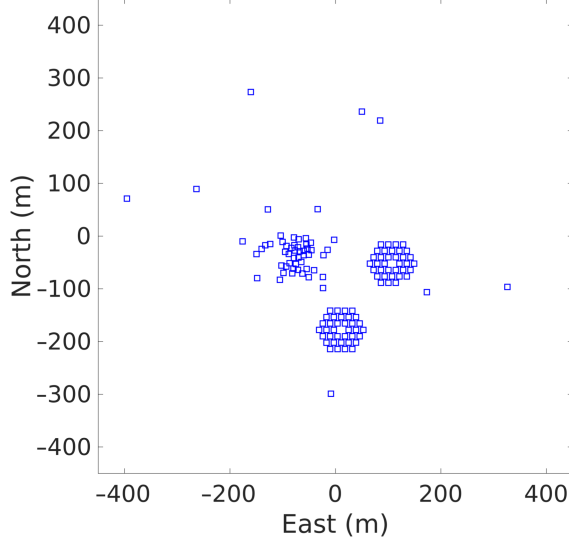


Figure 2.9: Layout of the Murchison Widefield Array (MWA). Each receiver is represented by a blue marker. The array consists of multiple tiles spread across the site to form a large interferometric baseline. Reproduced from [25].

mary target was the ISS, which was illuminated by nearby FM radio transmissions, as described in the scenario outlined in [64]. Researchers in [64], [65] developed a passive radar signal processing technique to derive the bistatic range and Doppler shift with a coherent processing interval of 1 second. This technique improved the detection performance by 25–40 dB compared with the previous case where only angle observations were possible [17]. Additionally, azimuth and elevation measurements were derived through interferometric processing. These four measurements were combined to perform IOD and tracking by using the Markov chain Monte Carlo algorithm.

Hennessy et al. [66] introduced the concept of Orbit Determination Before Detect (ODBD) for MWA, which constrains the search space to realistic orbital trajectories and improves detection efficiency. This algorithm incorporates orbital parameters into the radar ambiguity function and applies matched filtering to single-beam radar systems. The authors further validated the algorithm by applying it to a real measurement campaign at MWA conducted in 2018 and comparing it with the standard IOD method, such as Henrick-Gibbs, demonstrating the practical implementation of the algorithm, which further enhances the accuracy of debris detection [67]. While the authors proposed ways to constrain the search space, it may still require significant processing power for practical implementation.

Another measurement campaign was conducted in December 2019 using four transmitters (Geraldton, Perth, Albany, Mount Gambier) [25], and one of the detected targets, COSMOS 1707, was tracked for almost 90 s. The tracking results from the multistatic measurements are shown in Figure 2.10, with the top row as

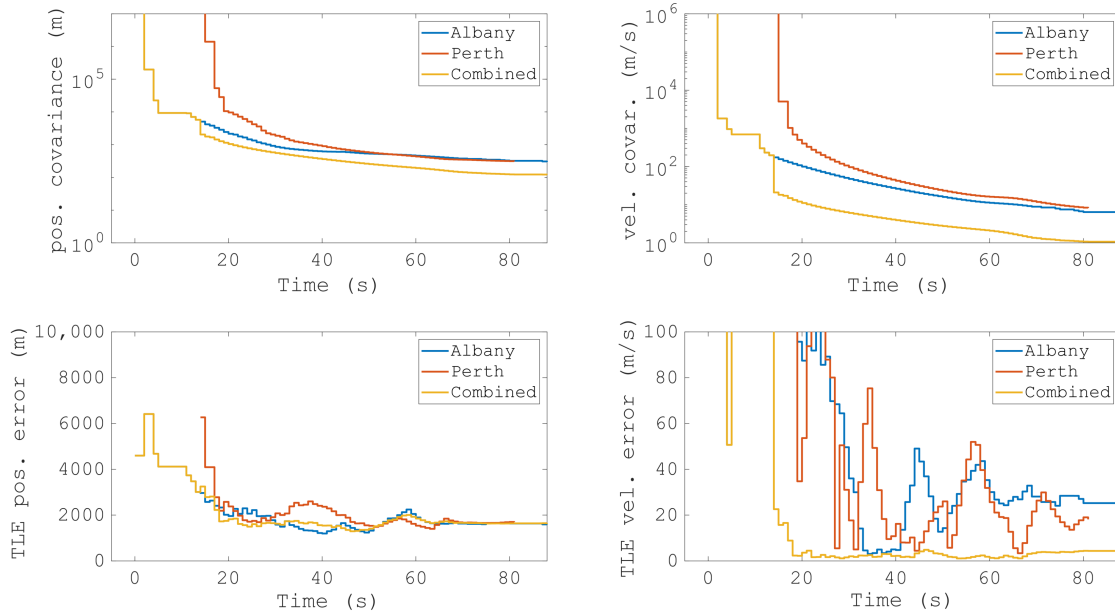


Figure 2.10: The resulting orbit predictions from the multistatic measurements of COSMOS 1707, conducted in December 2019 with the MWA radio telescope. The top rows show the covariance of the position estimate and the velocity estimate, and the bottom row shows the mean errors when compared with the TLE, reproduced from [25].

the covariance of position and velocity, and the bottom row shows the error estimates of position and velocity in comparison with the TLE ephemeris. The authors also mentioned that these results are typical for most of the objects detected at the MWA in a bistatic configuration. The measurements were combined at the orbit determination stage, and it can be seen in Figure 2.10 that the joint result from the Perth and Albany transmitters shows significant improvement in both position and velocity covariance. The mean error values, especially in the velocity, were reduced, which shows that the orbit accuracy improved with the combined data. Over the past decade, the development of MWA has been successful, with significant improvements in passive radar signal processing techniques that have enhanced the ability to refine the orbit determination of space objects.

2.4.6 Low Frequency Array

The Netherlands Institute for Radio Astronomy, ASTRON, developed and built the Low Frequency Array (LOFAR) for radio astronomy, an international network of radio telescopes. LOFAR began operations in 2012 and currently comprises 52 independent stations. Each LOFAR station comprises two separate antenna arrays: the low-band antennas (LBA), operating below 80 MHz, and the high-band antennas (HBA), operating above 110 MHz, the latter being particularly suitable for observations in the Digital Audio Broadcasting (DAB) frequency range. [68],

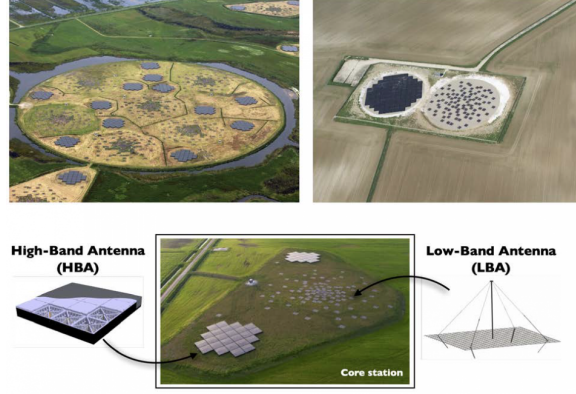


Figure 2.11: Representative views of LOFAR stations and antenna architectures. The top-left panel shows the Superterp core, the top-right panel shows the Chilbolton UK LOFAR station, and the bottom panel presents a core station with schematic representations of the High-Band Antennas (HBA) and Low Band Antenna (LBA) arrays. Credit: ASTRON

[69]. Figure 2.11 illustrates the configurations of the LBA and HBA antenna arrays. Earlier research conducted by a group of researchers at the Warsaw University of Technology (Poland) explored the application of LOFAR radio telescopes as passive radar receivers [70]. Initially, the focus was on the possibility of detecting airplanes, but the research was expanded to include the observation of space objects travelling in LEO. The research team carried out experimental trials to validate the concept, utilizing a LOFAR station as the receiver and commercial DAB transmitters as illuminators of opportunity for aerial object detection [71], [72].

In a previous study, researchers employed the LOFAR station PL610 in Borówiec, Poland, and a proximate DVB-T transmitter to detect ISS [73], [74]. The utilization of DVB-T offers the advantage of providing a broader bandwidth and potentially more precise range measurements compared with previously utilized DAB+ transmitters [73]. The results reported in [74] show that the application of Direct Path Interference (DPI) and clutter cancellation significantly improves the Cross Ambiguity Function (CAF) by suppressing strong interference components near zero bistatic range and Doppler. This produces a clearer target signature and supports the detection of weak echoes from distant objects, including the ISS, thereby demonstrating the potential of passive radar for space surveillance [75].

This capability has been further demonstrated through the detection of Starlink satellites [76], which have significantly lower radar cross-sections than the ISS. Recent studies have further advanced the use of LOFAR for space surveillance by exploiting the polarimetric properties of both the transmitted and received signals [77]. Data fusion of horizontal and vertical polarisation channels has been carried out, demonstrating the potential of polarimetric processing for space object observation. Given the well-established utility of polarimetry in Synthetic Aperture Radar (SAR) and Inverse Synthetic Aperture Radar (ISAR) applications [78], these results

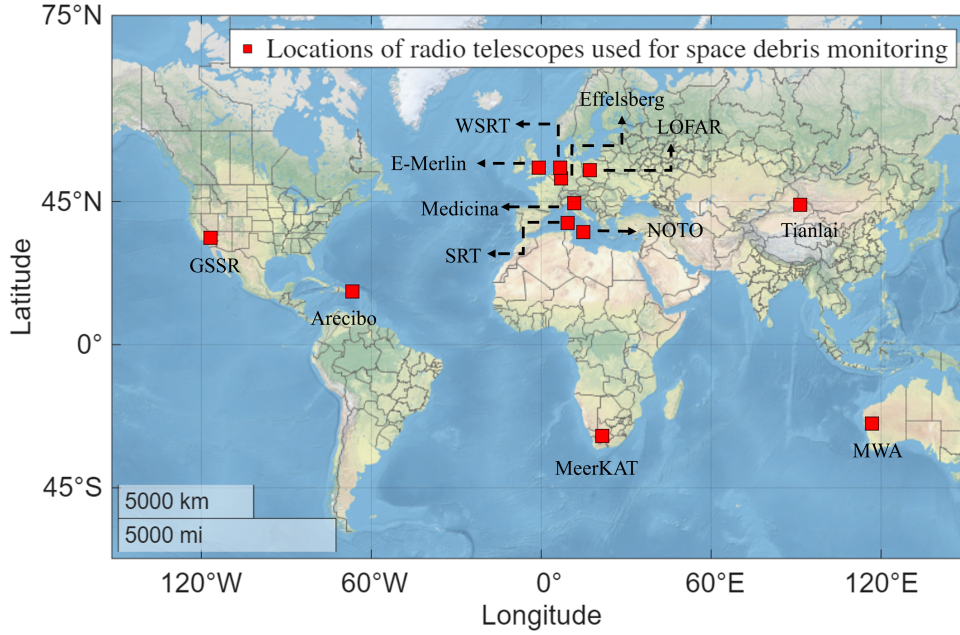


Figure 2.12: Locations of radio telescopes around the world involved in past space debris monitoring campaigns. (generated using MATLAB R2024a, www.mathworks.com).

suggest significant potential for future developments in polarimetric space object detection.

2.5 Discussion

The literature reviewed in this chapter highlights the growing role of radio telescope receivers in space surveillance and tracking applications. Although more than 50 radar systems worldwide are currently dedicated to monitoring space objects and debris, bistatic radar configurations employing radio telescopes offer an attractive combination of high sensitivity and cost-effectiveness for debris monitoring. Figure 2.12 presents the locations of radio telescopes that have been employed in reported space monitoring campaigns around the world [16]. The most relevant of these studies have been reviewed in this chapter.

A comparative summary of the radio telescopes discussed in this chapter is provided in Table 2.2, listing relevant attributes including location, setup, transmission features, and detection performance. The analysis presented in Table 2.2 and the review of existing literature reveal that more campaigns have been conducted with active transmitter configurations, likely due to the advantage of higher transmitted power. Nevertheless, opportunistic transmitters are also favoured because of their all-time availability and long exposure durations. Several radio telescopes MWA, and LOFAR, employ array-based receiver architectures that provide enhanced spa-

Table 2.2: Comparative overview of the radio telescope experiments discussed in this chapter.

Configuration	Sensors Involved (Tx/Rx)	Country	Operating Frequency	Waveform Type	Detection Performance	References
TIRA with Effelsberg Radio Telescope	TIRA (Tx), Effelsberg (Rx)	Germany	BPSK	Pulsed	Targets ≥ 1 cm RCS detectable at 1000 km	[27]
BIRALES	TRF (Tx), Medicina (Rx)	Italy	410–415 MHz	CW	Targets ≥ 1 m RCS detectable at 1000 Km	[79]
BIRALET	TRF (Tx), SRT (Rx)	Italy	410–415 MHz	CW	Targets ≥ -8 dBsm RCS detectable at 1000 km	[33]
Long baseline bistatic radar [†]	TIRA (Tx), MHR (Tx), WSRT (Rx), E-Merlin (Rx), SRT (Rx)	Germany, USA, Netherlands, UK, Italy e	1.333 GHz (TIRA) , 1.295 GHz (MHR)	Pulsed	Detection at GEO range	[50]
MeerKAT [†]	Denel Dynamics (Tx), MeerKAT (Rx)	South Africa	1350 MHz	Pulsed	N.A.	[58], [60]
Murchison Widefield Array (MWA) [†]	MWA (Rx)	Australia	80–300 MHz	Passive (FM broadcast)	Targets ≥ 0.5 m ² RCS detectable at 1000 Km	[25]
LOFAR	LOFAR PL160 (Rx)	Poland	110–240 MHz	Passive (DVB-T broadcast)	Targets ≥ 0.1 m ² RCS detectable	[72], [74]

[†] Multistatic-capable.

tial resolution and improved measurement accuracy through interferometric processing. In addition, their broad frequency coverage makes them well suited for exploiting illuminators of opportunity across different bands.

It is also worth noting that measurement campaigns have been conducted for both LEO and GEO objects, most efforts have targeted LEO, reflecting the higher debris density and associated collision risk in this orbital region. Nonetheless, monitoring GEO targets is particularly challenging because of their large distance from the Earth, and it involves coordinating multiple countries to establish the necessary bistatic configuration and requires high transmission power, as emphasized in Section 2.4.3. Another point that emerges from the reviewed campaigns is that some of the radio telescopes also operate in a multi-bistatic configuration. Although this introduces additional system complexity, it can significantly improve overall sensitivity. The move from bistatic to multi-bistatic operation also offers advantages in

terms of more precise localization and reduced measurement ambiguity, as discussed in Sections 2.4.3 and 2.4.5.

The BIRALES and BIRALET systems demonstrate that radio telescope-based bistatic radar has progressed beyond a proof-of-concept stage and now forms an operational component of the European Space Surveillance and Tracking (EUSST) programme. Recent advances in signal processing, particularly adaptive beamforming techniques [80], [81], further enhance the BIRALES system by enabling the extraction of angular information in addition to bistatic range and Doppler measurements, thereby supporting reliable orbit determination.

In addition to government initiatives, a few private companies are also contributing to SSA, such as LeoLabs from the USA and Silentium Defense from Australia [82], [83]. While LeoLabs uses phase-array technology to precisely track targets in space, the Maverick radar from Silentium Defense utilizes passive FM signals to detect and determine the orbit of debris. Furthermore, recent advances in computational power and the rapid development of machine learning and deep learning techniques have stimulated growing interest in applying data-driven approaches to orbit prediction and resident space object analysis [84], [85]. While such methods have achieved significant success in domains such as image classification, their application to orbital dynamics remains comparatively limited. One major challenge is the lack of well-curated, publicly available datasets specifically designed for long-term trajectory prediction, as most operational space surveillance data are restricted or not structured for machine learning applications. Consequently, research in this area is still at an exploratory stage despite its strong potential.

2.6 Research Gaps and Thesis Directions

This thesis addresses several key challenges in SDA, with particular emphasis on detection, orbit determination, and trajectory prediction. The research is motivated by limitations in existing sensing architectures, tracking methodologies, and predictive modelling techniques. Each chapter targets a specific gap identified in the literature and proposes novel approaches, methods, or system designs to overcome these limitations. The research presented in this thesis is organised around four main directions, each addressed in a dedicated chapter, and can be summarised as follows.

- Measurement campaigns using bistatic and multi-bistatic radar architectures with radio telescope receivers have demonstrated promising capabilities for space surveillance. While existing studies have largely focused on detection, the impact of radar observation geometry on tracking performance in the GEO regime remains largely unexplored, where the combination of large distances and low radar cross-section objects makes accurate tracking particularly demanding. Chapter 3 contributes to filling this gap through a systematic evaluation of the tracking performance of monostatic, bistatic, and multi-bistatic

radar configurations for GEO objects. In particular, the study assesses how the incorporation of bistatic measurements from radio telescopes, either individually or in combination with monostatic radar data, improves the accuracy of the estimated target state vector, while also examining whether these configurations provide a favourable trade-off between tracking performance, system complexity, and cost-effectiveness.

- Two Italian bistatic radar systems based on radio telescope infrastructure, BIRALES, and BIRALET demonstrate the practical feasibility of repurposing astronomical facilities for space surveillance. However, many radio telescopes, particularly single-dish systems, provide only bistatic range and Doppler measurements, which limits observability and makes IOD and subsequent tracking challenging. The present work addresses this limitation by applying a trilateration-based formulation to construct the target state vector using measurements from multiple radio telescopes. The method is then extended through an additional set of equations to estimate the acceleration vector, thereby enabling the detection of non-Keplerian motion. The proposed method is validated using the BIRALES and BIRALET receivers together with the Noto radio telescope through simulations of a LEO-to-GEO transfer scenario, demonstrating improved tracking performance within a 9×1 Unscented Kalman Filter (UKF) framework. The complete formulation and validation of the proposed method are presented in Chapter 4.
- Most passive radar demonstrations reported in the literature exploit radio astronomy facilities such as MWA and LOFAR, which were originally designed for scientific observation rather than continuous space surveillance. Access to such instruments is consequently constrained by competing astronomical programmes, limiting measurement availability and operational flexibility. Motivated by this limitation, Chapter 5 presents InterFeX, a dedicated radio-astronomy-inspired passive radar architecture designed specifically for SDA. Unlike existing systems, InterFeX supports dedicated surveillance campaigns conducted independently of astronomical scheduling constraints. Digital beam-forming is employed to form simultaneous reference and surveillance channels directly from the array, eliminating the need for a separate reference antenna or external synchronisation. The system further exploits dual-polarisation reception and has been experimentally validated for the passive detection of LEO objects using commercial FM broadcast transmitters as illuminators of opportunity.
- Beyond the sensing and measurement contributions, accurate orbit propagation remains a complementary challenge in SSA. While the current machine learning techniques have been increasingly applied to orbit prediction, many existing approaches either rely on static models that cannot capture long-term

temporal dependencies or on sequential data-driven models that do not explicitly incorporate the governing physical laws of orbital motion. This limits their reliability for long-term trajectory prediction, particularly in dynamic orbital environments. To address this gap, Chapter 6 investigates a hybrid framework that combines the sequential learning capability of LSTM networks with the physical consistency provided by PINN models. By integrating data-driven prediction with physics-based constraints, the proposed approach aims to improve the accuracy, robustness, and generalization of long-term satellite trajectory prediction.

Together, these contributions address key challenges in sensing architectures, orbit determination, and long-term trajectory prediction, supporting the development of advanced capabilities for SDA.

Chapter 3

Radar Configurations for GEO Tracking

Chapter Overview

This chapter addresses the first research contribution of the thesis: a systematic performance evaluation of bistatic and multi-bistatic radar architectures that employ radio telescopes as bistatic receivers for the tracking of geostationary objects. The considered system geometries are described, covering long-baseline configurations combining one active radar transmitter with up to two radio telescope receivers, followed by the target selection and simulated orbital scenarios. An UKF-based tracking framework is formulated, and measurement noise is modelled according to each architecture's characteristics. The comparative analysis evaluates position accuracy, velocity accuracy, and statistical consistency via the Mahalanobis distance across all considered configurations.

3.1 Introduction

Geostationary Earth Orbit (GEO) is one of the most important orbital regions for operational satellites, especially for communication, broadcasting, and weather-related services. As a result, tracking and monitoring RSOs in GEO has become increasingly important [86]. However, monitoring objects in this region is particularly challenging because of the large observation distance. Optical sensors are well suited for long range observations but typically provide angle-only measurements. Their availability is often constrained by cloud cover and illumination conditions, which can lead to sparse data arcs and weakly constrained orbit solutions. In contrast, deep-space radar observations are available from only a small number of sites, since surveillance of objects at GEO distances requires very high transmitted power, as discussed in Section 2.4.3.

These challenges has led to growing interest in bistatic radar configurations, where

a ground-based radar transmitter is paired with a radio telescope as the receiver, offering improved sensitivity and coverage while mitigating some of the power and aperture limitations associated with monostatic systems at GEO distances. Although only a limited number of studies have explored long-baseline bistatic radar configurations for SSA [50], [56], these works have focused primarily on detection performance rather than continuous tracking.

This chapter investigates the impact of radar geometry on orbit determination performance in the GEO regime. A comparative analysis is conducted for monostatic, bistatic, and multi-bistatic radar architectures using a common sensor network composed of one high-power transmitter and two geographically separated radio telescope receivers. The objective is to quantify how spatial diversity and measurement type influence estimation accuracy, convergence behaviour, and filter consistency when identical dynamical assumptions and noise models are applied. All configurations are evaluated within a unified UKF tracking framework to ensure a controlled comparison.

3.2 Radar Sensor Network Architecture

3.2.1 Radar Geometries

In a conventional radar system, the transmitter and receiver are co-located and often use the same antenna for both transmission and reception, resulting in a monostatic configuration [87]. Figure 3.1a illustrates the basic geometry of a monostatic radar system. Conversely, a bistatic radar utilizes a transmitter and a receiver situated in separate locations, as depicted in Figure 3.1b. For both configurations, the signal is transmitted from transmitter Tx , reflected by the target, and then received at receiver Rx . Accordingly, the propagation path is described by the transmitter-to-target distance D_{Tx} and the receiver-to-target distance D_{Rx} , while the $Tx - Rx$ separation defines the baseline L_{baseline} .

As illustrated in Figure 3.1b, the bistatic angle, denoted by β , is the angle formed at the target between the transmitter-target and receiver-target directions. It can be expressed as

$$\beta = \cos^{-1}(\hat{\mathbf{r}}_{Tx} \cdot \hat{\mathbf{r}}_{Rx}), \quad (3.1)$$

where $\hat{\mathbf{r}}_{Tx}$ and $\hat{\mathbf{r}}_{Rx}$ are the unit vectors directed from the target toward the transmitter and receiver, respectively. Due to the relatively small distance between the transmitter and receiver compared to the target location in the GEO regime ($L_{\text{baseline}} \ll D_{Tx/Rx}$), most bistatic SST systems do not achieve sufficiently large bistatic angles and can be effectively considered quasi-monostatic.

Extending the bistatic configuration to include multiple transmitters and/or receivers, forming multiple bistatic pairs, generates a multi-bistatic radar configuration. The advantages of a multi-bistatic radar system include not only the ability to increase the SNR, but also the capability to observe the target from different

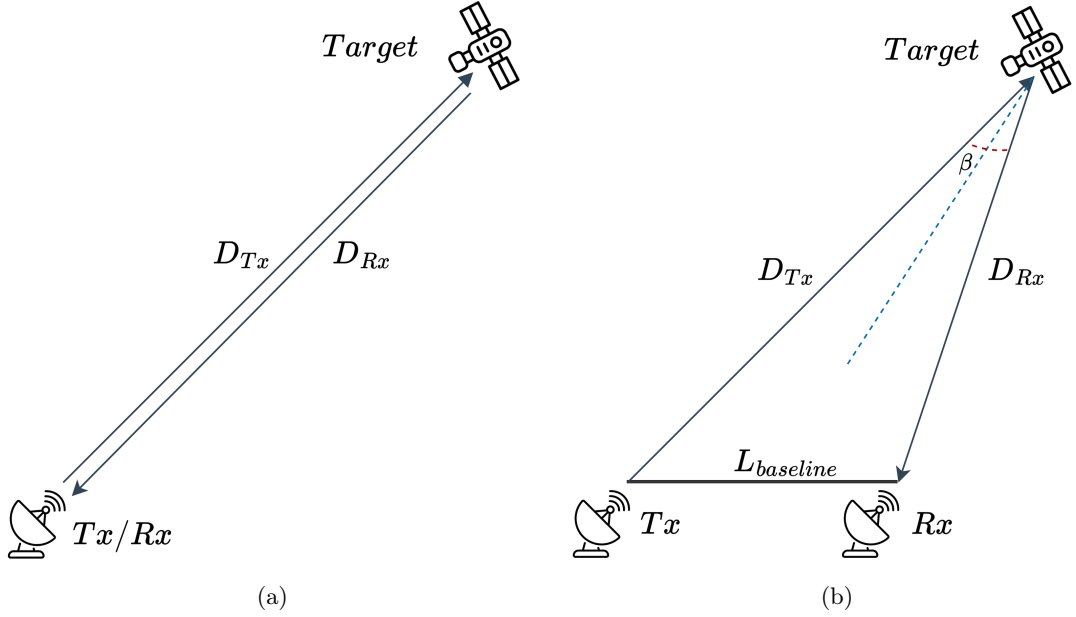


Figure 3.1: Geometric configurations of radar systems: (a) monostatic radar, with co-located transmitter and receiver, and (b) bistatic radar with spatially separated transmitter and receiver.

angles. This can potentially increase the reflected RCS and reduce the ambiguity in the measurements [56].

In practice, the performance of a surveillance system depends on the specific configuration of transmitters and receivers employed. As mentioned before, this study considers one transmitter and two spatially separated radio telescope receivers, which will provide complement bistatic measurements. The details of transmitter and radio telescopes used are described in following subsections.

3.2.2 Considered Transmitter and Receiver Systems

To evaluate monostatic, bistatic and multi-bistatic configurations, one transmitter (TIRA) and two large radio telescope facilities (e-Merlin and WSRT) are considered as receivers.

