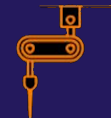


# TECHBOOST

## SATELLITE ORBIT DETECTION

-technology demo report



Inspired by ReOrbit

Oona Kuoppa

**ORBIT DETECTION OF A SATELLITE USING  
EXTENDED KALMAN FILTER AND RANDOM  
FOREST REGRESSION**

Implementing an Extended Kalman Filter and a Random  
Forest Regression-based approach for improved satellite  
orbit determination.

Aalto University  
January 2025  
TECHBOOST Project

Report

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# 1. Introduction

Satellites play a vital role in modern society, providing essential services such as navigation, weather forecasting, Earth observation, and global communication. Orbit detection is essential for satellite operations, such as for navigation and collision avoidance. Precise orbit detection is needed to maintain and adjust the satellite's flight trajectory, reducing issues like wobbling or drifting and ensuring effective collision avoidance [1], [2].

Orbit detection is necessary for satellites that must maintain precise positions within their orbits. An example of this is satellites in Geosynchronous Earth Orbit, which must remain within a specifically defined region to prevent potential interference with neighboring satellites. This position must be maintained, as perturbing forces gradually push the satellite out of the designated area, unless the satellite's orbit is periodically adjusted to correct it [3].

Orbit estimation is a complex task that consists of multiple sub-problems, such as Orbit Determination (OD) and Orbit Prediction. This project concentrated on OD, which involves determining a satellite's trajectory from observational data and system dynamics. However, sensors introduce noise, and dynamic models cannot fully account for all perturbations. Despite these limitations, methods like the Extended Kalman Filter (EKF) have become the industry standard for enhancing accuracy [4].

Although there have been major improvements, achieving flawless solutions for orbit determination remain difficult due to various challenges. Inaccuracies arise from noise in sensor data and flaws in the models. Machine learning (ML) has become a promising method for improving traditional techniques [5].

This project aimed to develop an efficient orbit determination method to improve the accuracy of position and velocity of a satellite, compared to measurements from Global Navigation Satellite System (GNSS) data alone. The approach involved using Extended Kalman Filter along with enhancing the dynamic model through Random Forest Regression (RFR). By incorporating RFR, the study aimed to refine orbit estimation by mitigating systematic errors that arise from unmodeled perturbative forces. The RFR was applied to detect and correct errors within the model, resulting in improved accuracy. By integrating RFR with the traditional EKF, a more precise method for orbit detection was successfully developed. The method was tested in a simulation environment for a satellite in a Molniya orbit, which is a highly elliptical orbit.

## 2. Literature Review

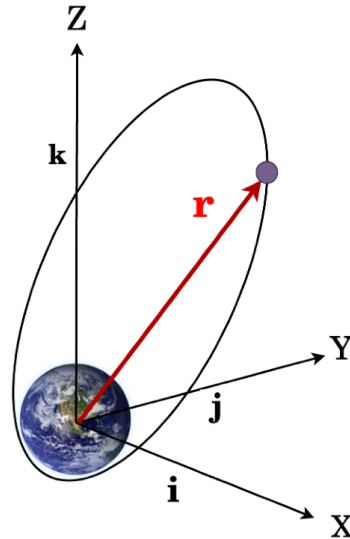
Orbit determination methods encompass a range of techniques. These include approaches such as Batch Least Squares Solution, which require extensive historical data and computational resources. More efficient real-time solutions involve recursive estimation techniques like the Kalman filter and its variants [6, 7, 8].

The Kalman filter framework has evolved significantly since its introduction, with adaptations such as the Extended Kalman Filter (EKF), Unscented Kalman Filter, and Particle Filter. The EKF is favored for its computational efficiency and ability to linearize nonlinear systems, making it highly suitable for orbit determination in many applications. On the other hand, the Unscented Kalman Filter and Particle Filter offer improved performance in highly nonlinear settings, though at the cost of increased computational demands [7], [9], [10], [11].

Recent advancements in machine learning have facilitated new approaches to orbit determination. Studies have demonstrated the effectiveness of hybrid methods where ML techniques are used to correct the limitations of physics-based models. Various implementations, including neural networks, support vector machines, and regression trees, have been proposed to enhance the accuracy of orbit prediction. The current research aligns with these advancements by integrating RFR with EKF to improve state estimation precision [2], [5], [12].