Transmitting Radar: TIRA

The primary transmitting facility considered in this study is TIRA, operated by FHR in Germany. TIRA is one of the few European radar systems capable of supporting surveillance operations in GEO regime due to its high transmitted power and narrow beamwidth. The TIRA radar facility, shown in Figure 3.2, serves as the monostatic transmitter and as well as receiver. In the present analysis, TIRA is modelled as a monostatic tracking radar that provides range, range rate, azimuth, and elevation



Figure 3.2: Tracking and Imaging Radar operated by FHR, Germany, Credits : FHR.

measurements. The radar operates at a center frequency of 1333 MHz, with a Half Power Beam Width (HPBW) of approximately 0.5° . These parameters define the achievable angular resolution and contribute directly to the measurement noise characteristics incorporated into the estimation framework.

e-MERLIN

The e-Merlin facility is a distributed radio interferometric array operated from the Jodrell Bank Observatory in the United Kingdom. The array consists of seven radio telescopes distributed across Great Britain, spanning a maximum baseline of approximately 217 km. In this work, only a single e-Merlin station is considered as a bistatic receiver, rather than the full interferometric array. The transmitted radar signal originates from the TIRA facility, and the scattered echo is received at the e-Merlin stations. The geographic separation between the transmitter and the e-Merlin array establishes a long-baseline bistatic geometry, which contributes additional spatial diversity to the measurement set. The HPBW of Knockin dish is approximately 0.5° . The high gain of the receiving system contributes to improved measurement precision in bistatic range and Doppler estimation. The e-Merlin receiving station used in this study is shown in Figure 3.3.

WSRT

The WSRT, located in the Netherlands at approximately 52.9° latitude and 6.6° longitude, is considered as a second bistatic receiver. WSRT consists of an array of large parabolic dishes operating as an interferometric system similar to e-Merlin. The WSRT antenna dish considered in this study has an HPBW of 0.6° . Similar to e-Merlin, WSRT provides bistatic range and bistatic range rate measurements derived from echoes transmitted by TIRA. Its high sensitivity and gain characteristics allow improved signal reception at GEO distances.

Collectively, both WSRT and e-Merlin enables the formation of multi-bistatic



Figure 3.3: Knockin antenna dish of the e-Merlin radio telescope at Jodrell Bank Observatory, United Kingdom, Credits: University of Manchester.

Table 3.1: Key radar parameters for TIRA, e-Merlin, and WSRT stations [50].

Parameter	TIRA	e-Merlin	WSRT
Latitude [°]	50.61	53.23	52.90
Longitude [°]	7.12	-2.30	6.60
Center frequency [MHz]	1333	—	—
HPBW [°]	0.50	0.50	0.60
Reference SNR [dB]	47.0	56.0	56.6
SNR gain [dB]	—	9.0	9.6

configuration with increased spatial diversity and distinct baseline orientations relative to the transmitter. The parameters for each sensor, including gain values and other relevant specifications, are summarized in Table 3.1, based on data from the previous studies [50], [54]. The link budget is evaluated in terms of a reference SNR for each bistatic receiver when paired with TIRA. For the monostatic case, a reference SNR of 47 dB is considered, corresponding to the maximum single-pulse performance for a target with an RCS of 0 dBsm at a range of 1000 *km*. The corresponding receiver gain, defined as the difference between the monostatic and bistatic sensitivities, is reported for each bistatic receiver in the last row of Table 3.1. The advantage of radio telescope receivers is evident, as e-Merlin and WSRT receiver are expected to provide nearly 10 dB of receiver gain when paired with TIRA, mainly due to their low system temperature in receive-only operation.

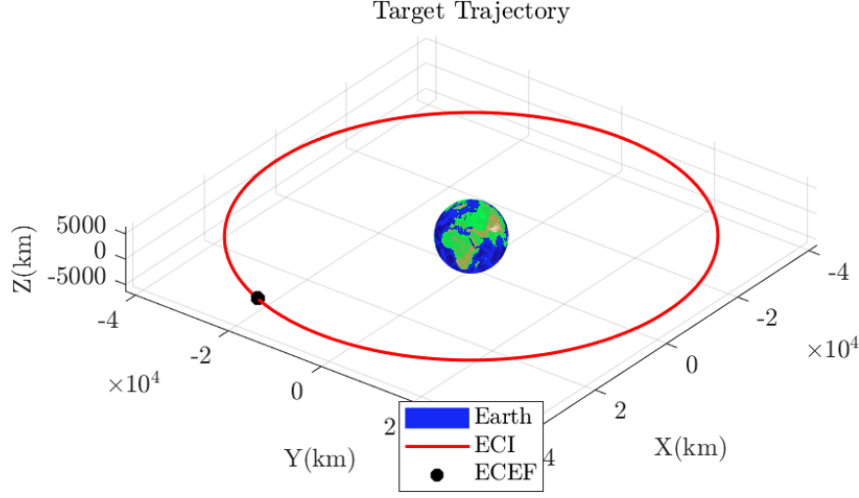


Figure 3.4: Trajectory of the SES-4 satellite propagated using the SDP4 model. The red curve represents the orbit in ECI frame. The black marker indicates the corresponding ECEF position at a selected epoch.

3.3 Target Selection and Orbital Scenario

For the comparative analysis, a telecommunication satellite SES-4 with an RCS of 79.4 m^2 was selected as the target, and synthetic data were generated with the TLE dataset obtained on February 3, 2025. After propagating the orbit using the SDP4 propagator, the state vector (position and velocity) is obtained in the Earth-Centered Inertial (ECI) coordinate system, and the system measurements are computed in the topocentric coordinate system for all the considered sensors [88]. The SDP4 model is selected over SGP4 since it is specifically suited for deep-space objects with orbital periods exceeding 225 minutes, where lunar and solar perturbations play a significant role and must be accounted for in the propagation. The propagated 24-hour trajectory of SES-4 in the ECI frame is illustrated in Figure 3.4. As expected for a GEO object, the trajectory shown in red colour completes one full revolution around the Earth over this interval. Additionally, the black marker in Fig. 3.4 denotes the position of the same target in the Earth-Centered, Earth-Fixed (ECEF) frame, in which target satellite appears nearly stationary with respect to the rotating Earth.

Another important factor in selecting the SES-4 satellite is its all time visibility from considered sensors. Figure 3.5 shows the ground track of SES-4 together with the sensor locations, where the green diamond denotes the TIRA transmitter/receiver and the red squares denote the bistatic receiving sites (e-Merlin and WSRT). For the selected GEO target, the relative geometry between the transmitter and receivers produces long baselines but very small bistatic angles. The TIRA–e-Merlin configuration exhibits the largest separation, approximately 710 km , while

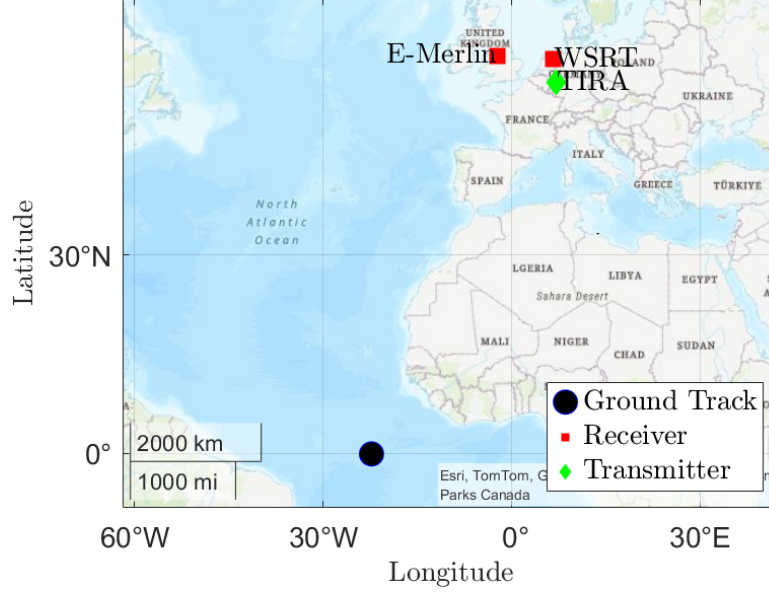


Figure 3.5: Ground track of the SES-4 satellite, with TIRA as the transmitter and e-MERLIN and WSRT as the receiving stations.

Table 3.2: Transmitter–receiver baseline and corresponding bistatic angle for the SES-4 target.

Transmitter	Receiver	Baseline [km]	Bistatic angle, β [°]
TIRA	TIRA	—	—
TIRA	e-MERLIN	710.03	1.040
TIRA	WSRT	256.76	0.283

the TIRA–WSRT baseline is about 257 *km*. Despite these differences, both configurations yield bistatic angles of less than 1°, reflecting the large distance of the target relative to the baseline lengths. The calculated values are summarized in Table 3.2.

An observation window of 5 minutes is selected to ensure sufficient measurement data for tracking. For each sensor site, measurements are generated in the local topocentric South-East-Zenith (SEZ) frame, from which the observation quantities are obtained. In the monostatic case (TIRA), the measurement vector includes range, range rate, azimuth, and elevation, whereas bistatic receiving sites provide bistatic range and bistatic range rate when paired with the TIRA transmitter. The simulated monostatic and bistatic range and range-rate time histories over the selected interval are shown in Figure 3.6. As expected for GEO targets, the range remains on the order of 10^4 *km*, while the range-rate magnitude is comparatively small and exhibits limited variation over the short observation window, reflecting the slow apparent motion of GEO objects with respect to ground-based sensors.

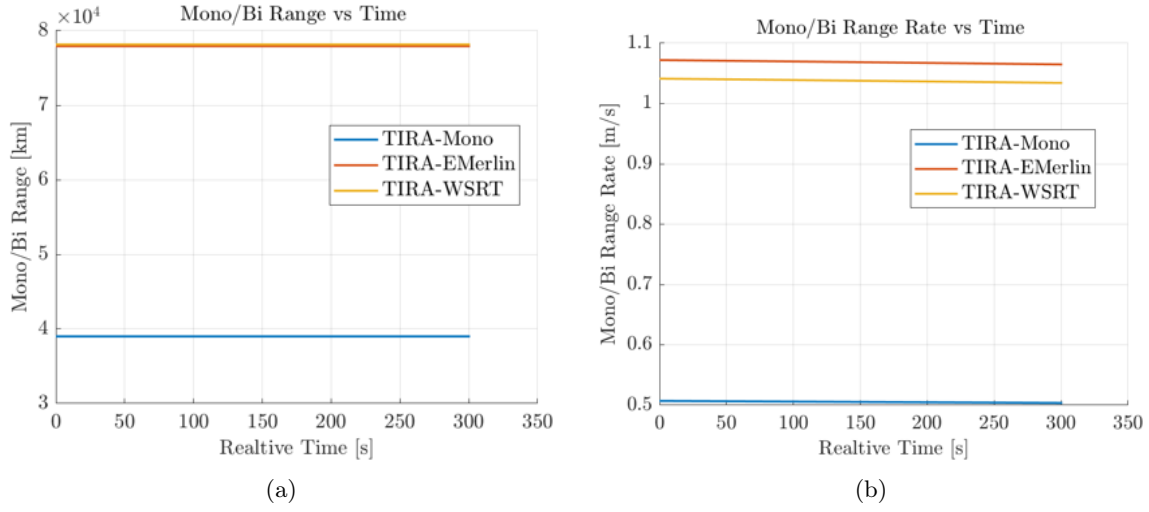


Figure 3.6: Simulated monostatic and bistatic measurements for the SES-4 satellite over the 5-minute observation window: (a) Monostatic and bistatic range measurements, and (b) Monostatic and bistatic range-rate measurements.

Table 3.3: Considered sensor combinations and corresponding measurement sets.

Configuration	Tx	Rx 1	Rx 2	Rx 3	Notation	Measurements	Dim
Monostatic	TIRA	TIRA	–	–	T	$\rho_T, \dot{\rho}_T, az_T, el_T$	4
Bistatic	TIRA	–	e-Merlin	–	E	$\rho_E^b, \dot{\rho}_E^b$	2
Monostatic + bistatic	TIRA	TIRA	e-Merlin	–	TE	$\rho_T, \dot{\rho}_T, az_T, el_T, \rho_E^b, \dot{\rho}_E^b$	6
Bistatic	TIRA	–	–	WSRT	W	$\rho_W^b, \dot{\rho}_W^b$	2
Monostatic + bistatic	TIRA	TIRA	–	WSRT	TW	$\rho_T, \dot{\rho}_T, az_T, el_T, \rho_W^b, \dot{\rho}_W^b$	6
Multi-bistatic	TIRA	TIRA	e-Merlin	WSRT	TEW	$\rho_T, \dot{\rho}_T, az_T, el_T, \rho_E^b, \dot{\rho}_E^b, \rho_W^b, \dot{\rho}_W^b$	8

* Tx:-transmitter, Rx:-receiver, and Dim:-measurement dimension.

3.4 Simulated Scenarios

The geometries discussed in Section 3.2.1 enables the evaluation of the effect of different configurations and measurement dimensions on orbit determination accuracy. To evaluate the performance systematically, six distinct tracking scenarios were defined, each incorporating a unique set of measurement inputs derived from the available monostatic and bistatic geometries. Throughout this study, the config-

urations are denoted as T (TIRA), E (e-Merlin), and W (WSRT), with combinations such as TE (TIRA + e-Merlin), TW (TIRA + WSRT), and TEW (TIRA + e-Merlin + WSRT) representing different setups.

- **Case 1 (T)** represents the monostatic configuration using only TIRA measurements, which include range (ρ_T), range rate ($\dot{\rho}_T$), azimuth (az_T), and elevation (el_T) at discrete epochs.
- **Case 2 (E)** involves tracking based solely on bistatic measurements which includes bistatic range (ρ_E^b) and bistatic range rate ($\dot{\rho}_E^b$) from the e-Merlin radio telescope, forming a bistatic link with TIRA.
- **Case 3 (TE)** examines the performance when combining monostatic measurements from TIRA with bistatic measurements from e-Merlin.
- **Case 4 (W)** utilizes only bistatic measurements which are bistatic range (ρ_W^b) and bistatic range rate ($\dot{\rho}_W^b$) from WSRT for tracking.
- **Case 5 (TW)** combines monostatic measurements from TIRA with bistatic measurements from WSRT.
- **Case 6 (TEW)** explores the most comprehensive configuration, where monostatic measurements from TIRA and bistatic measurements from both e-Merlin and WSRT are combined.

Table 3.3 summarize these configurations in detail to facilitate a clear understanding of the different scenarios evaluated in this study.

3.4.1 Orbit Tracking Using the Unscented Kalman Filter

To compare the tracking performance of various radar configurations, we employ an UKF to estimate the target's state. The UKF is well-suited for GEO tracking due to the nonlinearity of the measurement models, and its effectiveness has been demonstrated in previous studies [89]. For simplicity, a numerical propagation model based on two-body gravitational motion is used to propagate the state dynamics within the Kalman filter. In our tracking algorithm, the true state vector includes GEO satellite position and velocity coordinates in the ECI reference frame. The true state vector ($\mathbf{x}_k$) is computed using SDP4 propagator to ensure consistency with orbital dynamics. The initial state covariance matrix ($\mathbf{P}_0$) is chosen according to the known accuracy of the TLE and SDP4 propagation models [12]. In the simulations, the initial covariance matrix is set as

$$\mathbf{P}_0 = \text{diag} (10^8, 10^8, 10^8, 10^2, 10^2, 10^{-4}) . \quad (3.2)$$

The covariance is defined for the state vector

$$\mathbf{x} = \begin{bmatrix} x & y & z & \dot{x} & \dot{y} & \dot{z} \end{bmatrix}^T . \quad (3.3)$$

The process noise covariance matrix is set as

$$\mathbf{Q} = \text{diag} (10^{-5}, 10^{-5}, 10^{-5}, 10^{-7}, 10^{-7}, 10^{-7}) . \quad (3.4)$$

The process noise is intentionally kept small for both position and velocity components, as the analysis primarily focuses on the effects of measurement noise.

Moreover, the initial state vector required for filter initialization remains the same for all configurations, with the only factor that differs being the type of measurement obtained from each configuration. The update step in the UKF therefore employs configuration-dependent measurement functions to derive measurements from the predicted state vector, such as range, azimuth, elevation, and range rate from the monostatic radar, and bistatic range and bistatic range rate from the radio telescope receiver. The filter computes the Kalman gain by weighting the measurement residual according to the associated uncertainty. Differences in performance are expected to arise from the information content of the measurements. The monostatic filter receives four pieces of information per update, including direct angular information, whereas the pure bistatic filter receives only two, namely bistatic range and bistatic range rate. Another important factor is the measurement noise matrix $\mathbf{R}$ for each configuration, which directly influences the filter confidence in each type of measurement.

Based on the available measurement types from particular sensor, $\mathbf{R}$ is defined in Section 3.4.2 to ensure a reliable comparison. Once all configurations are defined, the UKF tracking framework presented in this section is applied to each considered case (Table 3.3) to allow a consistent comparison. The corresponding procedure for tracking framework is summarized in Table 3.5.

3.4.2 Measurement Noise Modelling

Within the tracking framework, the measurement noise covariance matrix $\mathbf{R}$ plays a central role in weighting observations during the update step. The standard deviations of radar measurement errors are derived from the radar resolution capabilities and SNR. These errors are inversely proportional to the square root of the coherent integrated SNR, which reflects improved precision at higher SNR levels [90]. Measurement modelling therefore provides the basis for constructing the elements of the noise covariance matrix $\mathbf{R}$, defined separately for each radar configuration.

For monostatic and bistatic radar configuration, the standard deviation of range measurement noise, σ_{Range} , can be expressed as

$$\sigma_{\text{Range}} = \frac{\Delta R}{\sqrt{2 \times \text{SNR}}} , \quad (3.5)$$

where ΔR denotes the range resolution determined by the radar bandwidth and pulse characteristics. Similarly, Doppler or range rate uncertainty, $\sigma_{\text{RangeRate}}$, is

given by

$$\sigma_{\text{RangeRate}} = \frac{\Delta V}{\sqrt{2 \times \text{SNR}}} \Rightarrow \sigma_{\text{RangeRate}} = \frac{\lambda}{2T_{\text{CPI}}\sqrt{2 \times \text{SNR}}}, \quad (3.6)$$

where ΔV is the velocity resolution, λ is the radar wavelength, and T_{CPI} is the coherent processing interval. This relationship shows that velocity estimation accuracy depends on both system design parameters and signal quality.

Angular measurements, including azimuth and elevation, follow a similar dependence on antenna characteristics and SNR. The corresponding standard deviation can be modeled as

$$\sigma_{\text{az/el}} = \frac{\Delta\theta_{\text{BW}}}{1.6\sqrt{2 \times \text{SNR}}}, \quad (3.7)$$

where $\Delta\theta_{\text{BW}}$ is the antenna 3 dB beamwidth. A narrower beamwidth combined with a higher SNR leads to improved angular accuracy. The constant 1.6 arises from empirical estimation bounds associated with monopulse tracking radar performance. These error models are used to define the measurement uncertainties adopted in the UKF. The numerical values used in the simulations for the different radar configurations are summarized in Table 3.4.

Table 3.4: Measurement noise standard deviations used for the different radar configurations.

Measurement	TIRA	TIRA-E-MERLIN	TIRA-WSRT
Range, σ_{Range} (m)	1.009×10^4	18.75	18.75
Azimuth, σ_{Az} (rad)	3.3034×10^{-4}	–	–
Elevation, σ_{El} (rad)	3.3034×10^{-4}	–	–
Range rate, $\sigma_{\text{RangeRate}}$ (m/s)	0.0036	0.0014	0.0013

The measurement noise covariance matrix $\mathbf{R}$ is constructed according to the measurement vector available for each radar configuration. Assuming independent measurement errors, the corresponding measurement variances are placed along the diagonal of $\mathbf{R}$. Consequently, the dimension of $\mathbf{R}$ is not fixed, but depends on the number and type of measurements used in a given simulation. For example, when only range and range-rate measurements are available, $\mathbf{R}$ is a 2×2 diagonal matrix containing the corresponding variances. When six measurements are simultaneously used, $\mathbf{R}$ becomes a 6×6 diagonal matrix, with each diagonal element given by the square of the standard deviation associated with the respective measurement. Thus, $\mathbf{R}$ is adjusted for each sensor configuration while retaining the measurement noise levels reported in Table 3.4.

3.5 Comparative Analysis

To evaluate the orbit determination performance across all considered tracking cases, the Mean Absolute Error (MAE) is adopted as the primary metric. The MAE

Table 3.5: UKF-based tracking framework applied to all considered cases.

Step	Procedure
Initialization	
1	Define the ECI state vector $x_k = [x \ y \ z \ \dot{x} \ \dot{y} \ \dot{z}]^T$.
2	Set identical initial estimate $\hat{x}_0$ and covariance P_0 for all configurations.
3	Define process noise covariance Q .
4	Select configuration c from Table 3.3 and assign measurement model $h_c(\cdot)$ and noise covariance R_c with the help of Table 3.4.
Recursive filtering for $k = 1, \dots, N$	
5	Compute Cholesky factor $S_{k-1} = \text{chol}(P_{k-1})$ and generate $2n + 1$ sigma points from $\hat{x}_{k-1}$.
6	Propagate sigma points through the process model to obtain $X_{i,k}^-$.
7	Compute predicted state mean $\hat{x}_k^-$ and covariance P_k^- .
8	Transform sigma points into measurement space using $Y_{i,k}^{(c)} = h_c(X_{i,k}^-)$.
9	Compute predicted measurement mean $\hat{y}_k^{(c)}$ and innovation covariance $P_{yy,k}^{(c)}$.
10	Compute cross covariance $P_{xy,k}^{(c)}$ and Kalman gain $K_k^{(c)}$.
11	Update state $\hat{x}_k^+ = \hat{x}_k^- + K_k^{(c)}(y_k^{(c)} - \hat{y}_k^{(c)})$.
12	Update covariance $P_k^+ = P_k^- - K_k^{(c)}P_{yy,k}^{(c)}(K_k^{(c)})^T$.
Comparison Metrics	
13	Compute the mean absolute error for position and velocity.
14	Evaluate the filter uncertainty using the state estimation error covariance P_k and its derived metrics.

quantifies the average deviation between the estimated and true state vectors over multiple Monte Carlo runs. Specifically, separate formulations are used for position and velocity components, as defined in (3.8) and (3.9), respectively.

$$\text{MAE}_{\text{pos}} = \frac{1}{N} \sum_{i=1}^N \left\| \mathbf{x}_i^{(1:3)} - \mathbf{x}_{i,\text{true}}^{(1:3)} \right\| \quad (3.8)$$

$$\text{MAE}_{\text{vel}} = \frac{1}{N} \sum_{i=1}^N \left\| \mathbf{x}_i^{(4:6)} - \mathbf{x}_{i,\text{true}}^{(4:6)} \right\| \quad (3.9)$$

Here, $\mathbf{x}_i^{(1:3)}$ and $\mathbf{x}_i^{(4:6)}$ denote the position and velocity components of the estimated state vector at the i -th Monte Carlo run, while $\mathbf{x}_{i,\text{true}}$ represents the corresponding true state vector, which is derived from SDP4 propagation. A total of $N = 100$ Monte Carlo simulations were performed for each tracking case, using the complete set of radar measurements. In addition to MAEs, the position and velocity covariances were also computed to provide further insight into the consistency and confidence of the state estimates across different tracking scenarios. These covariances help evaluate how well the filter is capturing the uncertainty in the estimated

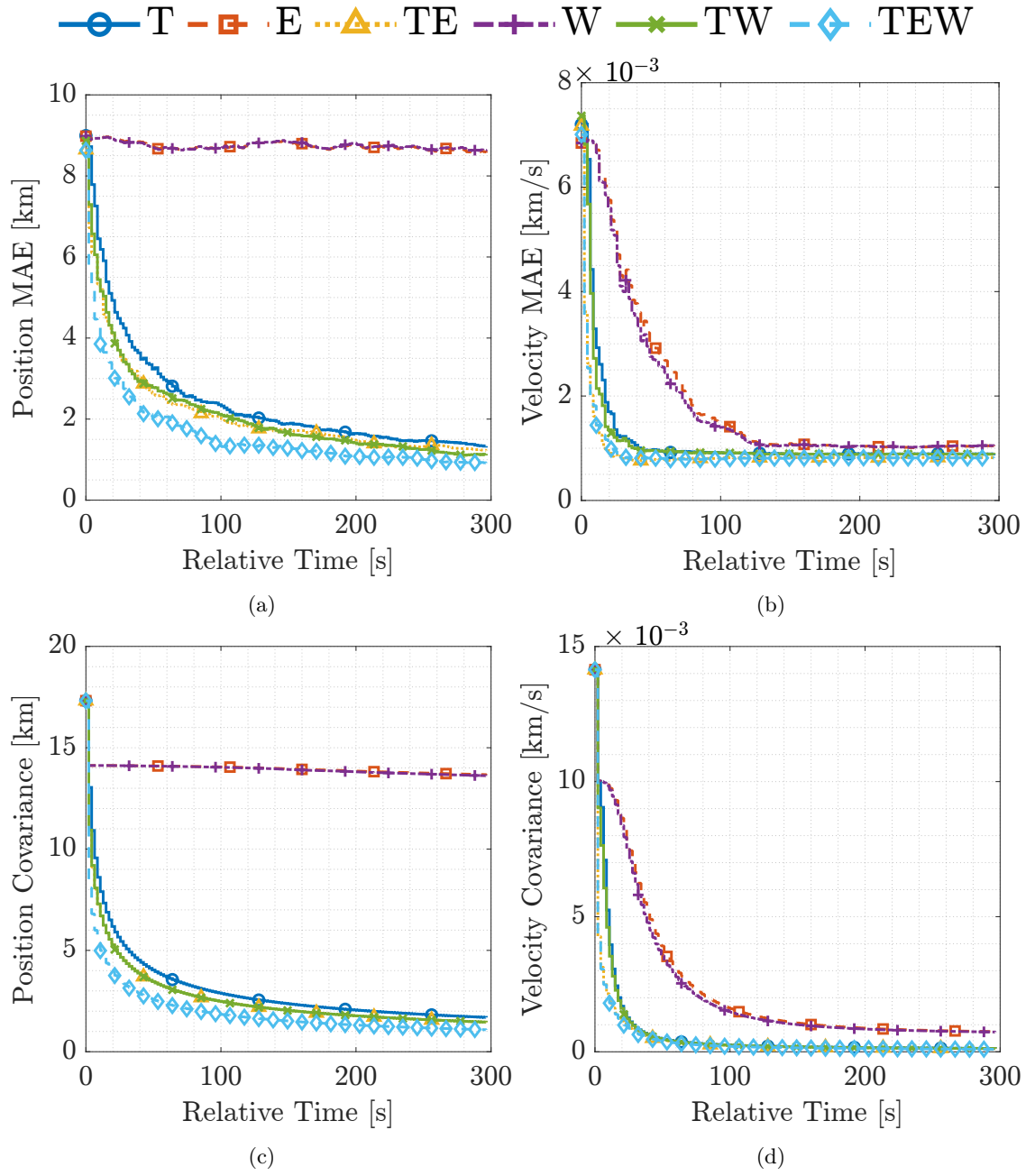


Figure 3.7: Performance comparison of different radar configurations with legend at the top of the plot: (a) Position mean absolute error, (b) Velocity mean absolute error, (c) Position covariance, and (d) Velocity covariance.

state. Figure 3.7 presents the orbit determination performance across six tracking configurations for both position and velocity MAE, along with their respective covariance estimates over time.

3.5.1 Position Performance

As shown in Figure 3.7a, Cases TE, TW, and TEW yield the lowest position MAE, highlighting the benefits of incorporating additional or more diverse measurements. In contrast, Cases E and W demonstrate the poorest performance in position estimation, with MAE remaining nearly constant throughout the tracking interval. This lack of convergence is attributed to the limited observability provided by the reduced set of independent measurements, specifically, bistatic range and range rate ($\rho_{E/W}^b, \dot{\rho}_{E/W}^b$) which are insufficient to drive convergence of the initial state error. A similar trend was observed in [58], where MeerKAT radar simulations using only bistatic range and Doppler measurements resulted in poorer performance compared to configurations that also included angular data, which significantly improved estimation accuracy.

When excluding Cases E and W from consideration, Cases TE and TW show slightly better position MAE than Case T (TIRA monostatic-only), demonstrating that the filter benefits from measurement diversity. Although Case T already provides relatively strong performance, the addition of bistatic data further enhances estimation accuracy. Case TEW, which is a multi-bistatic configuration, achieves the lowest overall MAE, confirming that spatial diversity and complementary measurement types significantly improve state estimation performance. A similar trend is observed in the position covariance results which is shown in Figure 3.7c. Case TEW exhibits the most rapid and stable convergence, indicating not only higher accuracy but also greater confidence in the state estimates. Cases TE and TW follow closely, while Case T shows comparable but slightly higher covariance. Cases E and W maintain higher covariance values throughout, consistent with their limited diversity in measurements.

3.5.2 Velocity Performance

Figure 3.7b presents the velocity MAE for all six tracking configurations. Similar to the position estimation trends, Cases T, TE, TW, and TEW demonstrate the lowest velocity errors, reflecting the benefit of incorporating diverse measurements, particularly those sensitive to velocity such as range rate. Case TEW (multi-bistatic) consistently outperforms all other configurations, with the MAE dropping below $1 \times 10^{-3} \text{ km/s}$, indicating highly accurate velocity estimation. However, Case T, TE and TW showed very low error similar to TEW configuration. In contrast, Cases E and W again show degraded performance, with a slower decrease and higher steady state error, due to the limited observability provided by bistatic range and range rate alone. Figure 3.7d supports these findings by showing the corresponding velocity covariance trends. Velocity covariance convergence is fastest and most stable in Case TEW, reinforcing the positive impact of combining monostatic and bistatic measurements. Cases T, TE, and TW show very similar convergence behaviour, indicating that monostatic observations alone can achieve comparable velocity per-

Table 3.6: Comparison of tracking errors for different sensor configurations under the same initial perturbation.

Case	Position MAE (km)	Velocity MAE (km/s)
Initial Error	8.9943	0.0072
T	1.3323	0.0009
E	8.5742	0.0010
TE	1.2286	0.0008
W	8.6146	0.0010
TW	1.1422	0.0009
TEW	0.9184	0.0008

formance to bistatic-enhanced configurations in velocity estimation. This behaviour may be attributed to the relatively negligible motion of GEO objects with respect to ground-based sensors, resulting in lower dynamic variation in the velocity estimates and reduced sensitivity to measurement diversity. In contrast, Cases E and W maintain relatively higher covariance throughout the tracking process. This reflects both the reduced filter confidence and higher estimation uncertainty in scenarios with fewer or less informative measurements.

Table 3.6 presents the comparison of MAE in position and velocity for each tracking scenario, all having same error in initial state vector at the start of UKF. The initial position error is approximately 8.99 km , as we use the same initial covariance which significantly reduces depending on the case configuration. In Case T, corresponding to the monostatic scenario, the position MAE decreases to 1.33 km , indicating a substantial improvement in tracking performance. Cases TE and TW also exhibit enhanced tracking accuracy, with final position MAEs of 1.23 km and 1.14 km , respectively. Notably, Case TEW, which involves a multi-bistatic configuration, achieves the most accurate result, reducing the position error to below 1 km . In contrast, Cases E and W show marginal improvement, with position MAEs of 8.57 km and 8.61 km , respectively values close to the initial error. This suggests that these configurations are more sensitive to initial covariance and less robust in terms of tracking performance. For velocity MAE, all scenarios achieve an error below 1 m/s , with the lowest values 0.8 m/s observed in Cases TE and TEW, further highlighting the effectiveness of these configurations in reducing estimation errors.

3.5.3 Mahalanobis Distance

Another metric, Mahalanobis Distance (MD) is calculated to assess the consistency of the filter and to identify potential outliers in the measurement residuals [91]. This metric incorporates the covariance of the measurement noise, enabling a more robust assessment than simple residual norms. When dealing with real data, this assessment is particularly valuable, as noise and model deviations can significantly impact filter consistency. For a given residual vector $\tilde{\mathbf{z}}_k$ and its associated measurement noise

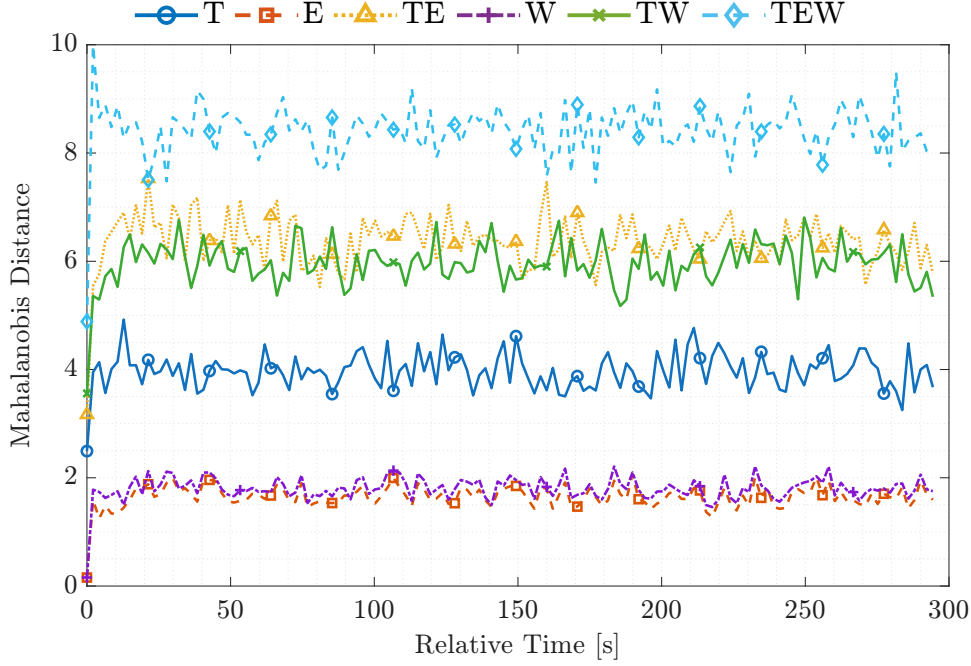


Figure 3.8: Time history of the Mahalanobis distance for different cases, showing that metric remains bounded within the expected measurement dimension over the entire observation interval.

covariance matrix $\mathbf{R}_k$, MD_k at time step k is defined as follow:

$$MD_k = \tilde{\mathbf{z}}_k^T \mathbf{R}_k^{-1} \tilde{\mathbf{z}}_k \quad (3.10)$$

Figure 3.8 presents the MD computed from the residuals over time. MD is expected to remain bounded within a statistically defined threshold for a consistent filter. Under the assumption of Gaussian measurement noise, its expected value approximates the dimension of the measurement vector. Furthermore, this consistency can be numerically verified in the last column of Table 3.3, where the dimension of the measurement is reported for various sensor configurations.

3.6 Summary

This chapter presented a comparative analysis of tracking performance using monostatic, bistatic, and multi-bistatic radar configurations for a geostationary target. Different sensor combinations and measurement types were considered within a unified Unscented Kalman Filter (UKF) framework to assess their impact on state estimation accuracy. The results demonstrate that incorporating bistatic observations from radio telescope receivers can significantly enhance tracking performance compared with a purely monostatic configuration, while multi-bistatic arrangements provide further improvements in robustness and observability. The study highlights

the trade-offs between performance, system complexity, and measurement availability, and confirms the potential of distributed radar architectures for effective monitoring of objects in the GEO regime. The analysis so far considers non-maneuvring targets, where range and Doppler measurements from a single bistatic radio telescope receiver alone are insufficient to fully constrain the orbit determination problem. Chapter 4 addresses this by developing a multi-bistatic orbit determination framework, further extending the investigation to the more demanding case of manoeuvring targets.

Chapter 4

Thrust-Aware Orbit Determination with Multi-bistatic Radio Telescope Receivers

Chapter Overview

This chapter presents the second research contribution: a thrust-aware orbit determination and tracking framework for manoeuvring satellites observed by a network of bistatic radio telescope receivers. Initial orbit determination based on trilateration provides the starting point for the UKF, with the framework further extended to retrieve non-Keplerian acceleration components, enabling the estimation of thrust-induced forces during continuous orbital manoeuvres. The simulation scenario is constructed around a realistically manoeuvring target undergoing LEO-to-GEO transfer, and the results demonstrate the improvement in position, and velocity accuracy.

4.1 Introduction

Many operational satellites perform orbital maneuvers for collision avoidance, station keeping and orbit transfer particularly during low-thrust propulsion phase [92]. Also, studies on low thrust transfer with electric propulsion have been increasing for future missions, such as during LEO to GEO transfer and nano-satellites missions [93]. These maneuvers introduce additional acceleration components that are not captured by conventional two-body or perturbation models, thereby challenging traditional orbit determination algorithms. Classical approaches to maneuver estimation rely on post-maneuver analysis, typically inferring thrust effects from variations in orbital elements such as the semi-major axis [94]. This difficulty is further compounded when observations are obtained from bistatic radar systems employing radio telescope receivers. In particular, single dish antennas provide only

bistatic range and Doppler measurements and do not provide angular information. As a result, observability is limited making IOD and subsequent tracking more challenging.

To address this limitation, this chapter introduces a thrust-aware estimation framework that extends the classical state vector formulation. A modified trilateration technique is developed for initial estimation of the total acceleration vector directly from synchronized range, range-rate, and range-rate-rate measurements acquired by multiple sensors. This technique is detailed in Section 4.2.2. By separating the gravitational component from the recovered acceleration, an initial estimate of the thrust vector is obtained. This estimate is then incorporated into an augmented 9×1 state vector within an UKF tracking framework. The proposed methodology enables simultaneous estimation of position, velocity, and thrust, thereby improving convergence and stability during continuous maneuver scenarios. The performance of the proposed approach is assessed through Monte Carlo simulations conducted under constant tangential thrust conditions for a LEO-to-GEO transfer mission. The obtained results are evaluated in terms of Root Mean Square Error (RMSE) and the accuracy of the recovered Keplerian parameters.

4.2 Initial Orbit Determination

Different sensor modalities provide different sets of observables. Optical sensors typically provide angular-only measurements, such as right ascension and declination. Monostatic radars can provide four primary observables: range, range rate, azimuth, and elevation. In contrast, radio telescopes employed as bistatic receivers are generally treated as providing range and Doppler, that is, range rate, as primary observables, depending on the processing chain and system configuration.

4.2.1 Traditional IOD Methods

For space object tracking, these observables must be converted into an estimate of the target state vector, which can then be refined through sequential filtering. Angular-only measurements are commonly processed using classical initial orbit determination techniques such as the Laplace and Gauss methods. Radar-based measurements can be converted into an initial state using approaches such as site-track processing or three-observation methods such as Gibbs or Herrick–Gibbs, which exploit the geometry and the time separation between successive observations. Comprehensive treatments of these classical methods can be found in standard astrodynamics references [88], [95]. However, when only range and range-rate measurements are available from multiple spatially separated sensors, trilateration provides an effective alternative for estimating the target position and velocity at a given epoch [88], [96]. This approach is also widely employed in bistatic passive radar systems for tracking targets in Cartesian coordinates. In passive radar configurations, multiple illuminators of opportunity typically illuminate the scene while a common

receiver collects the scattered signals. By exploiting the bistatic geometry between the transmitters, receiver, and target, it is possible to estimate the target location.

Recent advancements in receiver systems and processing techniques enable additional information to be extracted from the received signal, including the time derivative of Doppler, which corresponds to range-rate-rate. This section first reviews the classical trilateration formulation, which estimates position and velocity, and then introduces a new set of equations that incorporates range-rate-rate to recover the target acceleration. This acceleration estimate is subsequently used to form an initial thrust estimate, which is critical for improving convergence and stability in thrust-aware tracking frameworks.

4.2.2 Method of Trilateration

Trilateration is an initial orbit determination approach that estimates the target state using time-synchronized measurements acquired from multiple spatially separated sensors. In its classical form, the method exploits slant range ρ and range rate $\dot{\rho}$ observations to determine the position and velocity of a space object at a common epoch. At least three sensors are required to uniquely recover the three-dimensional position and velocity, assuming independent line-of-sight geometries.

A key requirement of trilateration is that the measurements used in the solution correspond to the same time instant. When truly simultaneous measurements are available, the initial solution can be obtained in closed form without iterative refinement. The following subsection presents the mathematical formulation of the trilateration method used in this work. All vectors are expressed in the ECI frame.

Position Vector Estimation

As illustrated in Figure 4.1, let the target position vector be denoted by $\mathbf{r}$, and the position vector of the i -th sensor site by $\mathbf{r}_{site,i}$. The slant-range vector between the sensor and the target is

$$\boldsymbol{\rho}_i = \mathbf{r} - \mathbf{r}_{site,i}. \quad (4.1)$$

Taking the squared magnitude of (4.1) yields

$$\rho_i^2 = \mathbf{r} \cdot \mathbf{r} - 2\mathbf{r} \cdot \mathbf{r}_{site,i} + \mathbf{r}_{site,i} \cdot \mathbf{r}_{site,i}, \quad i = 1, 2, 3. \quad (4.2)$$

Since the measurements are assumed to be obtained at the same epoch, the target position vector $\mathbf{r}$ does not carry a sensor subscript. To eliminate the quadratic term $\mathbf{r} \cdot \mathbf{r}$, the equation corresponding to $i = 1$ is subtracted from those for $i = 2$ and $i = 3$. This results in the linear relations (4.3), and (4.4), given as follow:

$$-\frac{1}{2} \left[\rho_3^2 - \rho_1^2 - (\mathbf{r}_{site,3} \cdot \mathbf{r}_{site,3} - \mathbf{r}_{site,1} \cdot \mathbf{r}_{site,1}) \right] = \mathbf{r} \cdot (\mathbf{r}_{site,3} - \mathbf{r}_{site,1}), \quad (4.3)$$

$$-\frac{1}{2} \left[\rho_2^2 - \rho_1^2 - (\mathbf{r}_{site,2} \cdot \mathbf{r}_{site,2} - \mathbf{r}_{site,1} \cdot \mathbf{r}_{site,1}) \right] = \mathbf{r} \cdot (\mathbf{r}_{site,2} - \mathbf{r}_{site,1}). \quad (4.4)$$

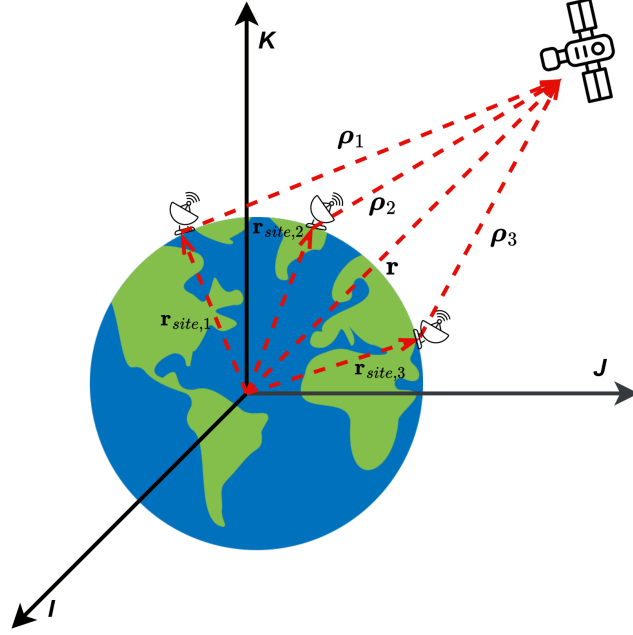


Figure 4.1: Geometry of satellite observation using multiple ground stations in the Earth-centred IJK coordinate frame. The vectors $\mathbf{r}_{\text{site},1}$, $\mathbf{r}_{\text{site},2}$, and $\mathbf{r}_{\text{site},3}$ represent the positions of the ground stations, while $\boldsymbol{\rho}_1$, $\boldsymbol{\rho}_2$, and $\boldsymbol{\rho}_3$ denote the line-of-sight vector from each station to the satellite.

For compactness, we define the left-hand sides as

$$d_3 = -\frac{1}{2} \left[\rho_3^2 - \rho_1^2 - (\mathbf{r}_{\text{site},3}^2 - \mathbf{r}_{\text{site},1}^2) \right], \quad (4.5)$$

$$d_2 = -\frac{1}{2} \left[\rho_2^2 - \rho_1^2 - (\mathbf{r}_{\text{site},2}^2 - \mathbf{r}_{\text{site},1}^2) \right]. \quad (4.6)$$

Expanding the dot products in (4.3), and (4.4) in component form,

$$d_3 = (r_{\text{site}3I} - r_{\text{site}1I})r_I + (r_{\text{site}3J} - r_{\text{site}1J})r_J + (r_{\text{site}3K} - r_{\text{site}1K})r_K, \quad (4.7)$$

$$d_2 = (r_{\text{site}2I} - r_{\text{site}1I})r_I + (r_{\text{site}2J} - r_{\text{site}1J})r_J + (r_{\text{site}2K} - r_{\text{site}1K})r_K. \quad (4.8)$$

As we can see (4.7), and (4.8) are linear in (r_I, r_J, r_K) . To obtain an explicit expression for $\mathbf{r}$, the unknown components are eliminated by forming linear combinations. In particular, (4.7) is multiplied by $(r_{\text{site}2J} - r_{\text{site}1J})$ and (4.8) is multiplied by $(r_{\text{site}3J} - r_{\text{site}1J})$, subtracting the two eliminates the r_J term and yields a relation between r_I and r_K . A similar combination is used to eliminate r_K and obtain a relation between r_I and r_J . Since the resulting expressions are lengthy, intermediate quantities (D, a_1, a_3) are introduced to simplify the notation.

$$D = (r_{\text{site}3K} - r_{\text{site}1K})(r_{\text{site}2J} - r_{\text{site}1J}) - (r_{\text{site}2K} - r_{\text{site}1K})(r_{\text{site}3J} - r_{\text{site}1J}), \quad (4.9)$$

$$a_1 = \frac{(r_{site2I} - r_{site1I})(r_{site3J} - r_{site1J}) - (r_{site3I} - r_{site1I})(r_{site2J} - r_{site1J})}{D}, \quad (4.10)$$

$$a_3 = \frac{(r_{site2I} - r_{site1I})(r_{site3K} - r_{site1K}) - (r_{site3I} - r_{site1I})(r_{site2K} - r_{site1K})}{-D}. \quad (4.11)$$

Putting all together, the components of the position vector can then be expressed as

$$r_J = a_3 r_I + a_4, \quad (4.12)$$

$$r_K = a_1 r_I + a_2, \quad (4.13)$$

where a_2 and a_4 are functions of d_2 and d_3 obtained from the same elimination process. Substituting these expressions into

$$r^2 = r_I^2 + r_J^2 + r_K^2 \quad (4.14)$$

and inserting into the original slant-range equation for $i = 1$ yields a quadratic equation in r_I

$$Ar_I^2 + Br_I + C = 0, \quad (4.15)$$

where the coefficients A , B , and C depend on the previously defined parameters.

The quadratic equation produces two possible solutions. The physically meaningful solution is selected by imposing a geometric visibility constraint. Specifically, the angle between the site position vector and the slant-range vector must satisfy

$$\cos(\theta) = \frac{\mathbf{r}_{site,1} \cdot \boldsymbol{\rho}_1}{\|\mathbf{r}_{site,1}\| \|\boldsymbol{\rho}_1\|}, \quad (4.16)$$

and only the solution corresponding to a physically valid line-of-sight configuration is retained.

Once r_I is determined, r_J and r_K are obtained from the linear relations above ((4.12), and (4.13)), thereby determining the target position vector at the measurement epoch. The next subsection derives the velocity vector using the corresponding range-rate relations.

Velocity Vector Estimation

The velocity vector is obtained by differentiating the slant-range relation with respect to time. Starting from (4.1), taking the time derivative yields

$$\dot{\boldsymbol{\rho}}_i = \dot{\mathbf{r}} - \dot{\mathbf{r}}_{site,i}, \quad (4.17)$$

where $\dot{\mathbf{r}}$ denotes the target velocity and $\dot{\mathbf{r}}_{site,i}$ represents the velocity of the i -th sensor in the ECI frame.

Taking the dot product of $\boldsymbol{\rho}_i$ with $\dot{\boldsymbol{\rho}}_i$ gives

$$\dot{\boldsymbol{\rho}}_i \cdot \boldsymbol{\rho}_i = (\dot{\mathbf{r}} - \dot{\mathbf{r}}_{site,i}) \cdot \boldsymbol{\rho}_i. \quad (4.18)$$

Since

$$\dot{\boldsymbol{\rho}}_i \cdot \boldsymbol{\rho}_i = \rho_i \dot{\rho}_i, \quad (4.19)$$

substituting into (4.18) yields

$$\rho_i \dot{\rho}_i = \dot{\mathbf{r}} \cdot \boldsymbol{\rho}_i - \dot{\mathbf{r}}_{site,i} \cdot \boldsymbol{\rho}_i. \quad (4.20)$$

Rearranging to isolate the target velocity term,

$$\dot{\mathbf{r}} \cdot \boldsymbol{\rho}_i = \rho_i \dot{\rho}_i + \dot{\mathbf{r}}_{site,i} \cdot \boldsymbol{\rho}_i. \quad (4.21)$$

For compactness, we define

$$M_i = \rho_i \dot{\rho}_i + \dot{\mathbf{r}}_{site,i} \cdot \boldsymbol{\rho}_i. \quad (4.22)$$

Equation (4.21) then becomes

$$\dot{\mathbf{r}} \cdot \boldsymbol{\rho}_i = M_i, \quad i = 1, 2, 3. \quad (4.23)$$

Collecting the three equations in matrix form, define

$$E = \begin{bmatrix} \boldsymbol{\rho}_1^T \\ \boldsymbol{\rho}_2^T \\ \boldsymbol{\rho}_3^T \end{bmatrix} = \begin{bmatrix} \rho_{1I} & \rho_{1J} & \rho_{1K} \\ \rho_{2I} & \rho_{2J} & \rho_{2K} \\ \rho_{3I} & \rho_{3J} & \rho_{3K} \end{bmatrix}, \quad (4.24)$$

and

$$\mathbf{M} = \begin{bmatrix} M_1 \\ M_2 \\ M_3 \end{bmatrix}. \quad (4.25)$$

The velocity vector can then be obtained by solving the linear system

$$\dot{\mathbf{r}} = E^{-1} \mathbf{M} \quad (4.26)$$

provided that E is non-singular.

Acceleration Vector Estimation

Having obtained the position vector $\mathbf{r}$ and velocity vector $\dot{\mathbf{r}}$ in the ECI frame, the formulation can be extended further if range-rate-rate measurements $\ddot{\rho}_i$ are available. The objective is to recover the instantaneous acceleration vector $\ddot{\mathbf{r}}$ using the previously derived relations.

Taking the time derivative of (4.21) yields

$$\ddot{\mathbf{r}} \cdot \boldsymbol{\rho}_i + \dot{\mathbf{r}} \cdot \dot{\boldsymbol{\rho}}_i = \rho_i \ddot{\rho}_i + \dot{\rho}_i \dot{\rho}_i + \ddot{\mathbf{r}}_{site,i} \cdot \boldsymbol{\rho}_i + \dot{\mathbf{r}}_{site,i} \cdot \dot{\boldsymbol{\rho}}_i \quad (4.27)$$

Here, $\ddot{\mathbf{r}}_{site,i}$ represents the acceleration vector of sensor location in the ECI system. Separating out the term of the acceleration vector of satellite and defining N_i with known variables for compactness

$$N_i = \rho_i \ddot{\rho}_i + \dot{\rho}_i^2 + \ddot{\mathbf{r}}_{site,i} \cdot \boldsymbol{\rho}_i + \dot{\mathbf{r}}_{site,i} \cdot \dot{\boldsymbol{\rho}}_i - \dot{\mathbf{r}} \cdot \dot{\boldsymbol{\rho}}_i. \quad (4.28)$$

The relation then becomes

$$\ddot{\mathbf{r}} \cdot \boldsymbol{\rho}_i = N_i, \quad i = 1, 2, 3. \quad (4.29)$$

Stacking the three equations in matrix form,

$$E \ddot{\mathbf{r}} = \mathbf{N}, \quad (4.30)$$

where E is the same geometry matrix defined previously in (4.24) and

$$\mathbf{N} = \begin{bmatrix} N_1 \\ N_2 \\ N_3 \end{bmatrix}. \quad (4.31)$$

Provided that E is non-singular, the acceleration vector can be obtained as

$$\ddot{\mathbf{r}} = E^{-1} \mathbf{N}. \quad (4.32)$$

Thus, by incorporating range-rate-rate measurements, the classical trilateration framework is extended from position and velocity recovery to direct estimation of the instantaneous acceleration vector in the ECI frame.