## 3. Research Methods

This study applies a hybrid orbit determination approach that combines physics-based modeling with data-driven corrections. The satellite's motion is modeled using Cowell's formulation, which integrates the equations of motion numerically. The reference frame used for calculations is the Earth-Centered Inertial (ECI) frame, in which the Earth is positioned at the origin and rotates relative to the frame.



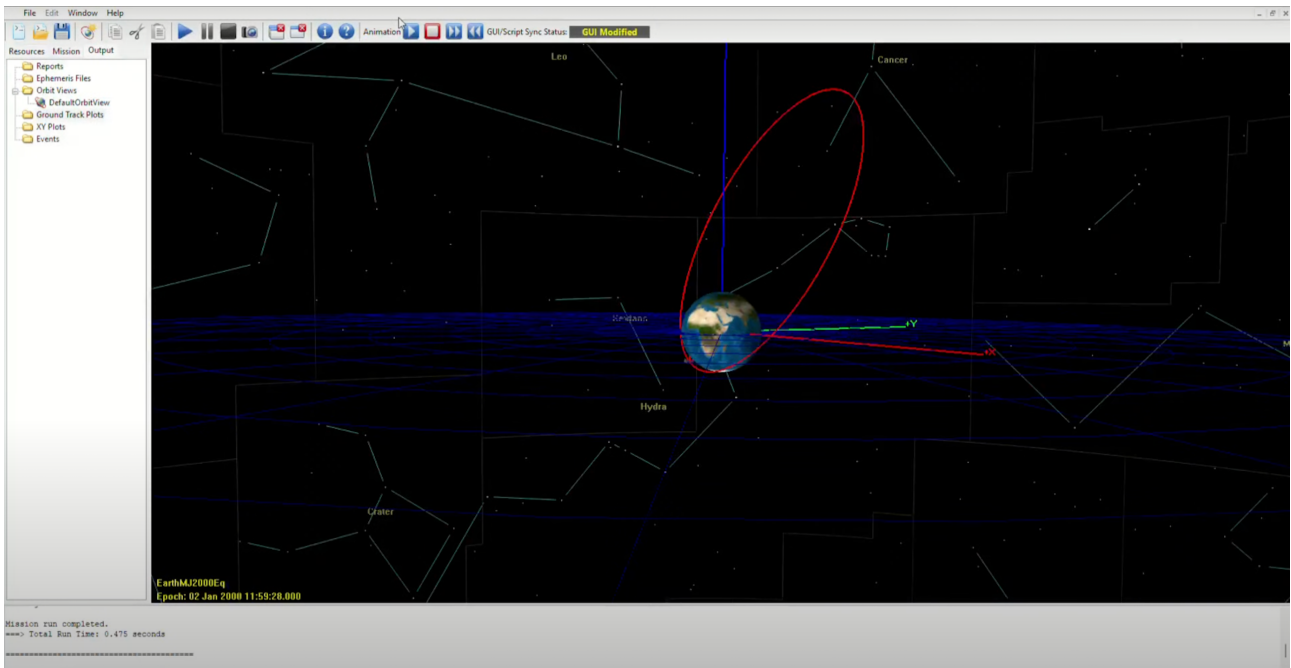
**Figure 1:** In the Earth-Centered Inertial (ECI) coordinate system, the Earth is located at the origin, and the unit vectors  $\mathbf{i}$ ,  $\mathbf{j}$ , and  $\mathbf{k}$  correspond to the X, Y, and Z axes, respectively. The figure also illustrates the satellite's orbit, with the position vector  $\mathbf{r}$  representing its 3D position.

This work is based on Newton's Second Law and the Law of Universal Gravitation as the fundamental principles for the dynamic model. Combining these two we get

$$\mathbf{a} = -G \frac{M}{|\mathbf{r}|^3} \mathbf{r}$$

where  $\mathbf{a}$  is the acceleration of the satellite,  $G$  is the gravitational constant ( $6.674 \times 10^{-11} \text{ m}^3\text{kg}^{-1}\text{s}^{-2}$ ),  $M$  is the mass of the central body (in this case, the Earth),  $\mathbf{r}$  is the position vector from the center of the Earth to the satellite and  $|\mathbf{r}|$  is the distance between the centers of the two masses.

The EKF is employed as the primary orbit estimator, which combines GNSS data and numerically integrated equations of motion, to update state predictions. However, due to the presence of unmodeled perturbative forces in the equations of motion—such as atmospheric drag, solar radiation pressure, and third-body gravitational effects—the dynamic model's predictions will inevitably contain some degree of error. To address these inaccuracies, an RFR model is trained on historical data to learn and correct these errors. The GNSS data used for testing is generated using NASA's General Mission Analysis Tool (GMAT), ensuring a realistic simulation environment.

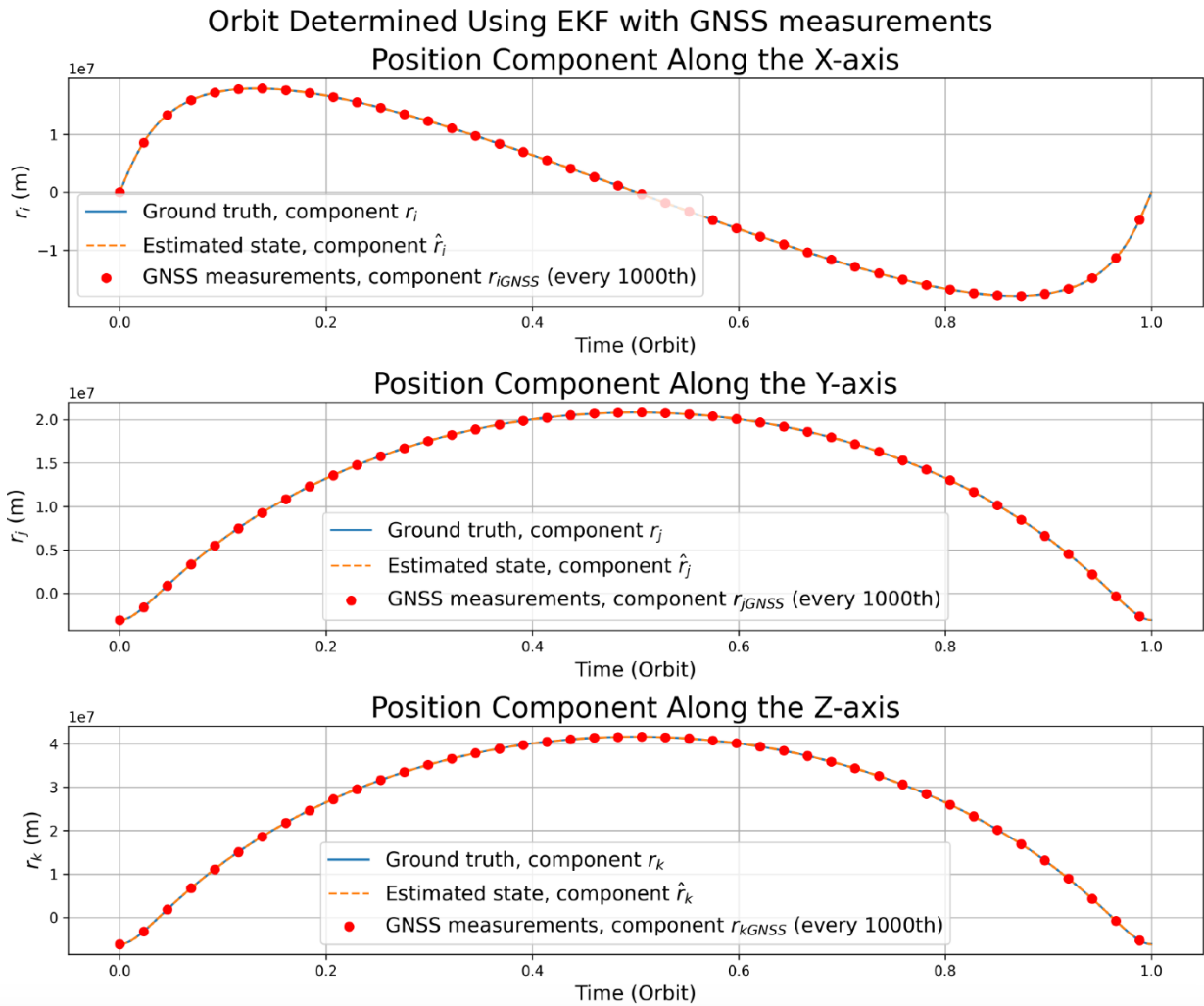