4.3 Orbit Determination Using UKF

Following the modified trilateration procedure described in the previous section, an initial estimate of the position $\mathbf{r}$, velocity $\dot{\mathbf{r}}$, and acceleration $\ddot{\mathbf{r}}$ is obtained at a common epoch. While this closed-form solution provides an instantaneous state estimate, continuous tracking requires a recursive estimation framework capable of propagating and updating the state in the presence of non-linear dynamics and measurement noise.

For this purpose, an Unscented Kalman Filter is used to refine the estimated orbit and improve the accuracy of the state solution. Compared to the Extended Kalman Filter (EKF), which relies on first-order linearization of the non-linear dynamics, the UKF propagates sigma points through the non-linear system directly. To achieve this, Julier and Uhlmann developed the Unscented Transform (UT), in which a set of deterministically chosen sigma points is used to capture the statistical properties of the initial estimate under a non-linear transformation. Once propagated through the non-linear function, these sigma points are then used to recompute the mean and covariance of the transformed distribution [97]. This approach mitigates errors

associated with linear approximations and improves robustness especially during manoeuvring conditions.

To enable real-time thrust estimation, the classical 6×1 Cartesian state vector is augmented to include the thrust acceleration components. The spacecraft state vector is defined as

$$\hat{\mathbf{x}} = [r_I, r_J, r_K, v_I, v_J, v_K, a_{th,I}, a_{th,J}, a_{th,K}]^T. \quad (4.33)$$

The first six components represent the position and velocity in the J2000 inertial frame, while the last three components correspond to the thrust acceleration expressed in the same coordinate system. Assuming a two-body gravitational model with continuous thrust acceleration, the state dynamics are given by

$$\dot{\hat{\mathbf{x}}} = \left[v_I, v_J, v_K, -\frac{\mu r_I}{\|\mathbf{r}\|^3} + a_{th,I}, -\frac{\mu r_J}{\|\mathbf{r}\|^3} + a_{th,J}, -\frac{\mu r_K}{\|\mathbf{r}\|^3} + a_{th,K}, 0, 0, 0 \right]^T, \quad (4.34)$$

where μ denotes the Earth's gravitational parameter and $\|\mathbf{r}\|$ represents the magnitude of the position vector. The thrust acceleration is modelled as constant over the short propagation interval, which implies

$$\dot{\mathbf{a}}_{th} = \mathbf{0}. \quad (4.35)$$

This modelling assumption allows the filter to estimate thrust as an additional acceleration component that accounts for non-gravitational forces and maneuver execution. To initialize the filter, we need full state vector $\hat{\mathbf{x}}_0$ which is outcome of modified trilateration method discussed in Section 4.2.2. An important point to note here is that trilateration IOD method only provides the total acceleration vector $\ddot{\mathbf{r}}$. By removing the gravitational component from $\ddot{\mathbf{r}}$, an initial estimate of the thrust acceleration can be formed with the help of (4.36),

$$\mathbf{a}_{th} = \ddot{\mathbf{r}} - \frac{-\mu \mathbf{r}}{\|\mathbf{r}\|^3}. \quad (4.36)$$

The IOD state vector $\hat{\mathbf{x}}_0$ and its covariance $\hat{\mathbf{P}}_0$ undergo UKF processing, numerically propagating to subsequent measurement [98]. In addition, the measurement vector $\hat{\mathbf{y}}_i$ is defined as a 9×1 vector obtained by combining the measurements collected from all three sensors, as given in (4.37). The corresponding measurement covariance matrix is denoted by $\mathbf{R}_i$, which is determined from the assumed system accuracy, following the same approach discussed in Section 3.4.2. The detailed processing for UKF is provided in Algorithm 1.

$$\hat{\mathbf{y}}_i = [\rho_1 \ \rho_2 \ \rho_3 \ \dot{\rho}_1 \ \dot{\rho}_2 \ \dot{\rho}_3 \ \ddot{\rho}_1 \ \ddot{\rho}_2 \ \ddot{\rho}_3]^T \quad (4.37)$$

The following section presents the simulation scenario adopted to assess the performance of the proposed initial orbit determination and tracking framework under realistic operational conditions.

Algorithm 1 Unscented Kalman Filter [98].

Given: scaling parameter κ , mean weights $w_m^{(j)}$, and covariance weights $w_c^{(j)}$ for $j = 1, \dots, 2n$

1. Define or update previous reference: $\hat{\mathbf{P}}_0, \hat{\mathbf{x}}_0$.
2. Read in the next observation: $t_i, \mathbf{y}_i, \mathbf{R}_i$.
3. Perform decomposition with cholesky decomposition

$$\bar{\mathbf{P}}_{i-1} = \mathbf{A}^T \mathbf{A}$$

and denote $\mathbf{a}^{(j)}$ as column $j = 1, \dots, n$ of $\mathbf{A}$.

4. Calculate sigma points:

$$\begin{aligned} \tilde{\mathbf{x}}_{i-1}^{(j)} &= \hat{\mathbf{x}}_{i-1} + \tilde{\mathbf{x}}^{(j)}, & \tilde{\mathbf{x}}^{(0)} &= \mathbf{0}, & j &= 0, \dots, 2n \\ \tilde{\mathbf{x}}^{(j)} &= \mathbf{a}^{(j)} \sqrt{n + \kappa}, & j &= 1, \dots, n & \tilde{\mathbf{x}}^{(n+j)} &= -\mathbf{a}^{(j)} \sqrt{n + \kappa}, & j &= 1, \dots, n \end{aligned}$$

5. Propagate all sigma points using numerical integration:

$$\text{Initial conditions: } \tilde{\mathbf{x}}_{i-1}^{(j)} \quad \text{Differential equation: } \dot{\mathbf{x}} = f(\mathbf{x}, t) \quad \text{Integration results: } \tilde{\mathbf{x}}_i^{(j)}$$

6. Calculate propagated state and covariance:

$$\begin{aligned} \bar{\mathbf{x}}_i &= \sum_{j=0}^{2n} w_m^{(j)} \tilde{\mathbf{x}}_i^{(j)} & \bar{\mathbf{P}}_i &= \sum_{j=0}^{2n} w_c^{(j)} \left(\tilde{\mathbf{x}}_i^{(j)} - \bar{\mathbf{x}}_i \right) \left(\tilde{\mathbf{x}}_i^{(j)} - \bar{\mathbf{x}}_i \right)^T + \mathbf{Q}_i \\ \bar{\mathbf{C}}_i &= \sum_{j=0}^{2n} w_c^{(j)} \left(\tilde{\mathbf{x}}_i^{(j)} - \hat{\mathbf{x}}_{i-1} \right) \left(\tilde{\mathbf{x}}_i^{(j)} - \bar{\mathbf{x}}_i \right)^T \end{aligned}$$

7. Transform sigma points and calculate predicted observation:

$$\tilde{\mathbf{y}}_i^{(j)} = G\left(\tilde{\mathbf{x}}_i^{(j)}, t_i\right) \quad \hat{\mathbf{y}}_i = \sum_{j=0}^{2n} w_m^{(j)} \tilde{\mathbf{y}}_i^{(j)}$$

8. Calculate predicted observation covariance, residuals, and Ψ :

$$\begin{aligned} \mathbf{S}_i &= \sum_{j=0}^{2n} w_c^{(j)} \left(\tilde{\mathbf{y}}_i^{(j)} - \hat{\mathbf{y}}_i \right) \left(\tilde{\mathbf{y}}_i^{(j)} - \hat{\mathbf{y}}_i \right)^T + \mathbf{R}_i \\ \mathbf{v}_i &= \mathbf{y}_i - \hat{\mathbf{y}}_i & \Psi_i &= \mathbf{v}_i^T (\mathbf{S}_i)^{-1} \mathbf{v}_i \end{aligned}$$

9. Use Kalman filter equations to update estimates:

$$\begin{aligned} \mathbf{V}_i &= \sum_{j=0}^{2n} w_c^{(j)} \left(\tilde{\mathbf{x}}_i^{(j)} - \bar{\mathbf{x}}_i \right) \left(\tilde{\mathbf{y}}_i^{(j)} - \hat{\mathbf{y}}_i \right)^T & \mathbf{K}_i &= \mathbf{V}_i (\mathbf{S}_i)^{-1} \\ \hat{\mathbf{x}}_i &= \bar{\mathbf{x}}_i + \mathbf{K}_i \mathbf{v}_i & \hat{\mathbf{P}}_i &= \bar{\mathbf{P}}_i - \mathbf{K}_i \mathbf{S}_i \mathbf{K}_i^T \end{aligned}$$

10. Return to Step 1 and process the next observation.
-

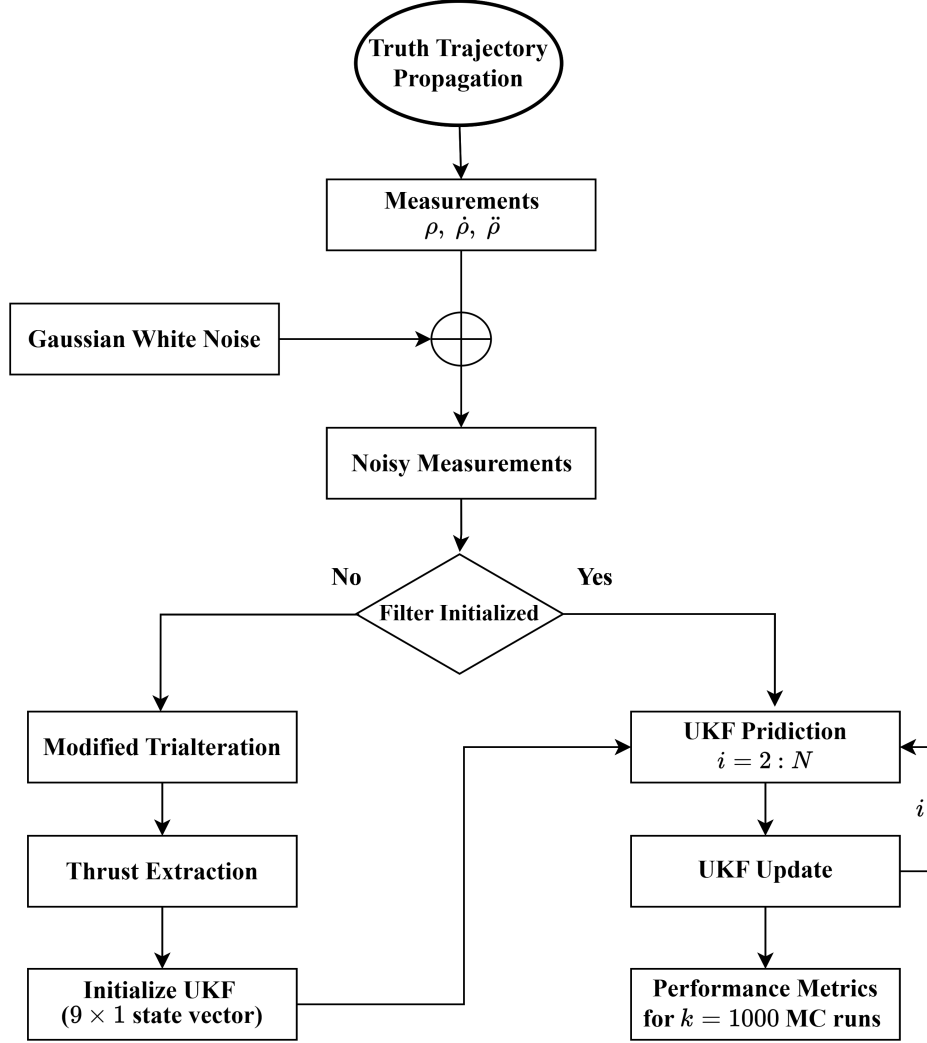


Figure 4.2: Flowchart of the thrust-aware orbit determination and tracking framework. Modified trilateration is used for initialization, after which the UKF operates recursively for $k = 2 : N$ through prediction and measurement update.

4.4 Simulation Scenario

Figure 4.2 illustrates the complete thrust-aware orbit tracking workflow adopted in this study. Firstly, a reference orbit is simulated using keplerian parameters listed in Table 4.1, where $a(m)$, e , $i(deg)$, $\Omega(deg)$, $\omega(deg)$, and $\nu(deg)$ represent the semi-major axis, eccentricity, inclination, longitude of ascending node, argument of periaapsis, and true anomaly, respectively. A constant tangential thrust of magnitude 8.89 mm/sec^2 has been considered for the analysis to validate the methodology. Figure 4.3 illustrates the reference ECI trajectory generated for a 24 h, where the

Table 4.1: Initial Keplerian orbital parameters used for the estimation process.

a (m)	e	i (deg)	Ω (deg)	ω (deg)	ν (deg)
8.3695×10^6	0.001266	51.9345	152.4280	353.7046	2.7037

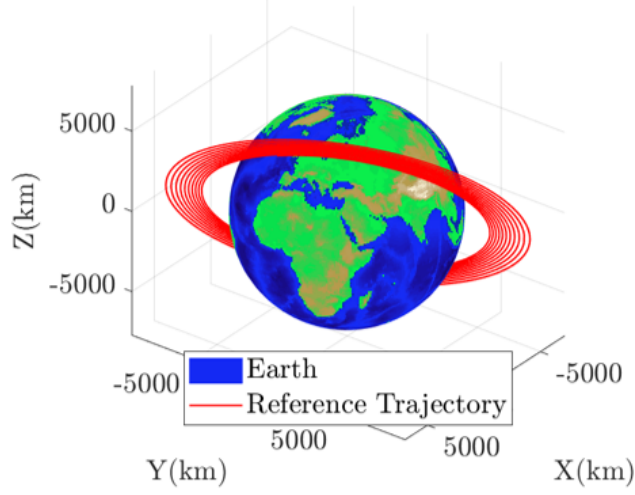


Figure 4.3: Simulated ECI trajectory of the target over a 24 h interval under a constant thrust acceleration of magnitude 8.99 mm/s^2 .

spacecraft dynamics include a constant thrust acceleration.

For this analysis, the considered sensor configuration consists of one transmitter in Pisa and three Italian radio telescope facilities, namely Medicina, the SRT, and Noto, similar to the multi-bistatic configuration presented by Cataldo *et al.* in [99]. The measurement vector $\mathbf{y}_i$ is formed by combining the observations collected at the three receiving stations. Figure 4.4, illustrating the one of the specific interval during which the target passes over the sensor locations. Based on this geometry, synthetic ground observations are generated in the local topocentric SEZ frame for each site. The measurement set comprises the slant range ρ , range rate $\dot{\rho}$, and range acceleration $\ddot{\rho}$, which are subsequently perturbed by additive zero-mean Gaussian noise to represent realistic observation uncertainty.

The framework proceeds by checking whether the filter has been initialized. If an initial state is not available, a modified trilateration method is used to obtain a first estimate of the target state. Later, UKF is initialized with a 9×1 state vector by adding the thrust components from acceleration output of modified trilateration. At each time index $i = 2, \dots, N$, the filter carries out a prediction step using the adopted process model and then performs the measurement update using the noisy observations. In this work, initial state covariance $\hat{P}_0$ is chosen to be 9×9 for the account of the new state variable, and can be seen in (4.38). In the same way, the measurement noise covariance matrix $\hat{R}_0$ has been chosen as it depends on the

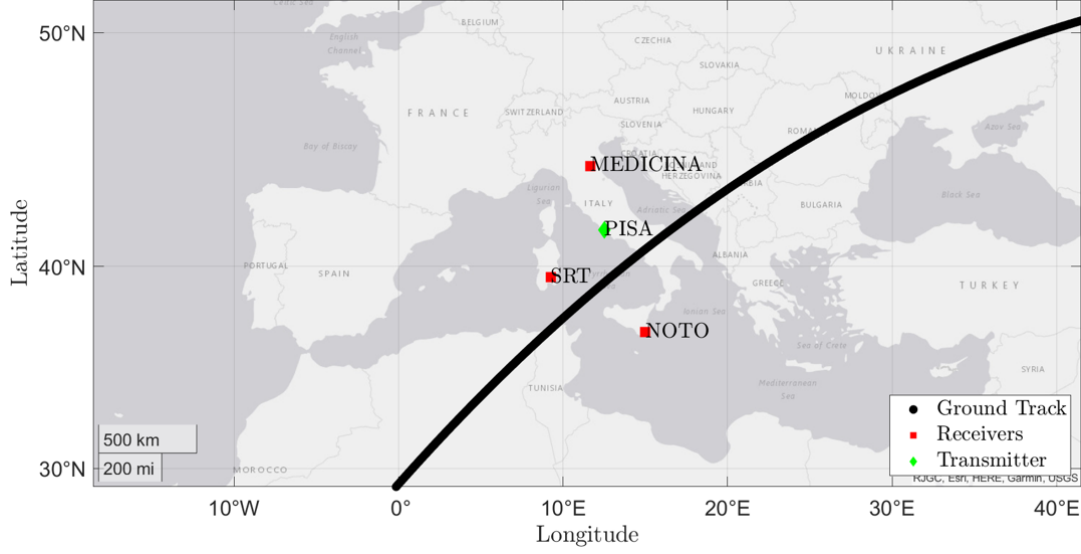


Figure 4.4: Ground track of the simulated target during passes within the visibility region of the considered sensor sites (Medicina, SRT, and Noto) with a transmitter located in Pisa.

accuracy of the measurements, and it is shown in (4.39). Likewise, process noise covariance matrix $\hat{Q}_0$ is taken to be the order of 10^{-5} , 10^{-6} , and 10^{-7} for the position, velocity, and acceleration due to thrust, respectively.

$$\hat{P}_0 = \begin{bmatrix} \underline{10^8} & \underline{0} & \underline{0} \\ \underline{0} & \underline{10^2} & \underline{0} \\ \underline{0} & \underline{0} & \underline{10^{-3}} \end{bmatrix} \quad (4.38)$$

$$\hat{R}_0 = \begin{bmatrix} \underline{10^4} & \underline{0} & \underline{0} \\ \underline{0} & \underline{1} & \underline{0} \\ \underline{0} & \underline{0} & \underline{10^{-4}} \end{bmatrix} \quad (4.39)$$

Here, the symbol $\underline{0}$ denotes the zero matrix rather than the numerical value zero. Furthermore, an integration time of 0.1 s is used for the Coherent Processing Interval (CPI) and for the propagation of the dynamic model. Finally, the performance is assessed using Monte Carlo simulations, where the full workflow is repeated for $k = 1000$ independent runs and the selected metrics are computed to characterize estimation accuracy and robustness.

4.5 Results

This section presents the performance of the proposed thrust-aware orbit determination framework. As an initial step, the modified trilateration approach is employed to obtain the IOD. The corresponding initial estimation errors are summarised in Table 4.2. It can be observed that the position errors are not uniformly distributed

Table 4.2: RMSE values of the state components obtained from the trilateration-based IOD.

r_I (m)	r_J (m)	r_K (m)	v_I (m/s)	v_J (m/s)	v_K (m/s)	$a_{th,I}$ (m/s ²)	$a_{th,J}$ (m/s ²)	$a_{th,K}$ (m/s ²)
122.90	934.14	785.21	2.23	9.22	7.78	0.0376	0.0177	0.0418

among the three components. The lowest error is obtained for the r_I component, with a value of 122.90 m, whereas the r_J and r_K components exhibit larger errors of 934.14 m and 785.21 m, respectively. A similar trend is observed for the velocity components, whose errors remain below 10 m/s for all three axes. Among them, v_I shows the smallest error of 2.23 m/s, while the largest error is associated with v_J , reaching 9.22 m/s.

For the thrust-acceleration estimates obtained with (4.36), the error magnitudes are in the order of 10^{-2} m/s². The highest error is observed for $a_{th,K}$, with a value of 0.0418 m/s², whereas the lowest error corresponds to $a_{th,J}$, equal to 0.0177 m/s². These results confirm that the modified trilateration-based initialisation provides a reasonable starting point for the subsequent thrust-aware filtering stage.

The RMSE of the estimated position, velocity, and thrust-acceleration components are illustrated in Fig. 4.5, where all errors are represented on a logarithmic scale. From Figure 4.5a, it can be seen that all exhibit a clear reduction over the observation interval. The r_J and r_K components start from 934.14 m and 785.21 m, respectively, and decrease rapidly during the early stage of filtering, eventually approaching values close to 80 m. By contrast, the r_I component starts from a comparatively smaller error of 122.90 m and further converges to below 10 m. After approximately 3 s, all three components show an almost steady trend, indicating stable convergence of the position estimate position coordinates.

A similar convergence trend is observed for the velocity components in Figure 4.5b. At the beginning, the error decreases rapidly, after which the rate of improvement becomes more gradual. The velocity RMSE reaches sub-m/s levels after approximately 2–3 s, with the v_I component converging to below 0.1 m/s. This indicates that the filter is able to reconstruct the dynamic state of the object over a small observation interval. Compared to the position estimates, the velocity components demonstrate slightly slower convergence.

The thrust-acceleration estimation results, shown in Figure 4.5c, exhibit a different behaviour. In contrast to position and velocity, the thrust-acceleration errors decrease abruptly during the initial stage and then rapidly approach a saturated level. This can be attributed to the adopted constant-thrust process model, which imposes a strong prior constraint on the system dynamics, thereby limiting the variability in the estimated thrust parameters.

Equally important, filter convergence is further assessed through the evolution of the covariance trace, following the criterion discussed in [98]. The state covariance matrix is updated at every UKF measurement update and provides a direct indica-

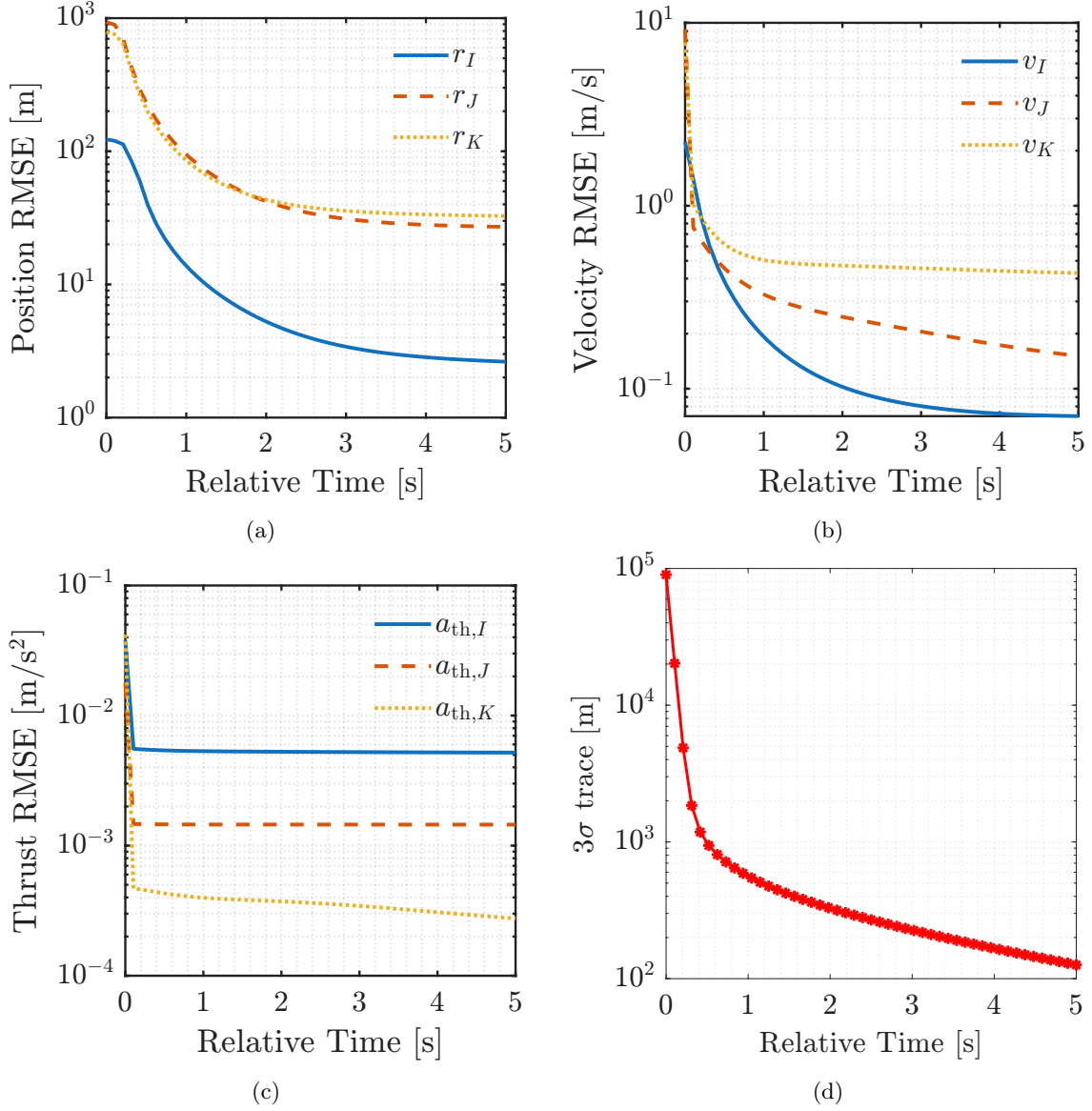


Figure 4.5: Estimation accuracy of the thrust-aware UKF over the observation interval: (a) position RMSE, (b) velocity RMSE, (c) thrust-acceleration RMSE, and (d) 3σ uncertainty from the covariance trace.

tion of the estimator uncertainty. As shown in Figure 4.5d, the 3σ covariance trace decreases monotonically with successive observations, which confirms progressive uncertainty reduction and supports convergence of the proposed tracking framework.