**Figure 2:** Screenshot of NASA’s General Mission Analysis Tool (GMAT), used for GNSS data simulation.

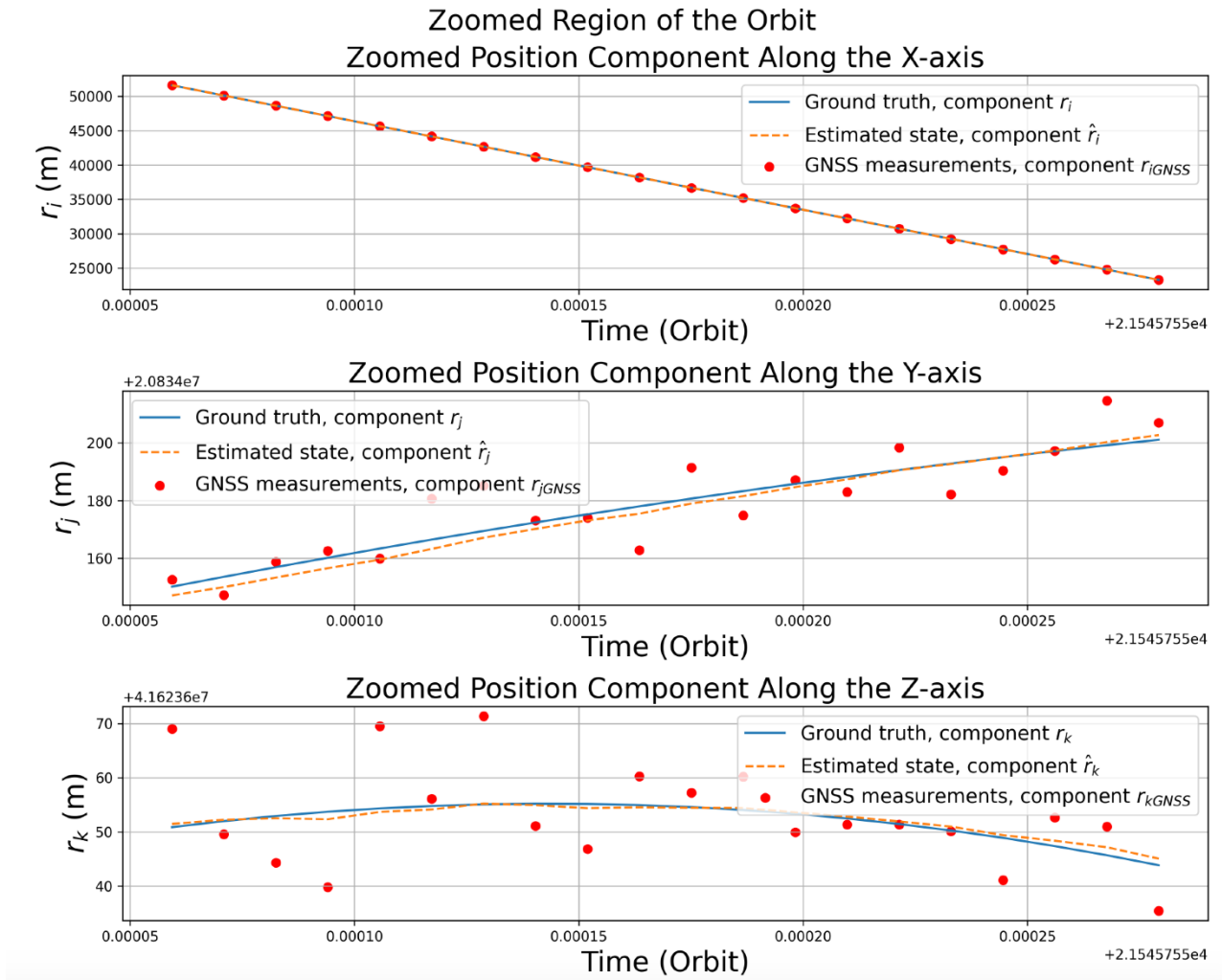
The evaluation of the hybrid model is performed through statistical error metrics such as Euclidean error and mean squared error (MSE). The effectiveness of the approach is assessed by comparing the GNSS-only solution, the standard EKF, and the EKF enhanced with RFR corrections.

## 4. Results

The results demonstrate a significant improvement in orbit estimation accuracy with the RFR-enhanced EKF model. The baseline GNSS-only method yields a mean error of 15.96 meters. By applying the EKF, this error is reduced. With the inclusion of RFR corrections, the error is further minimized to 4.339 meters, representing a substantial improvement in state estimation precision.

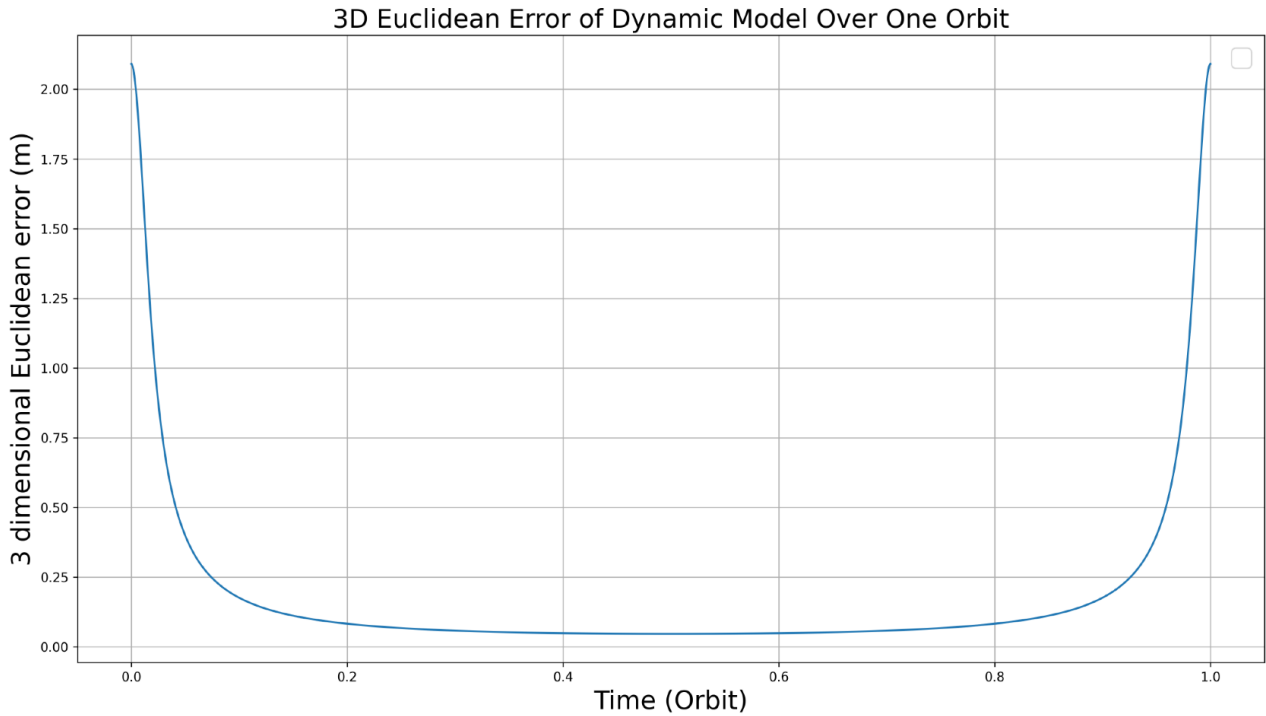


**Figure 3:** Position of the satellite throughout a single orbit using the RFR-enhanced dynamic model. The ground truth and estimated state are overlapping. Every 1000th observation from the GNSS measurements is displayed.