Additional analysis was carried out to further evaluate the accuracy of the proposed methodology by examining the errors in the Keplerian orbital parameters.

Table 4.3: Percentage error in the estimated Keplerian parameters at the end of the filtering process.

	a (m)	e	i (deg)	Ω (deg)	ω (deg)	ν (deg)
Error (%)	0.0056	5.1714	0.0012	0.0014	0.2439	0.2425

Table 4.3 summarises the calculated percentage error for each Keplerian parameter at the end of the filtering process. It can be observed that all Keplerian parameters, with the exception of the eccentricity, exhibit percentage errors below 1%, which indicates the good overall accuracy of the proposed approach. The eccentricity shows a comparatively larger error, close to 5%, suggesting that this parameter remains more sensitive to estimation uncertainties and may benefit from further refinement.

Overall, the results demonstrate that the proposed framework achieves stable convergence within a short observation window, with consistent reduction in both estimation error and associated uncertainty across all state components.

4.6 Summary

This chapter presented a Orbit determination and tracking framework incorporating thrust dynamics aimed at improving the accuracy of satellite state estimation during low-thrust transfer missions. The approach exploits measurements collected from multiple spatially separated radio telescope facilities operating in a multi-bistatic configuration. First, the conventional trilateration method was extended to provide an estimate of the instantaneous acceleration vector in addition to the position and velocity states. Subsequently, a tracking framework based on the UKF was developed, where thrust acceleration is incorporated directly into the dynamical model to enable simultaneous state and thrust estimation. The results demonstrate that integrating thrust estimation within the orbit determination process improves the reconstruction of the spacecraft trajectory.

Chapter 5

InteRFeX: Passive Radar Array for LEO SSA

Chapter Overview

This chapter presents the third research contribution, introducing InteRFeX, a radio-astronomy-inspired passive radar array designed for SDA of LEO objects. The system architecture and signal processing pipeline are described, covering digital beamforming for the formation of reference and surveillance channels, direction-of-arrival estimation for angular localisation, and cross-ambiguity function processing exploiting the dual-polarisation capability of the array. Experimental results from a dedicated observation campaign using commercial FM broadcast transmitters as illuminators of opportunity are presented and discussed, demonstrating the feasibility of the system for passive detection of LEO objects.

5.1 Introduction

Passive radar operates by exploiting existing radio frequency transmissions as sources of illumination, eliminating the need for a co-located, high-power transmitter at the receiving site [100]. A passive system detects and processes energy that has been scattered by non-cooperative targets, such as resident space objects, without altering the transmitted waveform itself. The illuminating sources in such configurations are often referred to as IoO: they may be commercial FM radio stations, digital television broadcasts (DVB-T or DVB-S). For illuminators like FM radio (88–108 MHz), low bandwidth (~ 200 kHz) produces coarse range resolution but high flux density advantageous for long-range detection [67]. DVB-T signals offer wider bandwidth (~ 8 MHz), yielding finer delay discrimination but requiring more sophisticated direct-path interference suppression given their complex modulation structure [101].

Radio telescopes arrays such as MWA, and LOFAR systems have established the

foundation for passive radar-based SSA using array-based signal processing techniques, as discussed in Chapter 2 (Sections 2.4.5 and 2.4.6). Access to such instruments is typically limited by competing astronomical programs, which restricts measurement availability and operational flexibility. In addition, conventional passive radar architectures generally employ a physically separate reference antenna to capture the direct-path signal from the transmitter, requiring precise time synchronization between reference and surveillance channels and complicating system deployment [102].

To address these limitations, this chapter introduces the InteRFeX radar array, a dedicated array-based receive only (passive) system designed for SDA. The system architecture and array configuration are described in Section 5.2. A key factor is that the system adapts radio-astronomy array concepts for surveillance operation, enabling repeatable measurements without reliance on astronomical observing schedules. The primary objective of the system is to detect, track, and catalogue objects in LEO, typically located between 250 and 2000 km above the Earth’s surface. In addition, the system is intended to support continuous monitoring of changes in the space object catalogue over time.

The InteRFeX radar array employs electronic beamforming steering by which both surveillance and reference beams are formed simultaneously to pinpoint towards target of interest and IoO. This configuration eliminates the need for an external reference antenna and synchronization while preserving coherent processing capability. In addition, the array incorporates dual orthogonal polarization receivers at each element, enabling simultaneous acquisition of horizontally and vertically polarized signals from FM transmitters. This capability enables flexible polarization combinations in post-processing and helps accommodate the mixed-polarization nature of modern FM broadcast transmissions, improving robustness of reference formation and target detection under practical operating conditions. Although recent studies have begun to consider polarization information in passive radar processing, its systematic exploitation in FM broadcast based SDA with large dual-polarized arrays remains at an early stage [77], [103], [104].

This chapter presents the experimental validation of the InteRFeX array as a passive bistatic radar for space domain awareness, based on a measurement campaign conducted in November 2025. The campaign targeted the ISS as a reference LEO object, exploiting commercial FM broadcast transmitters as IoO. A dedicated signal processing pipeline was developed to enable passive radar operation of the array, supporting simultaneous reference and surveillance channel formation, direction-of-arrival estimation, and bistatic parameter extraction. The dual-polarization capability of the array was further exploited to assess the influence of polarization pairing on detection and measurement performance.

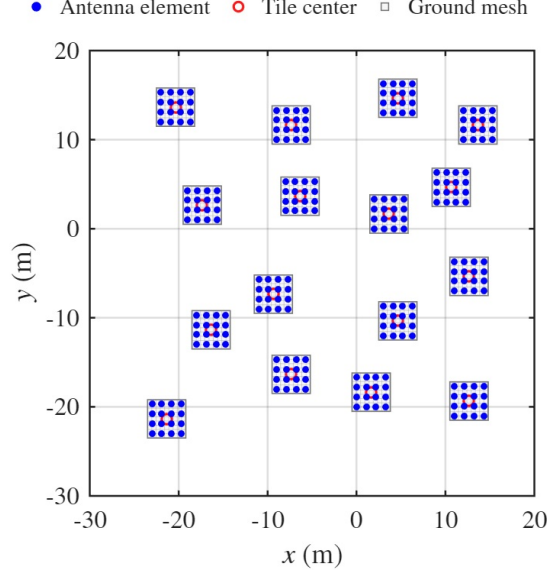


Figure 5.1: Array geometry showing the spatial distribution of Tiles. Blue dots represent the individual bow-tie antennas, whereas red circles indicate the centers of the Tiles. The grid mesh behind the tiles is represented here by grey squares.

5.2 System Description

The InterFeX Radar Array is a low-frequency passive radar array located at the Nova Systems Space Precinct in Peterborough, South Australia. It is a dedicated SDA instrument with the intention of enabling continuous data capture and monitoring of the Space Domain. InterFeX system has an operational frequency range of 70-300 MHz, and can observe in multiple operating modes, including as a radio interferometer, and, as described in this chapter, as a passive bistatic radar receiver. The array consists of 16 elements, called Tiles, situated in a randomly perturbed grid over a total area of approximately $35\text{ m} \times 35\text{ m}$. Each Tile has a design similar to that of the MWA [17], consisting of 16 dual polarization dipole antennas, laid out in a 4×4 grid with a 1.1 m separation between dipoles. The dipoles are located on a $50\text{ mm} \times 50\text{ mm}$ steel mesh base with a $5\text{ m} \times 5\text{ m}$ extent, which acts as a ground plane for the Tile. Each dipole pair contains low noise amplifiers (LNAs) and outputs X (East-West) and Y (North-South) linear polarization analogue signals. The schematic layout of the array geometry is shown in the Figure 5.1. The blue dots represent the individual bow-tie antenna elements, while the red circles denote the centers of the tiles. The ground screen mesh beneath each tile is schematically illustrated as a gray square. Figure 5.2 shows the InterFeX array as deployed at the Nova Systems Space Precinct in Peterborough, Australia. The bow-tie antenna elements and their ground screen panels are clearly visible, with the non-uniform

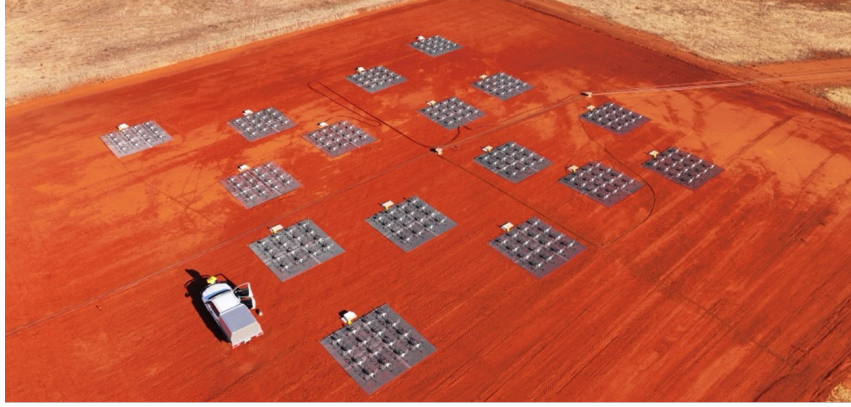


Figure 5.2: Wide-field view of the InteRFeX array at the Nova Systems Space Precinct in Peterborough, Australia. Image credit: Nova Systems¹.

spacing between tiles evident across the aperture.

A Beamformer unit adjacent to each tile sums these signals for each polarization in analogue and allows for the insertion of discrete delays to each of the 16 dipole signals, to allow the resulting maximum sensitivity of the tile to be steered in a range of directions from zenith down to approximately 30° elevation. The resulting summed X and Y polarization signals from each Tile are sent via coaxial cable to individual Airspy software defined radios (SDRs) per signal, which convert the analogue signals to digital data streams at a rate of 5 Msamp/sec as 16 bit real samples, resulting in a system bandwidth of 2.5 MHz. The resulting system output is 32 digitized data streams (16 Tiles $\times$ 2 polarizations per Tile). This multi-channel output feeds the digital beamforming stage, which enables flexible and agile electronic steering toward targets of interest. In this way, the analogue beamformer provides the first stage of spatial selectivity, while the recorded voltage data enable additional flexibility in the subsequent signal processing chain [105].

Figure 5.3a shows the normalized beam pattern produced by the 16 elements within a single Tile. Owing to the analogue beamforming performed at the tile level, the resulting beam remains relatively broad, with HPBW values of approximately 31.47° in the u -plane and 30.23° in the v -plane. In contrast, Figure 5.3b illustrates the beam pattern obtained when all 16 tiles are combined coherently. In this case, the beam becomes significantly narrower, with HPBW values of approximately 3.37° in the u -plane and 3.30° in the v -plane. This substantial beam narrowing results from the much larger effective aperture formed by the full tile array, where the inter-tile spacing is large relative to the operating wavelength. The results presented here correspond to an operating frequency of 107.9 MHz, which yields a wavelength of approximately 2.78 m, comparable to the inter-tile spacing.

¹The InteRFeX array was developed by Nova Systems in partnership with Curtin University, a node of the International Centre for Radio Astronomy Research (ICRAR). See: <https://www.novasystems.com/au>.

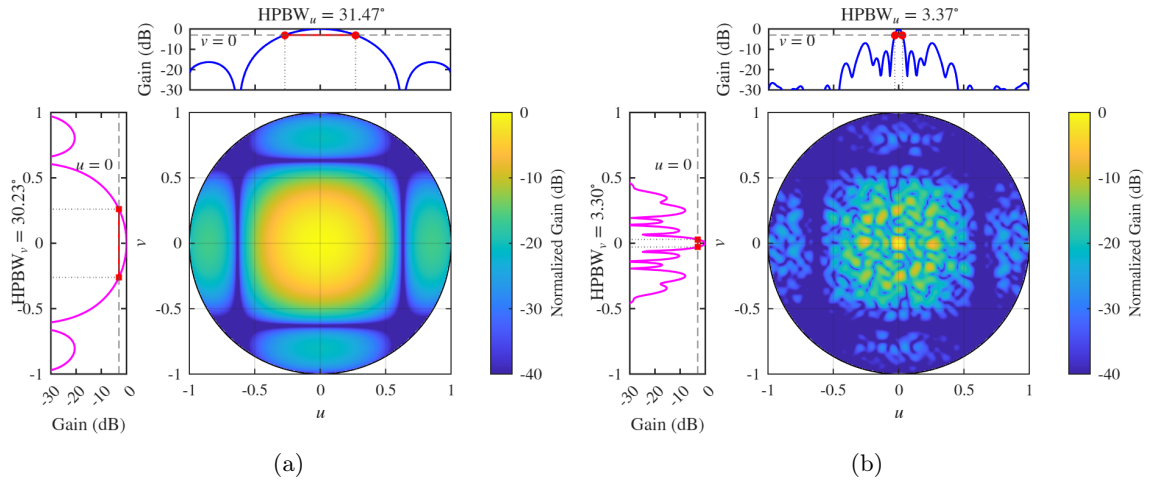


Figure 5.3: Normalized Y-polarized beam pattern comparisons in the (u,v) domain at 107.9 MHz for zenith pointing: (a) a single Tile with a (4×4) dipole array, and (b) the full 16-Tile array. The corresponding $(v=0)$ and $(u=0)$ cuts are shown in the top and left panels, respectively, highlighting the beam profiles and their HPBW.

The normalized beam response, obtained by coherently combining the signals from all 16 Tiles, is further visualized in three dimensions on the azimuth–elevation reference plane for the zenith-pointed beam, as shown in Figure 5.4. The resulting beam has a 3 dB width of approximately 3.3° , providing angular resolution suitable for precise localization and imaging. It is also worth noting that the Tiles are distributed over a substantially larger aperture in a non-uniform configuration, resulting in sparse sampling of the aperture plane. Such irregular placement suppresses the strong periodic grating lobes that would arise in a uniformly spaced array. Instead, the residual energy appears as a low-level side-lobe pedestal, a characteristic feature of low-frequency sparse arrays. Despite this, the configuration preserves a narrow main lobe while maintaining wide-band operational flexibility.

Moreover, FM radio transmitters operate in the frequency range 88–108 MHz with typical effective isotropic radiated power (EIRP) of several kilowatts, providing continuous wave illumination across the coverage area. DAB signals, operating in adjacent VHF bands (typically 110–250 MHz), offer similar advantages with well-defined signal characteristics supporting refined signal processing techniques. The operational band of InterFeX radar encompasses both FM and DAB frequencies, making these commercial broadcast signals naturally suitable as transmitters of opportunity.

5.3 Signal processing

The operation of a passive bistatic radar depends not only on the geometry of the transmitter, target, and receiver, but also on an appropriate signal processing

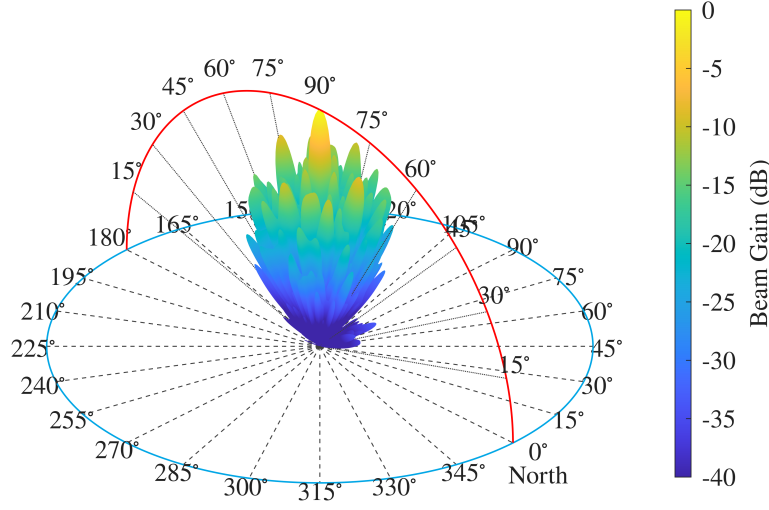


Figure 5.4: 3-D view of joint 16 Tiles normalized beam pattern pointed towards zenith.

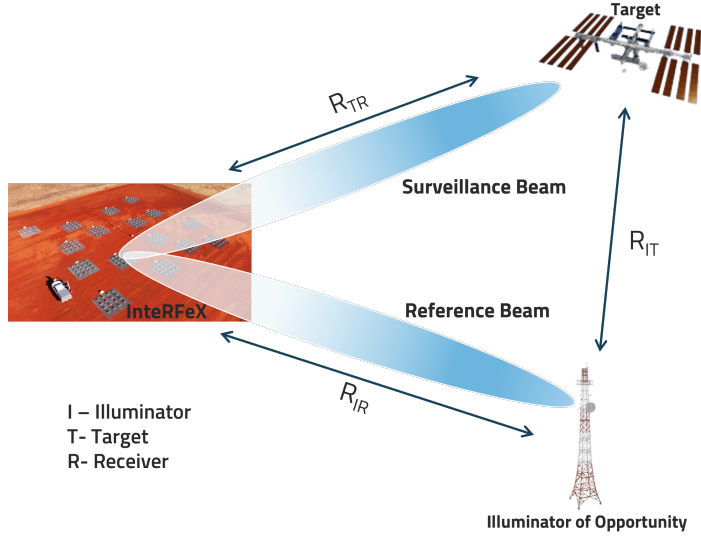


Figure 5.5: InteRFeX bistatic radar configuration for ISS observation, showing the illuminator of opportunity, receiver array, target, and reference and surveillance paths.

framework capable of extracting weak target echoes from the received signals [106]. This section presents the main processing steps considered in this work. The bistatic geometry considered in this work is illustrated in Fig. 5.5. The direct-path signal propagates from the illuminator to the InteRFeX receiver over the baseline R_{IR} , whereas the target echo follows the illuminator–target and target–receiver paths, denoted by R_{IT} and R_{TR} , respectively. The corresponding bistatic excess path length is given by

$$r_b(t) = R_{IT}(t) + R_{TR}(t) - R_{IR}. \quad (5.1)$$

The signal-processing chain begins with the hybrid analogue–digital beamforming architecture described in Section 5.2. The fixed zenith-pointed analogue beam of each 4×4 Tile defines the instantaneous field of view, while the 16 digitized Tile outputs are coherently combined in the digital domain to form simultaneous reference and surveillance beams, as shown in Fig 5.5. The reference beam uses a fixed digital steering vector corresponding to the known illuminator location, whereas the surveillance beam is steered toward the TLE-predicted target direction. Its steering vector is updated at each CPI to follow the expected target trajectory throughout the observation pass.

The illuminator of opportunity (in our case, an FM transmitter) emits a complex baseband waveform, denoted by $x(t)$. Since only the relative delay and phase evolution are relevant for subsequent correlation processing, constant amplitude attenuation and propagation phase terms are omitted, while the propagation delay and range-dependent carrier phase are explicitly preserved [106]. As the waveform propagates through the environment, it reaches the receiver via two primary paths: a direct path from the transmitter and a reflected path from the target. Based on the bistatic geometry illustrated in Fig. 5.5, the reference signal corresponding to the direct-path transmission, denoted by $x_{ref}(t)$, is given by :

$$x_{ref}(t) = x\left(t - \frac{R_{IR}}{c}\right). \quad (5.2)$$

Since this direct-path distance remains constant throughout the observation interval, the corresponding propagation phase is constant and can be absorbed into the reference-channel calibration without loss of generality. The surveillance beam, on the other hand, receives the target echo, which propagates along the bistatic path comprising the illuminator-to-target and target-to-receiver links. Accordingly, the echo signal, $x_{echo}(t)$ is modelled as :

$$x_{echo}(t) = x\left(t - \frac{R_{IT}(t) + R_{TR}(t)}{c}\right) \exp\left(-j \frac{2\pi (R_{IT}(t) + R_{TR}(t))}{\lambda}\right). \quad (5.3)$$

Since $x(t)$ represents the complex baseband waveform, the time-delay term models the propagation of the baseband envelope, whereas the exponential term represents the propagation-induced carrier phase associated with the varying bistatic path length. Following beamforming, the surveillance channel typically contains significant clutter and DPI from the reference signal. As the target echo power is considerably lower than these interference sources, a clutter removal technique, such as an adaptive filter, is applied to the surveillance channel [106]. Once the clutter is mitigated, the target’s trajectory can be characterized over a specific observation window. It is assumed that the target remains within the main lobe (3dB beamwidth) throughout a single CPI. In passive radar applications, this interval is typically a fraction of a second (0.5–1 s). The target motion over this interval is

characterized by the instantaneous bistatic excess path length, $r_b(t)$, given in (5.1). Over a single CPI, the target motion is modelled by a Taylor expansion of the instantaneous bistatic excess path length, $r_b(t)$, about the midpoint of the CPI, denoted by t_m ,

$$r_b(t) = r_b(t_m) + \left. \frac{dr_b(t)}{dt} \right|_{t=t_m} (t - t_m) + \mathcal{O}((t - t_m)^2). \quad (5.4)$$

Since the higher-order motion terms are assumed to have a negligible influence within a CPI, the expansion is truncated after the first-order term. Introducing the local time variable $\tau = t - t_m$, such that $\tau = 0$ corresponds to the CPI midpoint, gives

$$r_b(\tau) \approx R + V\tau, \quad (5.5)$$

where $R = r_b(t_m)$ is the bistatic excess path length evaluated at the CPI midpoint, and

$$V = \left. \frac{dr_b(t)}{dt} \right|_{t=t_m}, \quad (5.6)$$

is the rate of change of the bistatic excess path length with respect to time, evaluated at the CPI midpoint. The objective of the detection stage is to estimate these bistatic parameters from the received echo using the CAF, which performs a coherent correlation between the surveillance and reference channel [106]. For LEO targets, however, an exhaustive search over the entire range–Doppler space is computationally demanding due to the large search region. To reduce this computational burden, prior orbital information is incorporated into the signal processing chain. Specifically, publicly available TLE data² are propagated to the measurement epoch using the SGP4 propagator [12] to predict the nominal bistatic excess path trajectory, denoted by $\tilde{r}_b(\tau)$. This predicted trajectory is used to motion-compensate the reference signal by applying the corresponding propagation delay and range-dependent carrier phase,

$$x_{ref}^{comp}(\tau) = x_{ref} \left(\tau - \frac{\tilde{r}_b(\tau)}{c} \right) \exp \left(-j \frac{2\pi \tilde{r}_b(\tau)}{\lambda} \right). \quad (5.7)$$

The compensated reference signal therefore represents the echo expected from the TLE-predicted trajectory. Consequently, the CAF only needs to estimate the residual mismatch between the predicted and actual target motion. The residual bistatic range (ΔR) and bistatic range rate (ΔV) are defined as

$$\Delta R = R - \tilde{R}, \quad \Delta V = V - \tilde{V}, \quad (5.8)$$

where $\tilde{R}$ and $\tilde{V}$ denote the TLE-predicted bistatic excess path length and bistatic range rate, respectively. The CAF is then computed between the surveillance signal and the motion-compensated reference signal as

²TLE data was obtained from Space-Track.org, <https://www.space-track.org>

$$\chi(\Delta R, \Delta V) = \int_{-T/2}^{T/2} x_{echo}(\tau) x_{ref}^{comp*} \left(\tau - \frac{\Delta R}{c} \right) \exp \left(+j \frac{2\pi}{\lambda} \Delta V \tau \right) d\tau, \quad (5.9)$$

where T denotes the CPI and $(\cdot)^*$ represents complex conjugation. A correlation peak is obtained when the residual delay and phase compensation match the true target motion, thereby estimating the deviations from the TLE prediction. The estimated residuals can then be combined with the TLE-predicted bistatic parameters to recover the actual target trajectory. The complete signal-processing framework described in this section is summarized in Fig. 5.6.

In the proposed framework, the TLE information is used solely to initialize the motion compensation and constrain the subsequent CAF search to a local residual parameter space. Unlike pulsed radar, passive radar employing continuous-wave broadcast illuminators does not generally suffer from the classical range and Doppler ambiguities associated with pulse repetition frequency, except in certain cases where the repetitive structure of the transmitted waveform introduces measurement ambiguities [106]. Moreover, following motion compensation, the expected target response is centered near zero residual delay and Doppler, allowing the CAF search to be confined to a local residual delay–Doppler region surrounding the predicted trajectory. This suppresses spurious competing CAF peaks, thereby reducing the search space and significantly lowering the computational burden. The underlying CAF formulation, however, is not inherently dependent on prior orbital information. In the absence of prior orbital information, such as for uncatalogued space debris, the same processing framework remains applicable. Alternative search strategies, including Orbit Determination Before Detect (ODBD) and higher-order bistatic motion models, have been reported for detection without prior orbital information. These approaches typically require searching a much larger bistatic parameter space, resulting in significantly increased computational complexity [66], [107].

5.4 Experimental Results and Discussion

Initial experiments were conducted to assess the detection capability of the InteRFeX radar array, with the ISS selected as the observed object due to its large radar cross section. The measurement campaign began on 24 November 2025 at 23:32:45 UTC with a center frequency of 107.9 MHz. Because the FM transmitter bandwidth is limited to approximately 200 kHz, the achievable range resolution is relatively coarse, consistent with the inverse relationship between bandwidth and range resolution [106]. In contrast, passive radar systems can achieve comparatively high Doppler resolution because CPI can be selected flexibly.