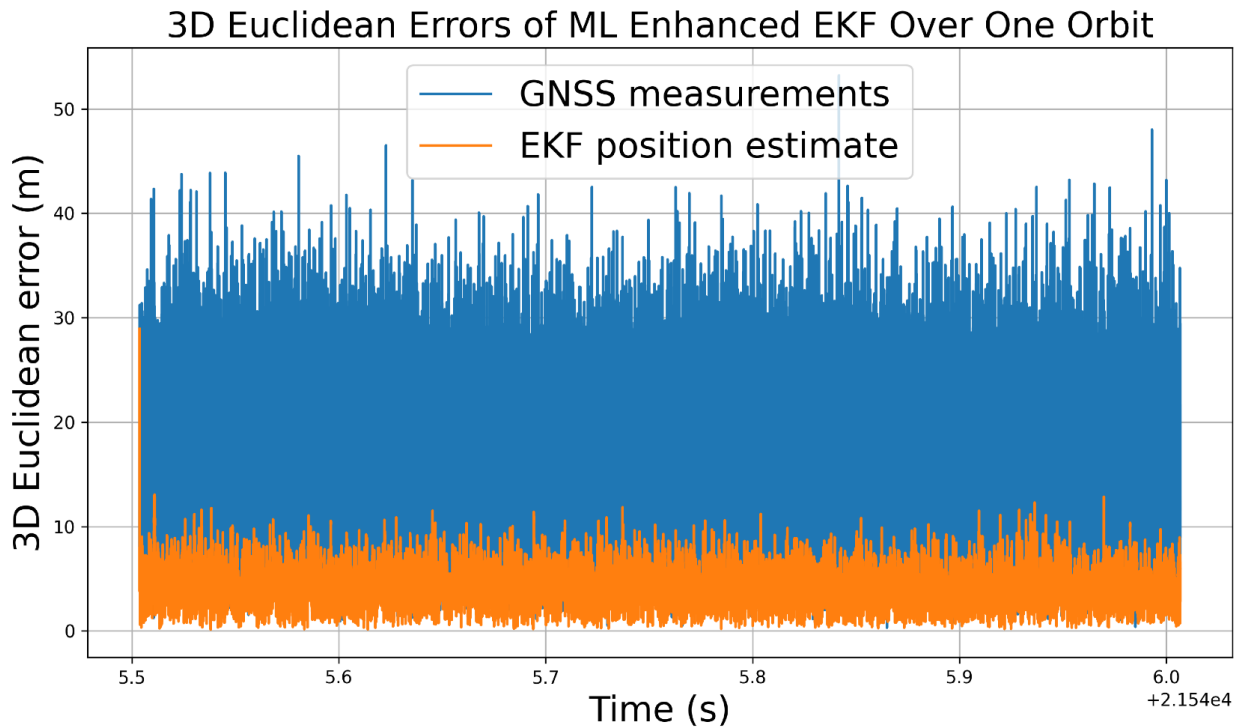


**Figure 4:** This is a zoomed in version of the figure 3 at the middle of the orbit, with RFR enhanced EKF model. The ground truth and estimated state are overlapping in the first plot.

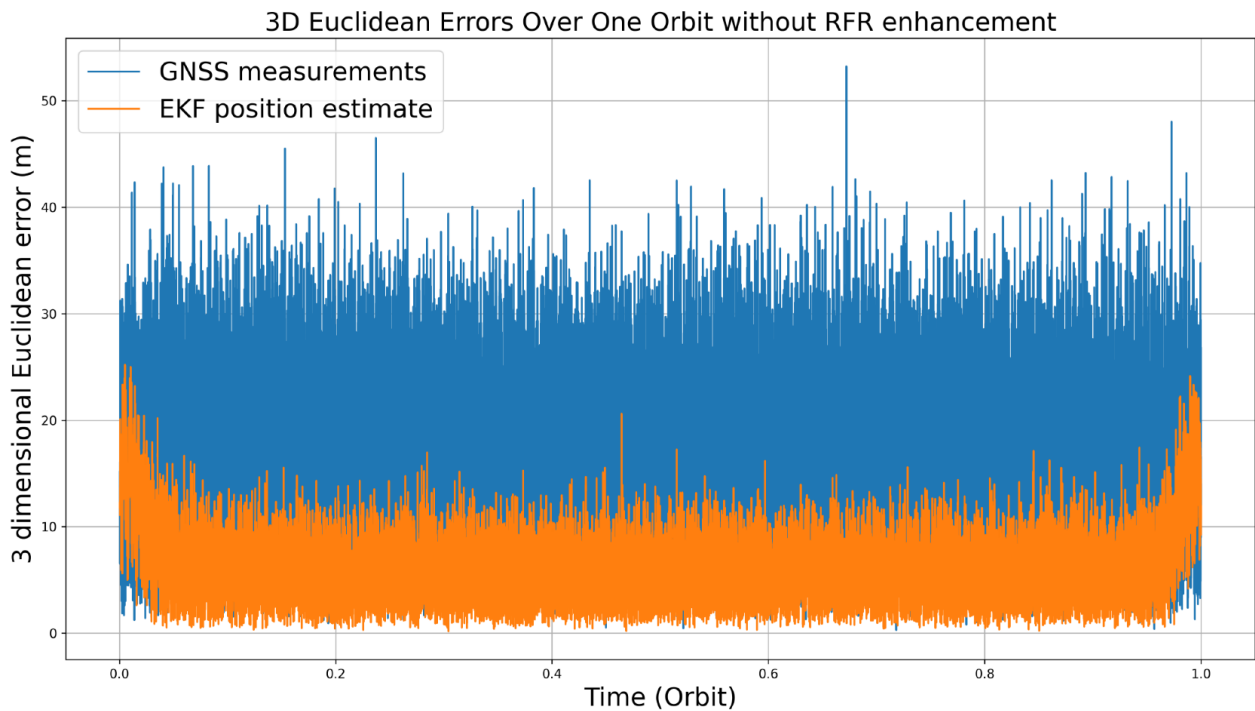
Further analysis indicates that the accuracy of the dynamic model varies depending on the orbital phase, with larger errors occurring near the Earth, as perturbative forces have a greater effect at these stages in the orbit. This is also seen in figure 5. The hybrid approach effectively mitigates these issues by compensating for systematic errors. The difference in Euclidean errors between the basic EKF model and the RFR-enhanced EKF model is illustrated in Figures 6 and 7.