For this experiment, the nearest available FM transmitter, 5RAM (Mt. Lofty), used as an IoO is located in the Adelaide region (34.978° S, 138.708° E), approximately 220 km from the receiver at an azimuth of 183°, with a maximum effective

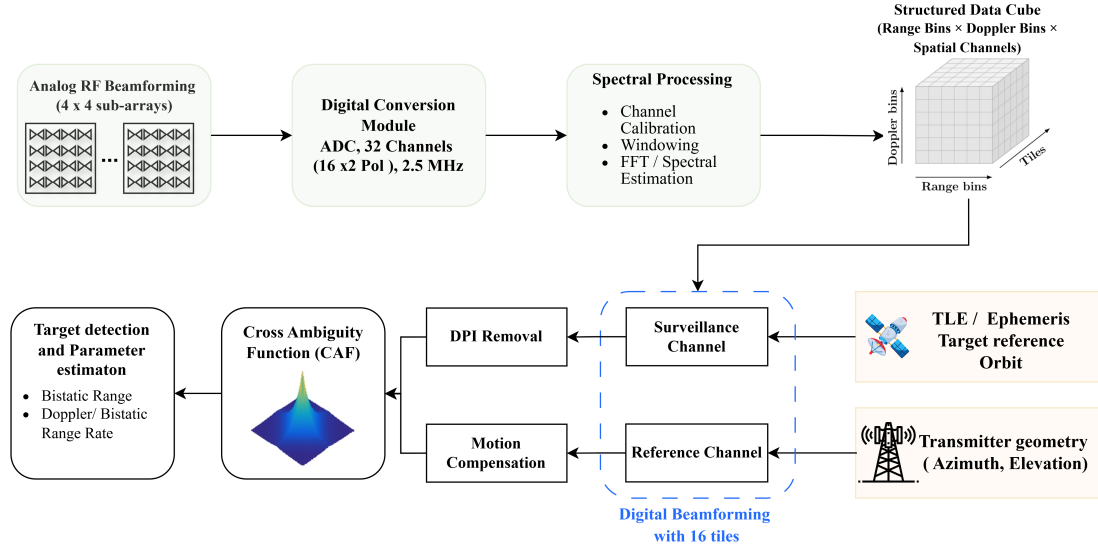


Figure 5.6: Flowchart of the proposed signal processing framework, illustrating the complete processing chain from beamforming to target parameter estimation.

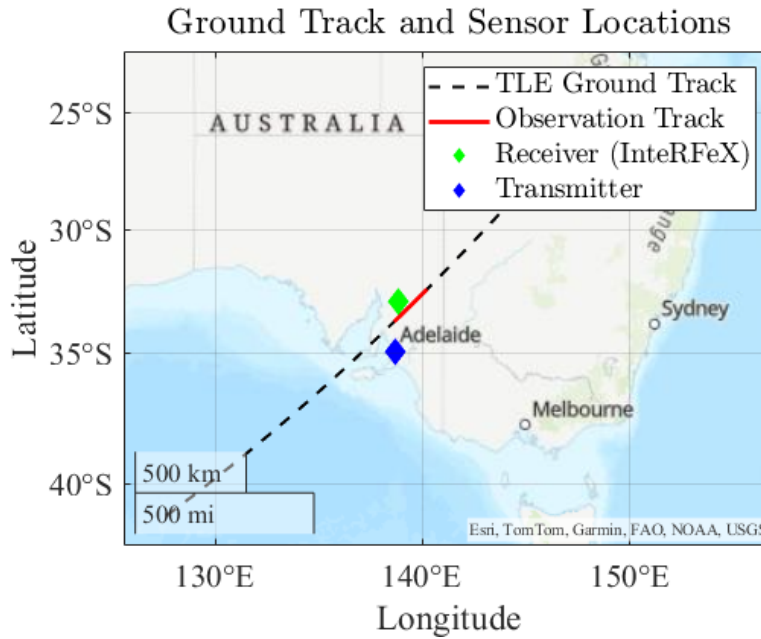


Figure 5.7: Ground track of the target over the transmitter–receiver region during the observation window.

radiated power of 20 kW. Figure 5.7 illustrates the TLE-predicted ground track of the ISS over South Australia around the measurement time. The passive radar site is indicated by a green diamond, while the transmitter location is shown by a blue

diamond, and the solid black line represents the orbital path of the ISS.

A 30-s interval, highlighted by the red curve in Figure 5.7, was selected for detailed analysis, as it corresponds to the period during which the ISS remained within the Tile field of view and yielded consistent detections. The predicted measurement parameters over the observation pass, namely elevation, azimuth, bistatic range, and bistatic range rate, are shown as functions of relative time in Figure 5.8, computed from the TLE reference trajectory. Moreover, TLE information was used to steer the surveillance beam and compensate for target motion, while angular estimation was performed independently using the received data. The resulting angular estimates were used to validate the observed trajectory and assess the angular resolution capability of InteRFEX. Detailed results are presented in the following sections.

5.4.1 Direction-of-Arrival Analysis

Several approaches exist for DoA estimation in passive radar domain, including delay-and-sum beamforming, Minimum Variance Distortionless Response (MVDR), and Multiple Signal Classification (MUSIC), each offering a different trade-off between resolution, computational complexity, and robustness [108]. In this study, MUSIC is adopted due to its high angular resolution and its capability to resolve closely spaced sources, which has also been demonstrated to be effective for space target detection in systems such as BIRALES [80].

The two-dimensional MUSIC pseudo-spectrum is evaluated and displayed in the direction cosine domain, in which coordinates are defined as

$$\begin{aligned} u &= \cos(\theta) \sin(\phi) \\ v &= \cos(\theta) \cos(\phi), \end{aligned} \tag{5.10}$$

where θ and ϕ denote the elevation and azimuth angles of arrival, respectively, measured relative to the array boresight. The unit circle $u^2 + v^2 \leq 1$ covers the entire visible hemisphere, and all physically realizable directions of arrival map to points within this boundary. The MUSIC pseudo-spectrum $P_{\text{MUSIC}}(u, v)$ is evaluated on a uniformly sampled grid across this domain and normalized to its peak value prior to display, as shown in Figure 5.9. This DoA power spectrum was computed over 1-s CPI for a snapshot recorded on 24 November 2025 at 23:43:19 UTC using the X-polarization channel.

In Figure 5.9, the red circle marker indicates the TLE-predicted direction of arrival, propagated to the epoch of the coherent processing interval via SGP4 propagator and projected into the local topocentric frame of the passive radar array. The white square marker indicates the MUSIC peak corresponding to the estimated direction of arrival of the ISS. The two markers show close spatial agreement within the direction cosine plane, confirming that the array successfully resolves the target against the background. The detection peak stands roughly 17 dB above the surrounding noise floor, with no competing peaks nearby, confirming a clean localization result for this interval. It is also worth noting that, another dominant feature

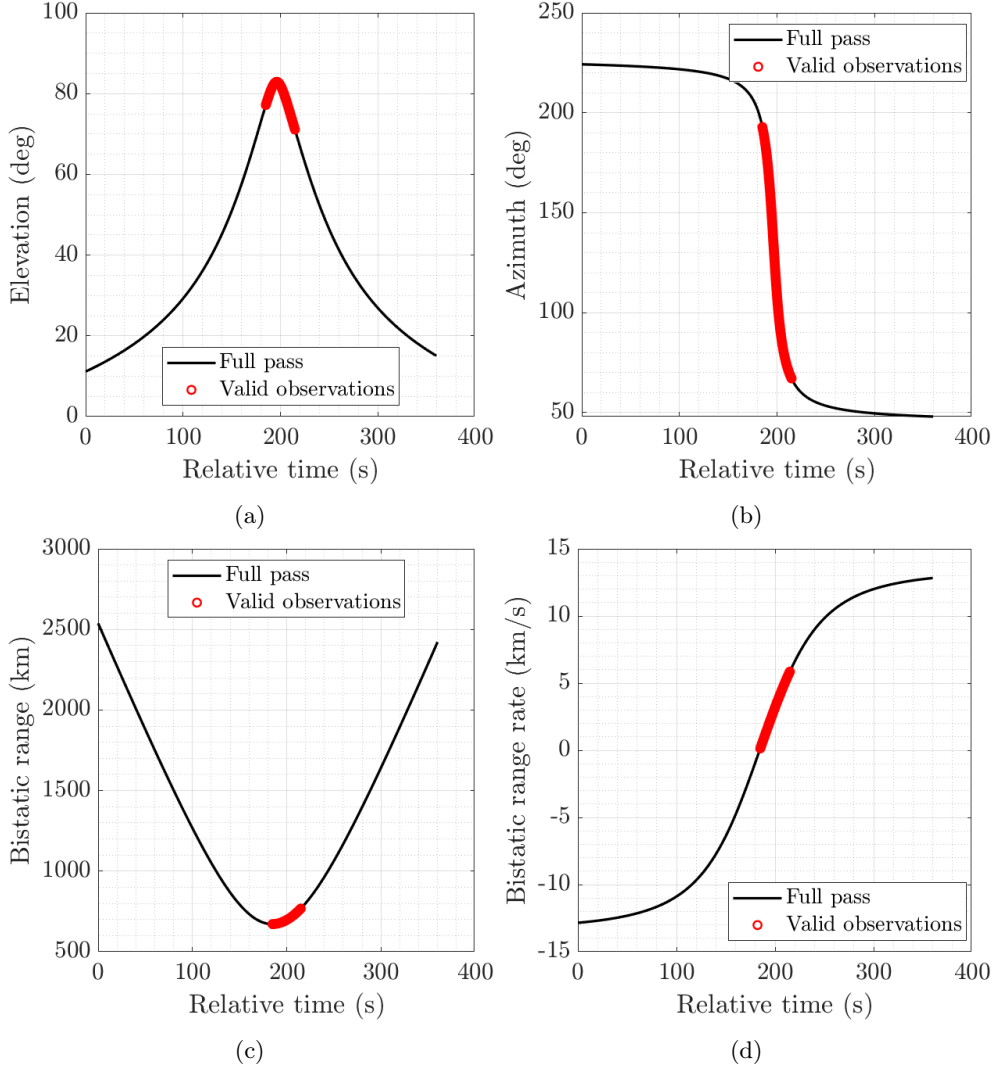


Figure 5.8: Time histories derived from the TLE-based reference pass in terms of: (a) elevation, (b) azimuth, (c) bistatic range, and (d) bistatic range rate. The black curves denote the full pass, while the red markers indicate the observed samples used in the analysis.

in the map at $u = 0.03, v = -0.18$, a brighter persistent peak is visible. This detection is consistent with the radio galaxy Centaurus A, which serves as an incidental confirmation that the array is coherently sensitive to astronomical sources at these frequencies. Furthermore, Figure 5.10 shows the MUSIC pseudo-spectrum in the $u - v$ plane at six selected frames across the ISS observation pass. In each frame, the detection peak remains in close agreement with the TLE-predicted direction, marked by the red circle, confirming that the array consistently tracks the angular trajectory of the target over the observation interval.

To track the ISS across local pass, a local-maximum detection algorithm was

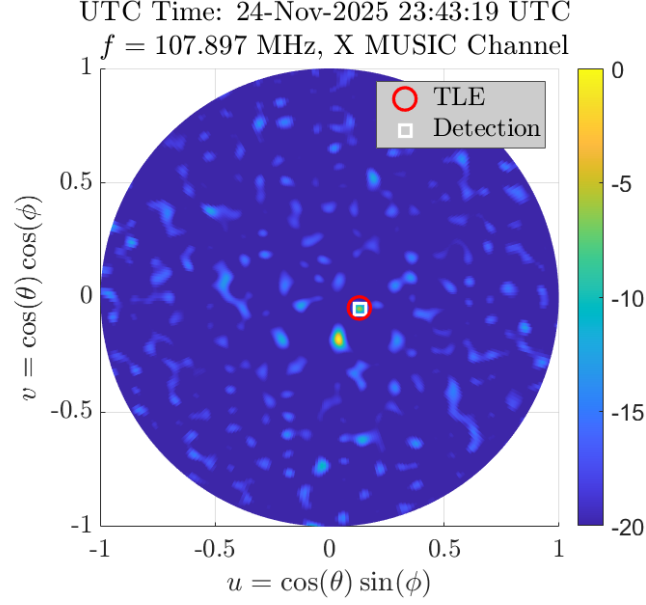


Figure 5.9: MUSIC direction-of-arrival pseudo-spectrum for the X-polarized channel. The dominant peak corresponds to the ISS, while the persistent source below and to the left of the ISS is the astronomical radio galaxy Centaurus A, as discussed in the text.

applied to successive DoA frames. The accuracy of each DoA estimate is quantified by the angular separation $\Delta\psi$ between the estimated direction of arrival and the reference direction predicted from the TLE, as defined in (5.11).

$$\Delta\psi = \arccos [\sin(el_e) \sin(el_r) + \cos(el_e) \cos(el_r) \cos(az_e - az_r)], \quad (5.11)$$

where (az_e, el_e) are the estimated azimuth and elevation obtained from the MUSIC peak and (az_r, el_r) are the corresponding TLE-derived reference values. This metric is preferred as the resulting scalar error is coordinate-frame-invariant and provides a physically meaningful measure of angular localization accuracy.

Figure 5.11 shows the angular separation $\Delta\psi$ as a function of relative time, where each point corresponds to a single DoA estimate extracted from a successive frame. The target was detected in all 30 frames within the 30-second observation window. The mean angular separation $\mu_{\Delta\psi}$ across the pass is approximately 0.45° , indicated by the black dashed line, and the $\pm 3\sigma$ bounds are shown as red dashed lines, where σ denotes the standard deviation of $\Delta\psi$ over all detected frames. The estimates remain well within the $\pm 3\sigma$ envelope throughout the observation window with a exception for single frame at $t = 26$ s, relative time. Moreover, the along-track and cross-track angular offset components, $\Delta\psi_{AT}$ and $\Delta\psi_{CT}$, are computed at each epoch by projecting the great-circle separation between the DoA estimate and the TLE reference onto the instantaneous track frame defined by the satellite's direction

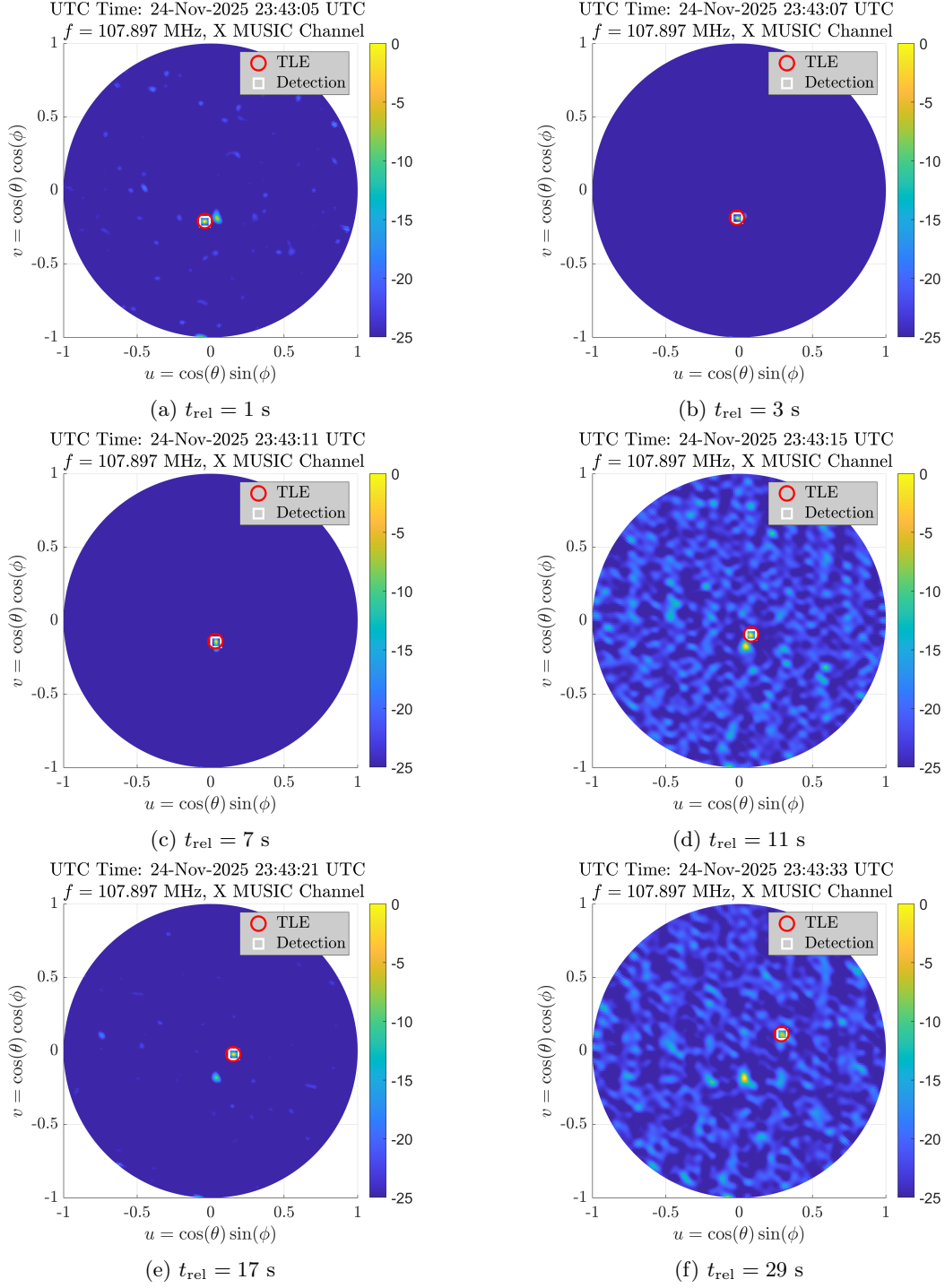


Figure 5.10: Time evolution of the MUSIC-based direction-of-arrival power map in the u - v plane for six selected relative time instants during the ISS observation pass. The red circle indicates the TLE-predicted angular position at each corresponding instant.

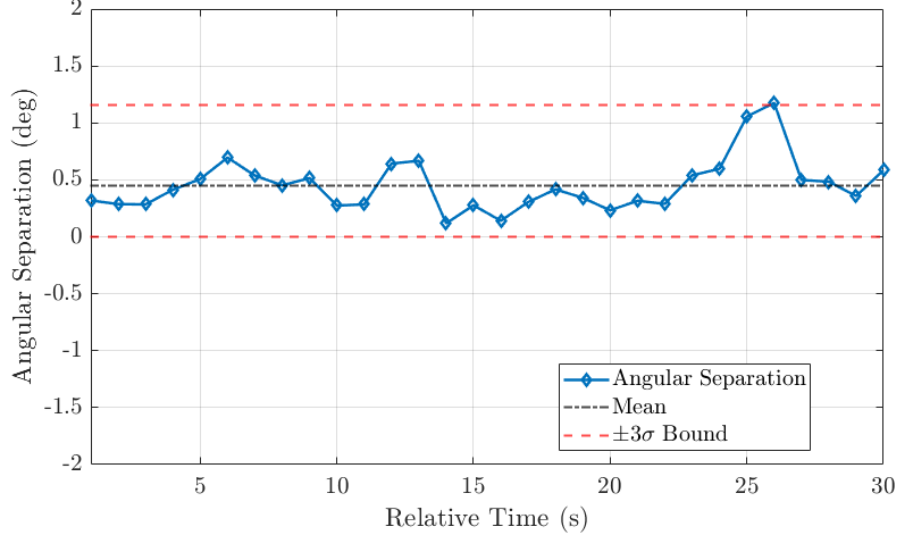


Figure 5.11: Angular separation $\Delta\psi$ between the estimated and TLE-predicted directions of arrival over a 30-second observation pass, with mean (black dashed) and $\pm 3\sigma$ bounds (red dashed) indicated.

of motion on the unit sphere. The two components are orthogonal by construction, with $\Delta\psi_{\text{AT}}$ sensitive to errors along the trajectory and $\Delta\psi_{\text{CT}}$ sensitive to errors transverse to it.

Figure 5.12a shows the temporal evolution of both components over the 30-second observation window, and Figure 5.12b shows their marginal distributions. The cross-track component exhibits a persistent negative bias of $\mu_{\Delta\psi_{\text{CT}}} \approx 0.38^\circ$ with a standard deviation $\sigma_{\Delta\psi_{\text{CT}}}$ of 0.19° , and its histogram is compact and approximately unimodal, indicating a systematic offset. Since $\Delta\psi_{\text{CT}}$ is by definition perpendicular to the satellite’s direction of motion, a timing offset cannot produce this signature, the observed bias is instead consistent with a residual phase calibration error or a small rotation in the array pointing model that displaces all DoA maxima in a fixed angular direction relative to the true track. The along-track component, in contrast, exhibits a near-zero mean of $\mu_{\Delta\psi_{\text{AT}}} \approx +0.05^\circ$, suggesting a negligible systematic timing offset between the DoA estimates and the TLE reference trajectory. However, $\Delta\psi_{\text{AT}}$ exhibits increased scatter ($\sigma_{\Delta\psi_{\text{CT}}} = 0.27^\circ$) with a notable exception near $t = 26$ s, where the offset reaches approximately $+0.9^\circ$. The localized nature of this exception, confined to a single epoch and predominantly along-track, suggests a momentary disturbance in the DoA power map rather than a systematic effect, multipath interference at that particular instant is a plausible contributing factor, though further investigation is required to confirm this. A summary of the performance metrics for the DoA analysis is provided in Table 5.1.

Taken together, the decomposition indicates that the dominant error source in

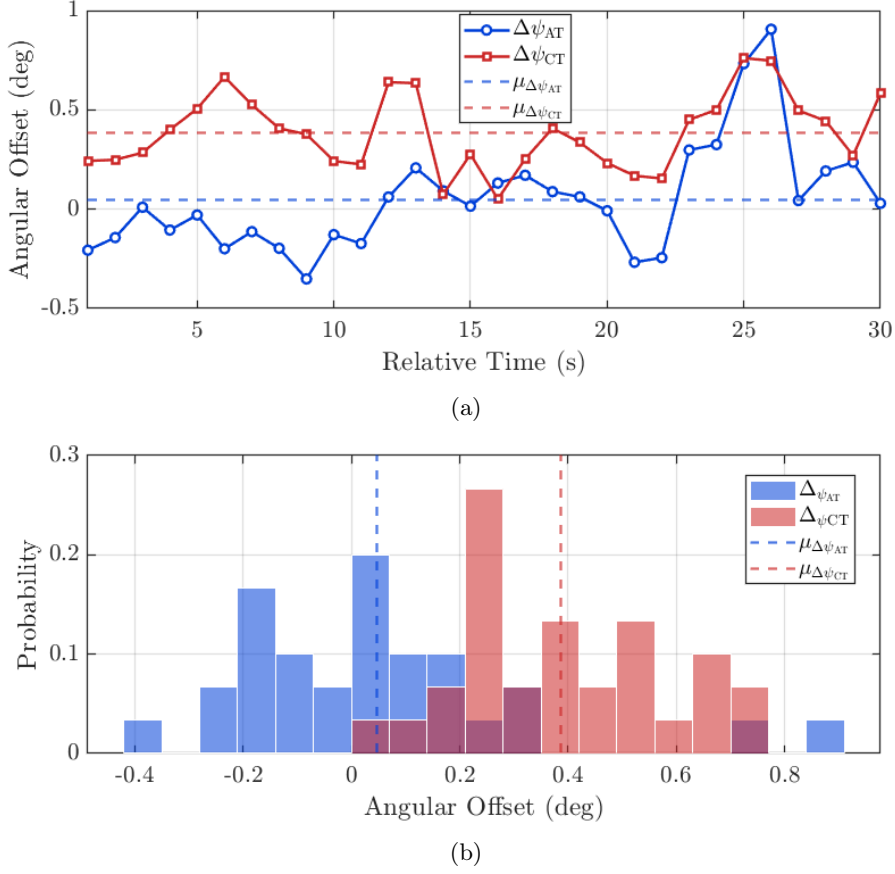


Figure 5.12: Along-track and cross-track components of the angular offset: (a) Time variation of the along-track and cross-track angular offset components over the observation interval, with dashed lines indicating the corresponding mean values, and (b) Probability distribution of the along-track and cross-track angular offset components, showing the concentration and spread of the offset components around their mean values.

Table 5.1: Summary of the MUSIC direction-of-arrival estimation performance metrics.

Metric	μ	σ
Detection rate	100%	
Angular separation $\Delta\psi$	0.45°	0.23°
Along-track offset $\Delta\psi_{AT}$	$+0.05^\circ$	0.27°
Cross-track offset $\Delta\psi_{CT}$	$+0.38^\circ$	0.19°

the current configuration is a systematic cross-track angular offset, most plausibly attributable to array phase calibration, rather than a timing or propagation-related effect. Nevertheless, the DoA estimates capture the expected angular evolution of the target over the observation window. These results demonstrate that the angular

trajectory of a LEO object can be extracted and validated with InterFeX, even without range–Doppler correlation processing. While the current results demonstrate reliable localization, adopting adaptive beamforming techniques [109], [110] and operating the array in fully coherent mode are expected to yield further improvements in angular accuracy.

5.4.2 Cross-Ambiguity Function Analysis

As described in Section 5.3, reference and surveillance beams were formed by compensating geometry-induced delays through phase adjustments, thereby increasing gain in the desired directions [111]. After beamforming, the reference signal was shifted in delay and Doppler according to the TLE-derived target parameters using (5.7), compensating the expected target motion prior to correlation. For each detected frame, CAF was computed using (5.9) over a 1-s CPI, yielding joint estimates of bistatic range and range-rate. Figure 5.13 presents the temporal evolution of the CAF in the bistatic range–range rate domain for selected time instants during the ISS observation pass. The dominant correlation peak is consistently observed in close proximity to the TLE-predicted bistatic range and range rate, marked by the red circle. The evolution across time demonstrates the stability of the detection as well as the ability of the proposed processing chain to track the target trajectory in the delay–Doppler domain.

To investigate the impact of polarization diversity, CAF processing was performed using different combinations of reference and surveillance polarization channels, using polarization pairs pq where p denotes the reference polarization and q denotes the surveillance polarization. The four polarization combinations evaluated in this work correspond to different transmit–receive polarization pairings of the horizontal (X) and vertical (Y) channels of the array. The co-polar combinations, XX and YY, receive signal energy that shares the same polarization state as the transmitted waveform, making them sensitive to targets whose scattering preserves the incident polarization. The cross-polar combinations, XY and YX, capture the depolarized component of the scattered signal, which arises from the structural geometry and surface properties of the target. For a large metallic structure such as the ISS, both co-polar and cross-polar returns are expected due to the complex multi-faceted scattering geometry of the satellite body and solar panels. The results presented here demonstrate that all four combinations are capable of detecting and localizing the target.

Figure 5.14 shows zoomed CAF maps around the expected bistatic range and range-rate of the ISS for four polarization combinations: XX, YY, XY, and YX. In each case, a localized peak is observed near the TLE-predicted position (red circle), indicating successful detection of the target in bistatic range–range-rate space. The detected peak locations (black crosses) are in close proximity to the predicted state across all polarization combinations, demonstrating that the system can exploit dual-polarization measurements to support passive detection. Although the peak

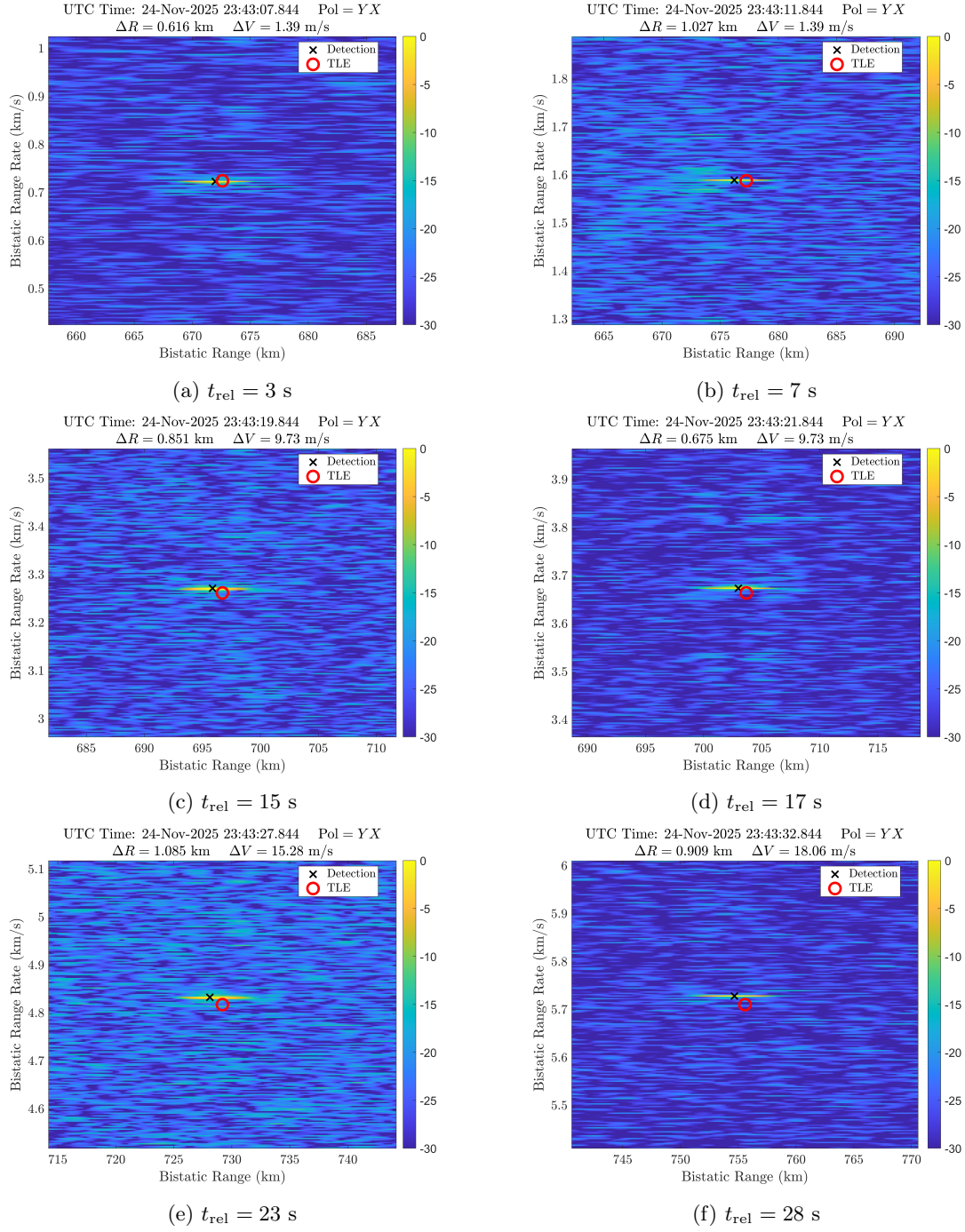


Figure 5.13: Time evolution of the CAF in the bistatic range–range rate domain for selected relative time instants during the ISS observation pass. The red circle indicates the TLE-predicted bistatic range and range rate at each corresponding instant.

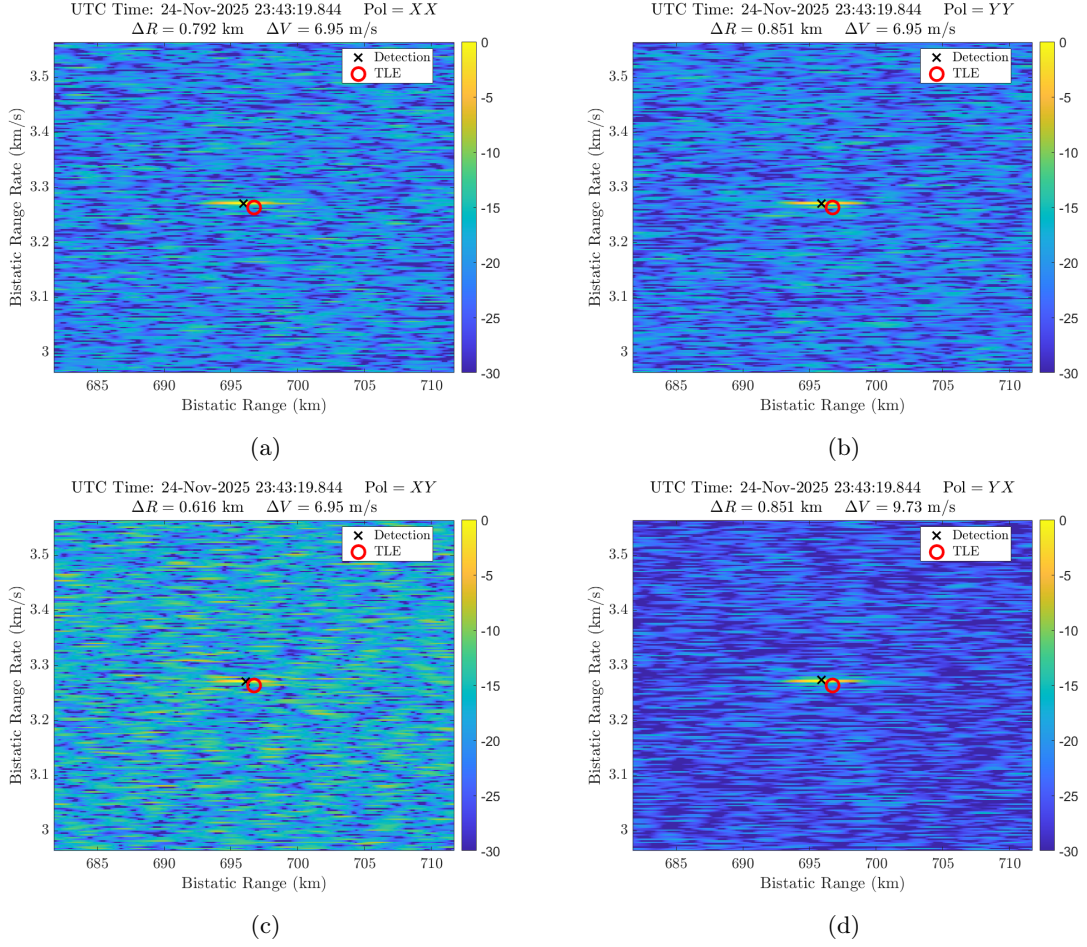


Figure 5.14: CAF zoom around the expected ISS bistatic range and range rate (red circle) for a selected timestamp, shown for different polarization combinations: (a) XX, (b) YY, (c) XY, and (d) YX.

strength and background structure vary among the polarization pairs, consistent target responses are obtained in all cases, confirming the robustness of CAF-based processing under mixed-polarization broadcast illumination. It should be noted that the CAF maps in Figure 5.14 correspond to a single snapshot acquired at 24 November 2025, 23:43:19 UTC, consistent with the DoA example (Figure 5.9) presented earlier. These plots are intended to illustrate instantaneous detection performance and polarization-dependent responses at a representative time during the pass, rather than statistical behavior over the full observation interval.

Table 5.2 summarizes the bistatic range deviation, bistatic range-rate deviation, and SNR corresponding to the CAF results shown in Fig. 5.14. These deviations are calculated with respect to the TLE-derived reference trajectory at the snapshot time of 24 November 2025, 23:43:19 UTC. The YX polarization yields the highest SNR

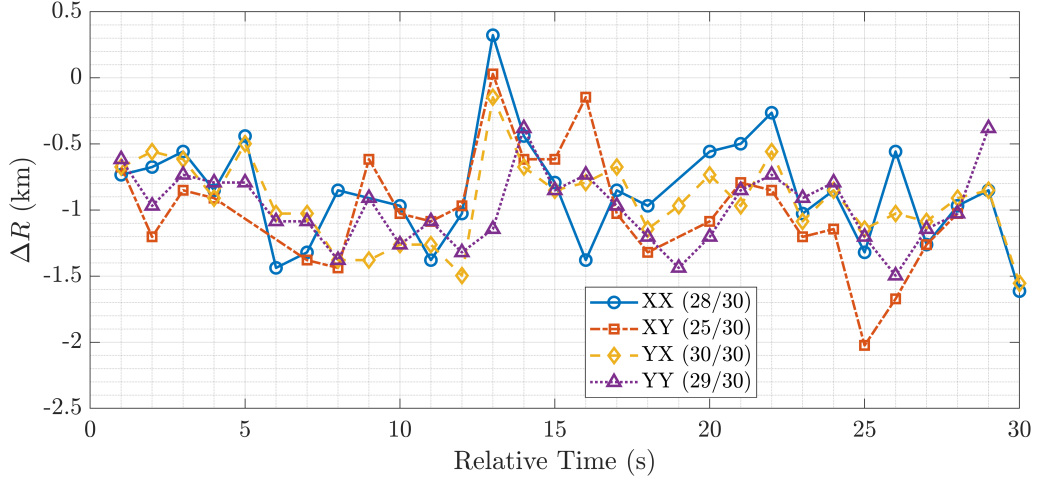
Table 5.2: Bistatic range and range-rate deviations relative to the TLE-derived reference, together with the SNRs of the four polarization channels, at 23:43:19 UTC on 24 November 2025.

Pol.	ΔR (km)	ΔV (m/s)	SNR (dB)
XX	0.792	6.95	19.70
YY	0.851	6.95	20.79
XY	0.616	6.95	16.03
YX	0.851	9.73	24.23

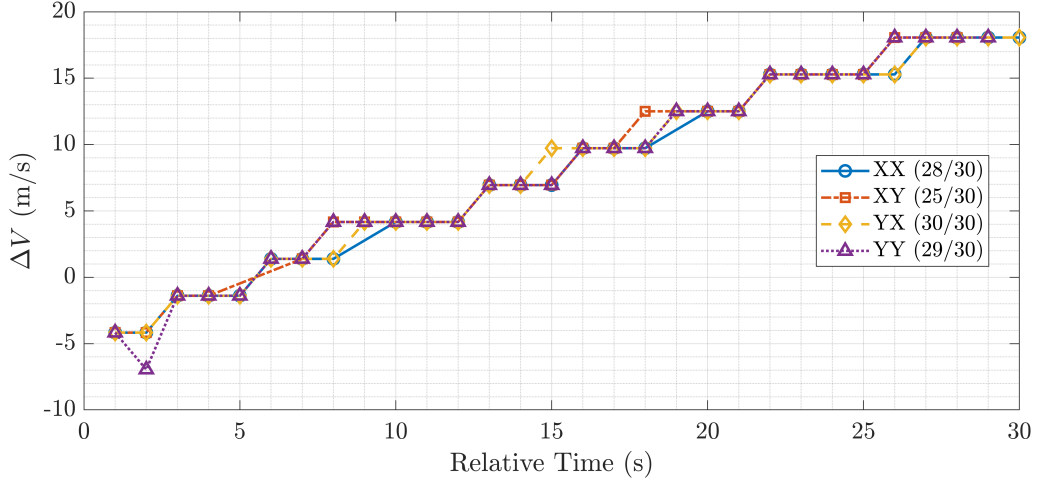
of 24.23 dB, whilst the XY combination produces the lowest at 16.03 dB, reflecting the cross-polarization isolation characteristics of the transmit-receive configuration. The XX and YY co-polar channels achieve intermediate SNR values of 19.70 dB and 20.79 dB, respectively. Moreover, ΔV is consistent across the XX, YY, and XY polarization pairs at 6.95 m/s, whilst the YX channel yields a slightly higher value of 9.73 m/s. In contrast, ΔR varies with polarization pairing. The smallest deviation is obtained for the cross-polarized XY case, whereas the YX and YX case yields the largest residual with respect to TLE of approximately 0.85 km. These differences indicate that polarization selection can influence instantaneous CAF localization performance under broadcast illumination, as it depends on target aspect geometry and propagation effects, including multipath, which affect received signal strength and residual interference.

To characterize performance beyond the instantaneous snapshot shown in Figure 5.14, CAF detections were extracted over the full 30-s observation interval for all polarization combinations. The temporal evolution of the bistatic range and range-rate deviations is shown in Fig. 5.15 for all polarization combination channels, with the detection counts indicated in the legend. The YX channel achieves the most complete coverage with all 30 detections, followed by YY with 29 out of 30, whilst the XY combination yields the lowest detection count at 25 out of 30 frames. The corresponding detection rates across all polarization channels are summarized in Table 5.3. All polarization combinations exhibit a similar temporal trend in both bistatic range and range rate deviations, though the magnitude of the deviations differs between polarization pairs.

The bistatic range deviations shown in Fig. 5.15a remains broadly negative across all channels throughout the pass, indicating a systematic under-estimation of bistatic range that is common to all polarization configurations and is therefore attributable to the TLE-based reference trajectory rather than to any polarization-specific effect. A brief reduction in the bistatic range and range-rate deviations towards zero is observed across all channels near $t \approx 12 - 13$ s, coinciding with the closest point of approach of the ISS. After this point, the trend returns to its earlier behavior, and the bistatic range gradually shifts toward more negative values as the pass progresses, which may be attributed to the increasing mismatch between the reference trajectory and the actual target trajectory.



(a)



(b)

Figure 5.15: Bistatic parameter deviations relative to the TLE-predicted reference over a 30-second observation pass for each transmit-receive polarisation pair: (a) bistatic excess range and (b) bistatic range-rate.

Figure 5.15b shows the corresponding bistatic range-rate deviation for the observation pass. In contrast to the range estimates, the range-rate measurements are highly consistent across polarization pairs, reflecting the dominant influence of CPI duration and target motion on Doppler estimation. The increasing range-rate deviation over time is likely due to residual mismatch between the TLE-based motion compensation and the true target dynamics. As can be seen in Figure 5.15b, the range rate deviation exhibits periodic step-like jumps, with each jump corresponding to a single Doppler/range rate resolution cell. For a CPI duration of 1 s at 107.9 MHz, the range rate resolution is $\Delta v = \lambda/T_{CPI} \approx 2.78 \text{ m/s}$, which is consistent

Table 5.3: Core performance metrics for different polarization channels pairs over a 30-second observation interval.

Pol	Det. (%)	RMSE _R (km)	STD _R (km)	RMSE _V (m/s)	STD _V (m/s)	Mean SNR (dB)
XX	93.33	0.953	0.416	10.88	7.35	18.44
YY	96.67	1.021	0.283	10.67	7.29	20.56
XY	83.33	1.084	0.436	10.67	7.00	18.57
YX	100.0	0.988	0.319	10.85	7.18	21.14

with step size observed in Figure 5.15b. The step-like behavior arises from the discrete Doppler grid, where the range-rate estimate shifts by one resolution cell as the true target Doppler crosses a bin boundary due to residual motion compensation errors from unaccounted high order terms. Small prediction errors accumulate over the observation interval, producing a growing Doppler offset. This effect is common when external ephemeris data are used without continuous state updating.

To quantify overall performance, statistical metrics computed over the detected frames are summarized in Table 5.3. The YX channel achieves the highest detection rate of 100%, followed by YY at 96.67%, XX at 93.33%, and XY at 83.33%, indicating that cross-polar reception in the YX configuration is most reliable for this target and geometry. In terms of bistatic range accuracy, the root mean square of the range deviations with respect to the TLE-derived reference (RMSE) ranges from 0.9 to 1.0 km across the tested configurations, with standard deviations (STD) between 0.28 km and 0.43 km. The YY configuration achieves the lowest variability (STD_R = 0.28 km), while XY shows the largest RMSE (1.08 km). It is important to note that the achievable bistatic range accuracy is fundamentally limited by the bandwidth of transmitted signals. For the FM broadcast signal used in this experiment, the effective bandwidth varies with the instantaneous programme content and can approach the nominal 200 kHz channel bandwidth. Using $\Delta R_b = c/B$, an effective bandwidth of 200 kHz corresponds to a best-case bistatic excess-path resolution of approximately 1.5 km [106]. In contrast, the range-rate RMSE is consistent across all four channels, lying between 10.67 m/s and 10.88 m/s, with corresponding STDs between 7.00 m/s and 7.35 m/s. The uniformity of the Doppler/range rate deviation across polarization channels further supports the interpretation that range-rate accuracy is governed primarily by the CPI duration and motion compensation rather than the polarization configuration.

Another metric of interest is the CAF-output target SNR across all detected frames in the 30-s observation interval. Fig. 5.16 summarizes its distribution for each reference-surveillance polarization combination using box plots, while the corresponding mean values over the complete pass segment are reported in Table 5.3. The YX combination provides the highest mean SNR of 21.14 dB, followed by YY at 20.56 dB, XX at 18.44 dB, and XY at 18.57 dB. The boxplots further show that

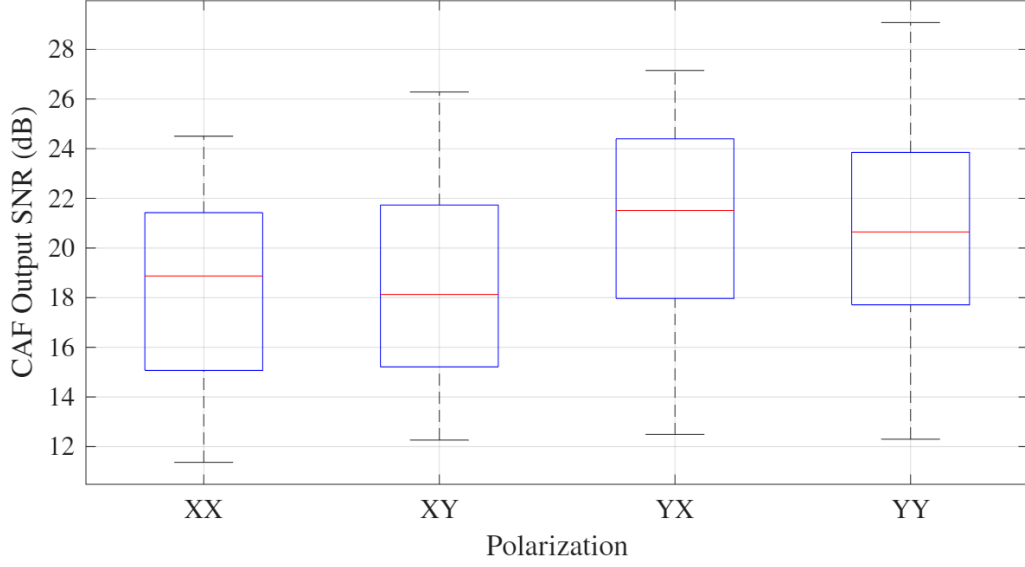


Figure 5.16: SNR distribution for each transmit-receive polarization combination over the 30-second observation pass.

YX and YY exhibit higher median SNRs, whereas XX and XY provide lower but broadly comparable distributions.

In addition to bandwidth-imposed constraints, polarization selection influences detection continuity and error stability. Configurations employing a Y-polarized reference channel (YX and YY) provide more stable tracking, with detection probability of 100 % and 96.67 % respectively, whereas the X-reference cases (XX and XY) exhibit occasional larger deviations and missed detections. This behavior may be attributed to polarization-dependent variations in received signal strength and residual interference under mixed-polarization broadcast illumination. The observed behavior is also influenced by the bistatic reflection geometry and target aspect, which modify the effective polarization coupling between the transmitter, target, and receiver, as well as by propagation effects such as multipath. Moreover, the high orbital velocity of LEO targets leads to noticeable variations in received echo power between successive CPIs, which can affect detection stability.

For the Adelaide FM transmitter, located at a baseline distance of approximately 220 km from the receiver, the ISS attains relatively high elevation angles with respect to the transmitter during portions of the pass. Under these conditions, the target may lie within lower-gain regions of the broadcast antenna pattern, reducing the effective illumination strength. Moreover, this FM broadcast transmitter in Adelaide radiates in mixed polarization to serve both horizontally polarized domestic antennas and vertically polarized vehicle antennas, distributing transmitted power across both polarization planes. As a result, all four transmit-receive polarization combinations receive illumination from the transmitter, which contributes

to the detections observed across all channels. Additionally, the long propagation path between the transmitter, target, and receiver makes the signal more sensitive to terrain obstructions and multipath reflections. These effects can weaken the received signal or cause partial cancellation, reducing the signal-to-noise ratio of the cross-correlation output and leading to occasional missed detections.

It should be emphasized that these results are preliminary. Although basic calibration procedures have been applied, refinement is ongoing, and residual biases may still be present in the reported measurements. Despite these limitations, the result analysis demonstrates that InterFeX can produce consistent bistatic as well as angular estimates for LEO targets using FM illumination. The polarization-dependent analysis presented here highlights that polarization selection can influence detection continuity under practical broadcast conditions and motivates further investigation using dual-polarization measurements. Coherent fusion of polarimetric channels has been explored in the context of passive radar and array processing [112], and represents a promising direction for improving detection reliability in space surveillance applications.

5.5 Summary

This chapter described and experimentally validated a passive radar signal processing pipeline for the InterFeX array, exploiting commercial FM transmitters as illuminators of opportunity for LEO space object detection. System performance was evaluated through MUSIC-based direction-of-arrival estimation and cross-ambiguity function processing, yielding angular localization and bistatic range and range-rate measurements of the target. The availability of dual-polarization data further enabled a polarization-dependent assessment of the detection performance. The results suggest that polarization pairing can influence detection continuity and deviations stability under practical broadcast illumination. The bistatic range-rate deviations remained broadly consistent across all polarization channels, indicating that Doppler estimation is governed primarily by the coherent processing interval and motion compensation rather than the polarization configuration. Overall, the demonstrated measurements provide a foundation for developing cost-effective passive radar systems for continuous monitoring and tracking of LEO objects, with the presented signal processing pipeline serving as a basis for enabling a dedicated passive radar mode within the InterFeX system.

Chapter 6

Physics-Aware Neural Network for Satellite Trajectory Prediction

Chapter Overview

This chapter presents the fourth research contribution: a hybrid LSTM–PINN framework for satellite trajectory prediction that embeds physical orbital constraints directly into the machine learning architecture. The chapter begins with a review of conventional orbit propagation methods and their limitations over long propagation intervals, followed by a survey of existing machine learning approaches to orbit propagation. The proposed model architecture, dataset selection criteria, and training formulation are then described. Results are compared against a stand-alone LSTM baseline and a standard numerical propagator, demonstrating that the physics-aware formulation achieves higher accuracy for long-term trajectory prediction while maintaining physical consistency.

6.1 Introduction

Orbit propagation is a fundamental component of SST, since it enables the prediction of the motion of a RSOs beyond the time instants at which observations are available. In practical surveillance and tracking scenarios, measurements are obtained only at discrete epochs, whereas the object evolves continuously under the influence of gravitational and non-gravitational forces. A propagation model is therefore required to estimate the state of the object at different time instants, allowing prediction of its future trajectory as well as reconstruction of its past motion. Thus, the orbit propagation function represents the mapping of the state vector from one epoch to another under the influence of orbital dynamics, as described by as follows:

$$\mathbf{x}(t + \Delta t) = f_{\text{OP}}(\mathbf{x}(t), \Delta t), \quad (6.1)$$

where f_{OP} denotes the orbit propagation function and Δt is the time step. Depending on whether Δt is positive or negative, the state may be propagated forward or backward in time. In this way, the propagator provides the mathematical connection between the known orbital state at a given epoch and the corresponding trajectory at later or earlier time instants. This capability is essential for several SST functions, including sensor pointing, observation planning, track maintenance, conjunction analysis, and orbit determination refinement.

A range of analytical and numerical propagators are employed to model and propagate the orbital state of satellites [98]. The SGP4 algorithm is the standard analytical propagator, that uses freely available TLE files to generate satellite ephemeris [113]. To maintain the computational efficiency, SGP4 omits higher-order perturbation terms, as the full complexity of orbital mechanics equations makes their inclusion impractical for routine propagation. In contrast, high-precision orbit propagators are numerical propagators that incorporate detailed force models, accounting for the higher-order terms omitted by SGP4 [114]. Although the numerical integration technique yields accurate orbit predictions within few meters, it requires computation of the object’s state vector for each time step increment. This results in significant computational overhead, especially over long propagation periods. Therefore, it is challenging to establish an accurate physics-based model using analytical and numerical methods and to predict satellite orbit with high accuracy and lower complexity. In this context, advanced Machine Learning (ML) algorithms have emerged as promising alternatives for predicting the trajectory of RSOs [115]. The current state-of-the-art machine learning techniques for orbit prediction are discussed in the following section.

6.2 Data-Driven Approaches to Orbit Propagation

The application of ML in orbit prediction has been an active area of research over the past decade, and considerable research effort has been devoted [85]. The study in [116], [117] utilized a Support Vector Machine (SVM) algorithm to enhance the accuracy of satellite orbit prediction by leveraging two publicly available datasets, the TLE catalogue and the International Laser Ranging Service catalogue, to validate the proposed machine-learning approach. In addition to SVMs, other supervised ML models such as Gaussian Processes (GPs) [118] and Artificial Neural Networks (ANNs) [119] have also been employed to improve orbit prediction accuracy in specific use cases. However, a key limitation of these approaches lies in their inability to effectively process sequential information. In many orbit prediction scenarios, particularly when learning to correct propagated states or forecasting future trajectories based on past behaviour, the data inherently follows a time series structure. While static ML models like SVMs, GPs, and ANNs can map input-output relationships, they do not capture temporal dependencies across consecutive orbit states. In contrast, models that are designed to learn from sequential data, such as Recurrent

Neural Networks (RNNs), are better suited for orbit prediction tasks where patterns unfold over time [120].