**Figure 5:** This figure demonstrates the performance of the dynamic model over the course of an orbit. It displays the error at each step when compared to the ground truth. Since the errors are not cumulative in this plot, it highlights the errors at each individual prediction step. As observed, the errors are significantly higher at the start and end of the orbit, which is near the Earth.



**Figure 6:** 3D Euclidean errors of the RFR-enhanced EKF and GNSS over an orbit.



**Figure 6:** Euclidean errors of GNSS positions and EKF position estimates throughout an orbit, without the RFR enhancement.

An ablation study was also conducted, demonstrating the impact of parameter tuning on the EKF's performance. Specifically, optimizing the process noise covariance matrix ( $\mathbf{Q}_k$ ) and the measurement noise covariance matrix ( $\mathbf{R}_k$ ) further enhanced

accuracy. Increasing the interval between GNSS measurements was shown to decrease the accuracy.

## 5. Discussion and Conclusions

This project evaluated the performance of the Extended Kalman Filter algorithm for orbit determination, with a focus on how different factors—such as the process noise covariance matrix  $\mathbf{Q}_k$ , the measurement noise covariance matrix  $\mathbf{R}_k$ , and the integration of a machine learning model—affect the accuracy of state estimation. Detailed testing and evaluation confirm that a relatively simple physics-based dynamic model can be significantly improved using machine learning enhancements. RFR proves to be an effective tool for correcting systematic errors in the dynamic model.

The research showed that properly tuning the process noise covariance matrix  $\mathbf{Q}_k$  and the measurement noise covariance matrix  $\mathbf{R}_k$  is crucial for improving estimation accuracy. This highlights the importance of careful calibration and optimization of both matrices. Also, further optimization of the noise matrices, particularly  $\mathbf{Q}_k$ , could improve performance, as residuals behave differently near Earth compared to greater distances. Making  $\mathbf{Q}_k$  more adaptive could help address this issue, though this approach would need further investigation.

The study found that shorter intervals between measurement updates result in smaller orbit determination errors with the EKF. This highlights the need for precise measurements and frequent updates to improve accuracy. However, reducing the update interval increases computational load, requiring a balance between accuracy and efficiency. A trade-off analysis should be conducted when developing orbit determination algorithms to determine the optimal update interval that meets accuracy requirements while balancing computational efficiency.

While the RFR-enhanced EKF model shows substantial improvements, its effectiveness across different orbits remains uncertain. The effectiveness of machine learning corrections depends on the availability of high-quality training data, and the model may require retraining for different orbital conditions. Future work should explore the applicability of alternative machine learning models and extend the method to other orbital scenarios, such as low Earth orbit and geostationary orbit satellites.

In conclusion, the study provides valuable insights into the development of robust orbit determination systems. Key findings emphasize the potential of machine learning models to enhance state estimation, particularly in regions near Earth. Additionally, the study underscores the significance of optimizing noise matrices and the effect of time step intervals on the accuracy of the estimation process. Further investigation into the model's applicability and generalizability, especially for

different orbits and real-world scenarios, is necessary. Additionally, it remains uncertain whether the optimization approach based on simulations can be successfully transferred to real-world applications. In real-world situations, the lack of ground truth data presents a significant challenge for directly applying this optimization.

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