Among these RNNs, the LSTM network is particularly effective due to its ability to retain relevant information across long sequences and filter out noise or less relevant variations in the data [121], [122]. Recent works [120], [123] have demonstrated the applicability of such networks in sequential estimation tasks, and similar architectures like Gate Recurrent Unit (GRUs), Grid-LSTM, and Long Short-Term Transformers are also being actively explored. However, conventional ML approaches primarily focus on learning system non-linearities from data without incorporating the fundamental governing physics. This can lead to models that lack physical interpretability, and may struggle with generalization beyond the training dataset. Therefore, there is a need for hybrid modelling strategies that combine the learning capability of data-driven methods with the physical consistency of orbital dynamics.

6.3 Proposed Orbit Propagation Framework

Recently, there has been growing interest in hybrid approaches that incorporate physical modelling into neural networks, enabling the learning process to remain consistent with known physics [124], [125]. Several studies have explored the combination of machine learning techniques with physics-based models. For instance, Zhou et al.[126] proposed a hybrid orbit determination framework that integrates LSTM models with Kalman filtering to address challenges associated with continuously maneuvering spacecraft. Similarly, recent work has demonstrated that the integration of PINN with conventional machine learning models can enhance robustness and generalization in systems governed by physical laws [127].

Motivated by these developments, a hybrid orbit propagation framework based on the integration of LSTM and physics-informed neural networks is developed in this work. The proposed approach combines the temporal learning capability of LSTM networks with the physical consistency enforced by PINN, thereby enabling accurate and reliable trajectory prediction in dynamic orbital environments. The detailed mathematical formulation of the proposed framework is presented in Section 6.5. By incorporating both data-driven learning and underlying orbital dynamics, the framework aims to improve generalization performance while maintaining computational efficiency. To evaluate its effectiveness, the proposed model is compared with a standalone LSTM model as well as a conventional numerical propagator implemented in General Mission Analysis Tool (GMAT) [128].

6.4 Dataset Description and Selection Criteria

The original datasets used in this study were obtained from the International Data Analytics Olympiad (IDAO), 2020 competition, provided by the Russian Astronom-

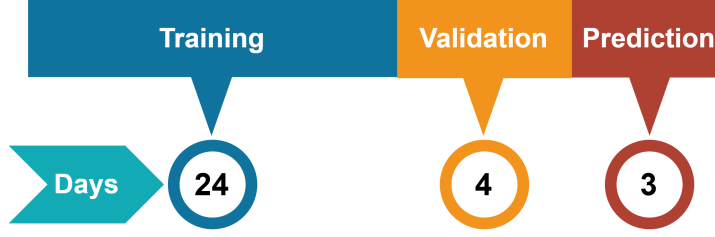


Figure 6.1: Dataset partitioning strategy, with 24 days for training, 4 days for validation, and 3 days for prediction.

ical Science Center [129]. The dataset consists of the position (x, y, z) and velocity (v_x, v_y, v_z) coordinates for 600 satellites measured in km and km/s respectively. The datasets were recorded at regular intervals during January 2014. To effectively structure the training and evaluation process, we divided the dataset as follows-

- 24 days of data are allocated for training the network, allowing the model to learn orbital patterns and dynamical behaviors.
- 4 days of data are reserved for validation, enabling performance assessment and hyper parameter tuning.
- The remaining 3 days of data are used for testing and making predictions, evaluating the model’s generalization capability on unseen data.

Figure 6.1 provides an illustration of this partitioning approach. To ensure clarity and facilitate detailed analysis, a single satellite with $ID = 0$ is considered for presenting the results from the dataset comprising 600 satellites. This allows for a focused evaluation of the model’s capability to capture and predict the trajectory of an individual object over time. Nevertheless, the proposed approach is general and can be readily extended to all satellites within the dataset.

6.5 LSTM–PINN Model Formulation

Several pre-processing steps were applied to prepare the data for training the Neural Network (NN). First, the timestamp data were converted into a numerical format for proper time-series modelling. Second, the position and velocity coordinates were normalized for stable training of NN. Finally, the raw time-series data were converted into overlapping sequences of 20-time steps (input window) for LSTM processing. In this study, we proposed a hybrid approach that integrates LSTM networks with PINNs to improve satellite trajectory prediction. The complete architecture of the proposed LSTM-PINN framework is shown in Figure 6.2. The input to the LSTM model consisted of sequential satellite state vectors, including the position (x, y, z) and velocity (v_x, v_y, v_z) coordinates. The proposed model architecture consists of an input layer that receives sequences of past satellite states,

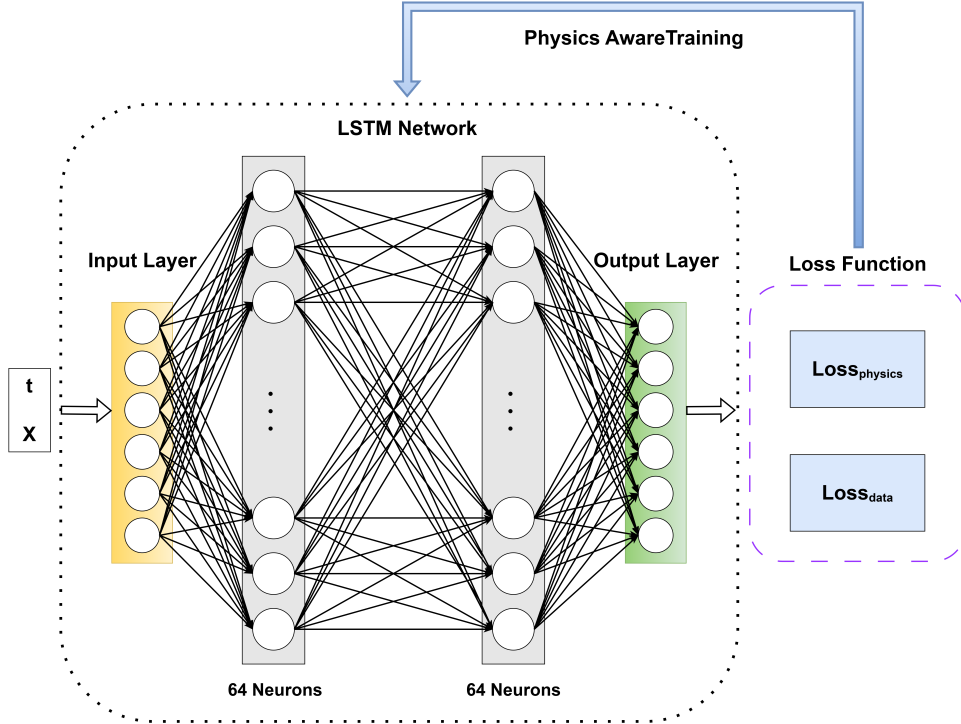


Figure 6.2: Architecture of the proposed LSTM-PINN framework, showing the input layer, LSTM network, output layer, and the combined loss function incorporating data-driven and physics-based components.

followed by two LSTM layers of 64 units each, employing a *tanh* activation function to capture nonlinearity [130]. A fully connected dense then maps the extracted features to a six-dimensional output, representing the predicted state variables for the next time step. The model was trained using the mean squared error loss function, which minimizes the difference between the predicted and true state vectors. To incorporate physical constraints, we defined a residual loss function based on the motion equations of the satellite. Equation (6.2) presents the derivation of the acceleration components resulting from the gravitational force acting on a satellite.

$$a_x = -\frac{\mu x}{r^3}, a_y = -\frac{\mu y}{r^3}, a_z = -\frac{\mu z}{r^3}, \quad (6.2)$$

where μ is the gravitational constant and r is the radial distance of the satellite from the center of the earth. Equations defining the residuals ($\mathcal{R}$) for orbital motion are formulated as follows:

$$\frac{dx}{dt} - v_x = 0, \frac{dy}{dt} - v_y = 0, \frac{dz}{dt} - v_z = 0 \quad (6.3)$$

$$\frac{dv_x}{dt} - a_x = 0, \frac{dv_y}{dt} - a_y = 0, \frac{dv_z}{dt} - a_z = 0 \quad (6.4)$$

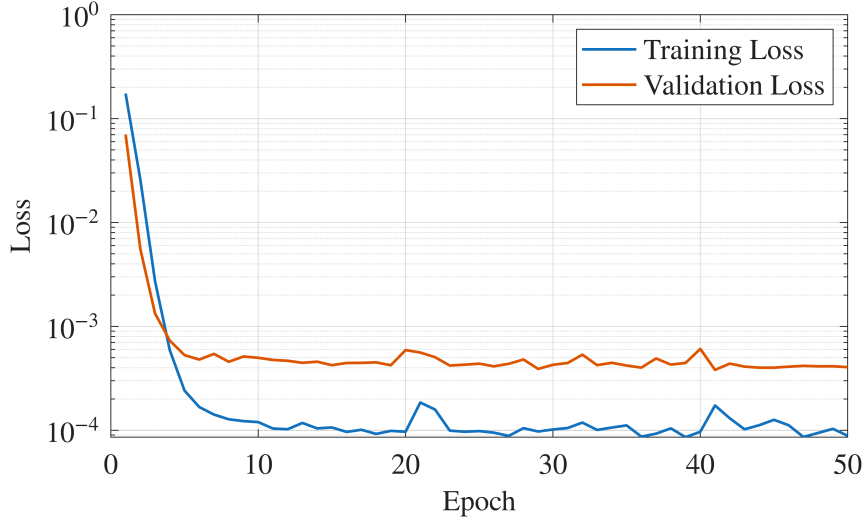


Figure 6.3: Training and validation loss for hybrid LSTM-PINN model.

The total loss function is consist of two components where Supervised learning loss (LSTM component) is given by :

$$\mathcal{L}_{\text{data}} = \frac{1}{N} \sum_{i=1}^N \|\hat{y}_i - y_i\|^2, \quad (6.5)$$

and Physics Loss (PINN residual constraint) is given by :

$$\mathcal{L}_{\text{physics}} = \frac{1}{N} \sum_{i=1}^N \sum_j \|\mathcal{R}_j(x_i, v_i, a_i)\|^2, \quad (6.6)$$

where $\mathcal{R}_j$ denotes the residual equation for each component. Results and performance metrics of the proposed approach are analyzed in the next Section.

6.6 Results

Performance evaluation of the proposed LSTM-PINN model was carried out on satellite ID = 0, drawn from a broader set of 600 satellites. Figure 6.3 shows that after a rapid reduction, both training and validation losses become nearly identical around epoch 10 and remain stable, suggesting effective model convergence. Furthermore, the model's predictions were compared to a baseline LSTM model to assess the impact of physics-informed constraints on the predictive accuracy and determine whether incorporating orbital dynamics improved the generalization capability of the NN. In addition to comparing the LSTM-PINN model with a baseline LSTM network, we also evaluate its performance against a high order Runge-Kutta (RK89) based numerical propagator implemented in the GMAT software [128]. This

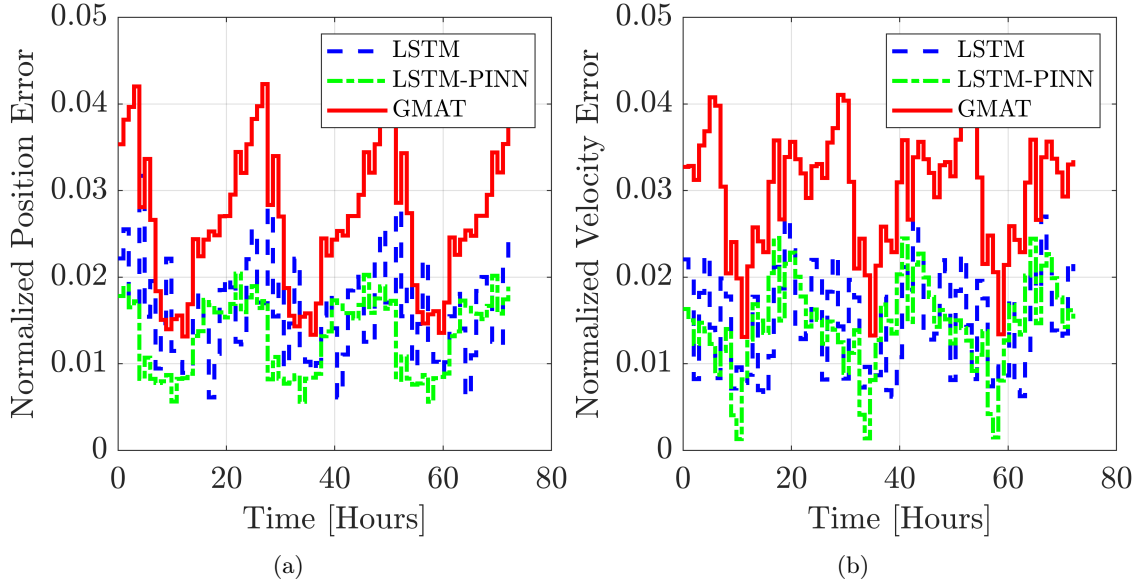


Figure 6.4: Normalized error comparison over a 72-hour prediction window for satellite ID = 0: (a) Normalized position error, and (b) Normalized velocity error.

comparison benchmarks the proposed model against a high-fidelity numerical propagator, as the commonly used semi-analytical SGP4 cannot be used due to missing TLE inputs in the dataset. This allows for a more meaningful assessment of prediction accuracy under realistic orbital dynamics.

Figure 6.4 presents the normalized position (6.4a) and velocity (6.4b) errors over a 72-hour prediction window for satellite ID = 0, comparing the performance of the LSTM, LSTM-PINN, and GMAT numerical propagator. As observed, the proposed LSTM-PINN consistently achieves lower error across the entire time window in both position and velocity, indicating improved predictive accuracy. The baseline LSTM also performs well, though it exhibits slightly greater fluctuations in the error profile, particularly in velocity. Although GMAT’s RK89 integrator is known for its high numerical accuracy, it shows the largest error in this case. This discrepancy can be attributed to two main factors. First, while the reference dataset is said to be high-fidelity, it does not specify which physical models were used, such as third-body effects or atmospheric drag, which makes it difficult to ensure a fair, one-to-one comparison. Second, we had to interpolate GMAT’s output to align with the timestamps in the dataset. Even a small timing mismatch, such as one second, can introduce several kilometers of position error. In addition, the GMAT simulations were performed using a 60 second integration step to match the dataset’s temporal resolution and keep computational demands reasonable. While smaller time step could lead to better accuracy, that would also increase complexity and runtime, reinforcing the trade-off between precision and efficiency in numerical propagation. In our analysis, reducing the step size from 60 seconds to 1 second led to a runtime

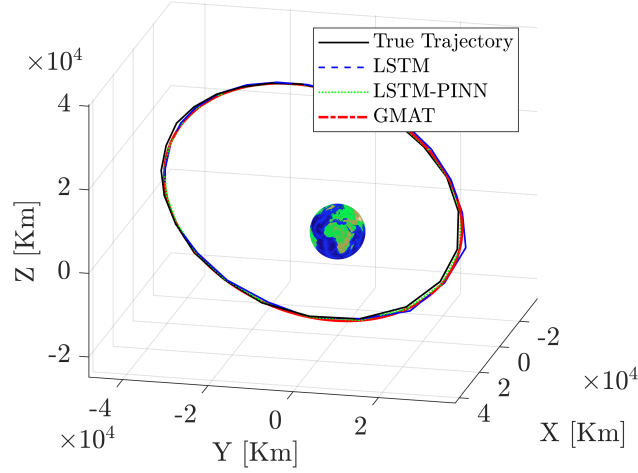


Figure 6.5: Comparison of three-dimensional orbital trajectories for satellite ID = 0.

Table 6.1: Comparison of the performance metrics obtained using the stand-alone LSTM, the proposed LSTM-PINN framework, and the GMAT propagator.

Metric	LSTM	LSTM-PINN	GMAT
Position MSE ($\times 10^{-4}$)	2.945	1.932	7.676
Position MAE ($\times 10^{-2}$)	1.614	1.321	2.640
Velocity MSE ($\times 10^{-4}$)	1.944	1.769	9.346
Velocity MAE ($\times 10^{-2}$)	1.254	1.166	2.982
R^2 score	0.9910	0.9948	0.9927

increase of more than 135 times. These challenges point to an important trade-off between the numerical accuracy of classical propagators and the practical constraints of working with real-world datasets.

Furthermore, three performance metrics - Mean Square Error (MSE), MAE and the coefficient of determination (R^2) were selected to analyze the results. Table 6.1 presents a comparative analysis of LSTM, LSTM-PINN, and the GMAT propagator in terms of position and velocity errors as well as the overall goodness of fit. The LSTM-PINN model outperformed the standalone LSTM across position-related metrics, with a 34.1% reduction in position MSE and an 18.1% decrease in position MAE. Meanwhile, velocity metrics show a modest improvement, with MSE reduced by 9% and MAE by 7%. The GMAT model exhibits the highest errors among the three. As discussed earlier, the unexpectedly high GMAT error arises due to uncertainty in the reference dataset’s modeling assumptions, the interpolation required to align timestamps, and the 60-second integration step used in simulations. Consistently, the R^2 score improves from 0.9910 for LSTM to 0.9948 for the LSTM-PINN, confirming the benefit of incorporating physics-based constraints.

In addition to the numerical metrics, Figure 6.5 offers a three-dimensional visualization of the true orbit (black) alongside trajectories predicted by the LSTM (blue dashed), LSTM–PINN (green dotted), and GMAT (red dash-dot) models. The hybrid model clearly outperforms both the baseline LSTM and GMAT predictions, closely aligning with the true trajectory. Although the dataset lacks satellite-specific metadata, it exhibits sufficient variability in orbital dynamics to support effective model training and generalization.

6.7 Summary

This chapter examined satellite trajectory estimation in non-linear orbital environments using a hybrid LSTM–PINN framework. By combining temporal learning with physics-based constraints, the proposed approach improved trajectory prediction compared with a stand-alone LSTM model and a conventional numerical propagator. The results show a significant reduction in prediction error, with the proposed hybrid model achieving approximately a 30% reduction in position error compared to the baseline LSTM approach, along with improved velocity estimation. This highlights that incorporating physical consistency within a data-driven model can enhance prediction accuracy and improve generalization. At the same time, the overall performance remains dependent on the choice of constraint weighting and the quality of the reference data. Overall, the presented framework offers a useful direction for achieving reliable and computationally efficient orbit prediction.

Chapter 7

Conclusions and Future Directions

7.1 Conclusions

This thesis investigates the use of radio telescope based bistatic and multi-bistatic radar systems for space surveillance and tracking, addressing key limitations of conventional SST infrastructure through the development of estimation frameworks, signal processing techniques, and data-driven predictive models. To this end, the work spans both active and passive radar configurations, covering geostationary and low Earth orbit regimes, and extends the scope of the SDA framework toward long-term trajectory prediction through a physics-informed machine learning approach. Together, these contributions show that radio telescope facilities can play a meaningful role in space surveillance, offering a cost-effective and technically credible complement to conventional dedicated systems.

The first contribution presented a systematic comparative analysis of monostatic, bistatic, and multi-bistatic radar configurations employing radio telescopes as passive receivers for GEO object tracking, with the study conducted using TIRA as the transmitter and e-Merlin and WSRT as bistatic receivers. The results demonstrate that the monostatic configuration achieves a position MAE of 1.33 km, while the multi-bistatic configuration combining the monostatic transmitter with two radio telescope receivers reduces this to 0.92 km, representing a improvement in position accuracy. Configurations relying solely on radio telescope receivers without the monostatic transmitter showed limited tracking capability, confirming that radio telescopes are most effective when operating as complementary bistatic receivers within a hybrid network rather than as stand-alone systems. These findings highlight the potential of distributed radar architectures for GEO surveillance, while illustrating the trade-offs between tracking performance, system complexity, and measurement availability.

The second contribution developed a thrust-aware orbit determination and tracking framework for manoeuvring objects observed by a multi-bistatic radio telescope network. An extension of the classical trilateration method enables the estimation

of non-Keplerian acceleration components alongside position and velocity, providing an initial estimate of thrust that initialize a thrust-aware UKF with an augmented 9×1 state vector. The framework demonstrates strong convergence behaviour in the presence of continuous manoeuvres, with position RMSE reducing from approximately 1 km to less than 100 m, and velocity RMSE converging below 1 m/s across all components over the observation interval.

The third contribution presents InterFeX, a dedicated passive radar architecture for SDA that adapts radio astronomy array capabilities for the detection and monitoring of LEO objects. This work presented and experimentally validated a passive radar signal processing pipeline for the InterFeX array, exploiting commercial FM broadcast transmitters as illuminators of opportunity for the detection and tracking of LEO space objects. The International Space Station trajectory was verified over a 30 s observation pass by comparing the estimated measurements with the TLE-predicted trajectory. The direction-of-arrival results achieved through MUSIC showed a mean angular separation of approximately 0.45° with an along-track offset of 0.05° and a cross-track offset of 0.38° . While the bistatic range and range rate error obtained through cross-ambiguity function processing remained within 1 km and 10 m/s respectively, confirming the consistency of the passive radar measurements with the expected orbital path. The availability of dual-polarization data further enabled a polarization-dependent assessment of the detection performance. The results suggest that polarization pairing can influence detection continuity and error stability under practical broadcast illumination. Across the four transmit-receive combinations evaluated, the YX channel achieved the highest detection rate of 100% and the highest mean SNR of 21.14 dB, whilst the XY combination yielded the lowest detection rate at 83.33% and a mean SNR at 18.57 dB.

The fourth contribution explores data-driven satellite trajectory prediction as a complementary component of the SDA framework, through a hybrid LSTM-PINN approach that embeds orbital mechanics constraints directly into the learning process. By integrating temporal sequence modelling with orbital dynamics, the proposed approach captures complex motion behaviour while maintaining physically consistent solutions. The results indicate a clear improvement in prediction accuracy compared to purely data-driven methods, particularly in scenarios with limited data or constrained computational resources. The study also highlights key challenges, including sensitivity to the weighting of physical constraints and the dependence on high-quality training datasets. Nevertheless, the proposed hybrid framework demonstrates strong potential for improving long-term trajectory prediction, bridging the gap between physics-based modelling and data-driven approaches in space surveillance applications.

Overall, the contributions presented in this thesis demonstrate that the integration of radio telescope receivers with advanced estimation and signal processing techniques provides a promising framework for improved space object monitoring. The results highlight the importance of multi-bistatic radar configurations, robust esti-

mation strategies, and hybrid modelling approaches in addressing the challenges associated with limited observability and non-cooperative target dynamics. Moreover, this work demonstrate that contribution of radio astronomy to SSA extends beyond infrastructure alone, since its measurement principles and processing methodologies can also be successfully applied to space object detection and tracking. Despite these advances, several challenges remain that motivate further investigation.

7.2 Future Work

The following recommendations are made based on the conclusions drawn in the preceding section.

- **Real Measurement Validation:** A significant next step is the validation of the proposed methodologies using real measurement data. Current investigations on GEO target tracking (Chapter 3) and low-thrust orbit transfer analysis (Chapter 4) presented in this thesis have been assessed primarily through simulation-based scenarios, their performance should be further verified using experimental datasets. In this context, real measurement campaigns involving TIRA, e-Merlin, and WSRT, similar to the configuration discussed in Chapter 3, have already been conducted. Their detailed processing and analysis will provide an important basis for confirming the practical benefits of long-baseline bistatic and multi-bistatic radar configurations.
- **Enhanced Dynamic Modelling and Orbit Propagation:** The current implementation of the numerical propagator used within the estimation framework, as employed in both Chapter 3 and Chapter 4, is based on simplified dynamical models that do not account for several perturbing effects. In particular, contributions such as atmospheric drag, solar radiation pressure, and third-body perturbations are not explicitly included. Future work will focus on incorporating these higher-order perturbations to obtain a more accurate representation of real target dynamics. Furthermore, the current numerical integration scheme can be improved by adopting more advanced propagation methods with superior error characteristics, which is expected to enhance estimation accuracy, particularly for long-term tracking.
- **Passive Radar System Development and Full Processing Pipeline:** The passive radar system, InteRFex described in this the Chapter 5 is currently at an initial demonstration stage and requires further refinement in terms of calibration, synchronization, and overall robustness. Future work will focus on extending the system toward a complete end-to-end processing framework, covering all stages from detection to orbit determination and long-term tracking. This includes improving the detection capability for smaller RCS targets, as well as enabling reliable trajectory estimation using passive measurements. In

addition, more detailed polarization-dependent analysis can be investigated to better exploit the dual-polarization capability of the array and enhance target characterization. Furthermore, the current analysis has been carried out using only a single FM transmitter as an illuminator of opportunity. Future work can investigate the use of multiple transmitters, which would enable improved target localization through multi-static configuration.

- **Data-Driven Orbit Propagation:** Adaptive constraint tuning within the PINN framework represents a natural next step, where the physical loss weighting is allowed to adjust dynamically during training rather than remaining fixed. Alongside this, the availability of more comprehensive training datasets spanning diverse orbital regimes and resident space object types, including highly elliptical and GEO orbits, would be crucial in establishing the generalisation capability of the proposed approach beyond the scenarios considered in this thesis.

Taken together, this thesis demonstrates that radio telescope receivers, when integrated within bistatic and passive radar architectures, offer a compelling combination of high sensitivity, geometric flexibility, and cost-effectiveness for space surveillance. The findings establish a solid foundation for future work, including validation against real tracking measurements, incorporation of higher-fidelity propagation models, extension of the passive radar pipeline to full orbit determination, and further exploration of data-driven learning approaches for orbit propagation supported by more comprehensive training datasets. As space activity continues to expand, such approaches represent a promising direction for the development of resilient and high-performance space surveillance systems.

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