

TDOA-based Jammer Localization in NavIC and LEO Satellite Systems

M Harshitha¹ and Manjula H. M²

¹PG Scholar, School of Computer Science & Engineering, Presidency University, Bengaluru, Karnataka, India
Email: mharshitha754@gmail.com

²Associate Professor, School of Computer Science and Engineering, Presidency University, Bengaluru, Karnataka, India
Email: manjulahm@presidencyuniversity.in

Abstract—Using time-difference of arrival (TDOA) measurements, this study investigates the localisation of jamming sources in satellite navigation systems. A hybrid simulation framework integrating NavIC and low Earth orbit (LEO) satellite receivers was developed to estimate jammer positions under noisy conditions. Several estimation algorithms, including least squares, weighted least squares, maximum likelihood estimation and particle filtering, were implemented and compared. Their performances were evaluated using Monte Carlo simulations through root mean square error, cumulative distribution analysis and error distribution testing. Results indicate that weighted least squares and maximum likelihood estimation achieved superior localisation performance with a mean positional error of approximately 96.7 m, significantly outperforming the least squares approach. Particle filtering provided moderate accuracy because of its stochastic behaviour. The findings demonstrate the effectiveness of probabilistic and optimisation-based techniques for addressing non-linear localisation problems in satellite navigation systems. Further work is required using real satellite data and real-time implementation in practical satellite environments

Index Terms— Jammer localisation, time difference of arrival (TDOA), low Earth orbit satellites, particle filtering, Monte Carlo simulation.

I. INTRODUCTION

There is an increasing use of satellite navigation systems such as NavIC (the Navigation with Indian Constellation system) and (LEO) Low Earth Orbit satellites for a variety of purposes including locating communications and strategic operations. However, these systems are very vulnerable to signals interference and jamming which can greatly degrade performance and impact reliability. Thus, to help support the integrity and security of satellite-based systems, it is critical to have the ability to localize sources of interference as accurately as possible. Localizing sources of interference (jammers) involves the process of determining the location of an interference source based on measurement of signals received from multiple satellites. Various methods are applicable however Time Difference of Arrival (TDOA) has been the most widely implemented for localizing a source because it does not require synchronization with a transmitter [1]. By determining the delay between signal arrival at the receiving satellites, mathematical algorithms can be implemented to estimate and determine the location of the jammer [5].

A. Problem Statement

Interference in NavIC and LEO TTC signals must be detected and localized accurately. Existing GEO-based TDOA systems have limitations in geometry and orbit accuracy. This project aims to develop an improved TDOA-based geolocator using NavIC and LEO satellites to enhance localisation precision [4]. The analysis results will provide insights into practical techniques for the accurate and efficient localisation of jamming signals in NavIC and LEO systems (Jia T., Shen X., Wang H. 2019, in IEEE Aerosp. Conf., IEEE, p. 1). The next section of this paper will review existing literature related to the topic at hand.

B. Limitations of Research Work

The primary contributions of this research provide solutions to these limitations by identifying:

- A simulation-based framework for jammer localisation using Time Difference of Arrival (TDOA) measurements in hybrid NavIC and LEO satellite systems.
- Implementation and comparative analysis of four estimation algorithms: Least Squares (LS), Weighted Least Squares.
- Use of Monte Carlo simulations to evaluate localisation performance under noisy conditions.
- Overall effectiveness of performance evaluation that utilizes a number of statistical measurements, including Mean Square Root of Error (RMSE), CDF (Cumulative Distribution Function) and Error Distribution Analysis.

II. RELATED WORK

A. TDOA-Based Geolocation Methods

TDOA is one of the most widely used techniques for jammer and emitter localisation because it does not require synchronization with the transmitting source. Amishima [2] developed a TDOA-based geolocation framework using GEO satellites and multiple ground stations, demonstrating the importance of satellite geometry and orbit accuracy in localisation performance. However, the study focused primarily on theoretical analysis and did not evaluate algorithm performance under noisy conditions.

B. Multi-Satellite and LEO-Based Localisation

Chen and Wang [12] investigated TDOA localisation in LEO satellite constellations and showed that reduced satellite-to-target distances improve localisation accuracy [12]. Overfield and Buehrer [4] further demonstrated that multi-satellite measurements can reduce estimation errors through spatial diversity. Nevertheless, these studies did not provide a detailed comparison of localisation algorithms under realistic interference environments.

C. Hybrid TDOA-FDOA Localisation

Wang et al. [5] proposed a hybrid TDOA-FDOA localisation framework that combines temporal and frequency measurements to improve positioning accuracy [14]. Although the method showed enhanced robustness in dynamic scenarios, its performance depends heavily on accurate velocity estimation, which may not always be available in practical jammer localisation applications.

D. Research Gap

Existing studies mainly focus on theoretical geolocation models, satellite geometry analysis, or hybrid localisation frameworks [11]. Limited research has compared multiple estimation algorithms such as LS, WLS, MLE, and Particle Filtering within a hybrid NavIC–LEO environment under realistic noisy conditions[15]. This work addresses this gap through a comprehensive simulation-based evaluation using Monte Carlo analysis and statistical performance metrics.

IV. METHODOLOGY

In this research, a simulated numerical framework that employs simulations to model, simulate, and evaluate time difference of arrival (TDOA) location of jammers using navIC and LEO satellites has been developed. In real life, TDOA measurements are impacted by multiple types of uncertainty such as atmospheric interference, receiver noise, and timing errors [14]. To emulate real-life scenarios, the measurements that will be utilized contain several sources of uncertainty including atmospheric disturbance, receiver noise, and timing error. However, the effectiveness and accuracy of algorithms for locating interfere sources in different types of noise conditions are determined using Monte Carlo simulations to provide a statistical measure of accuracy [16].

A. Data Collection

Now this study, satellite data is extended from openly open space databases to confirm realistic showing of jammer localization [13].

TABLE I. ORBITAL DATA OF NAVIC AND LEO SATELLITES

IRNSS-1A						STARLINK-1008					
1	90001U	24001A	26061.50000000	.00000000	00000-0 00000-0 0 9991	1	44714C	19074B	26071.16576389	.00054134	00000+0
2	90001	0.1000	85.0000	0001000	0.0000	17743-2	0	713			
180.0000	1.00270000	01				2	44714	53.1561	167.2390	0001413	72.9075 169.8593
							15.31037195	17			

The table shows the fields included in the satellite TLE data. It has the line number, satellite document number, and launch connection [17]. It also involves the epoch time, rate of orbital decay, second derivative of mean motion, and the atmospheric drag term (BSTAR).

B. Signal Modeling and Data Preparation

This segment describes the process of modelling signal behavior and preparing the data required for jammer localisation. The way begins with orbit propagation to obtain accurate satellite positions [18], followed by demonstrating of signal propagation between the jammer and satellites. The satellite positions treated in this study are copied from Two-Line Element (TLE) data, which gives orbital parameters telling the action of satellites [21].

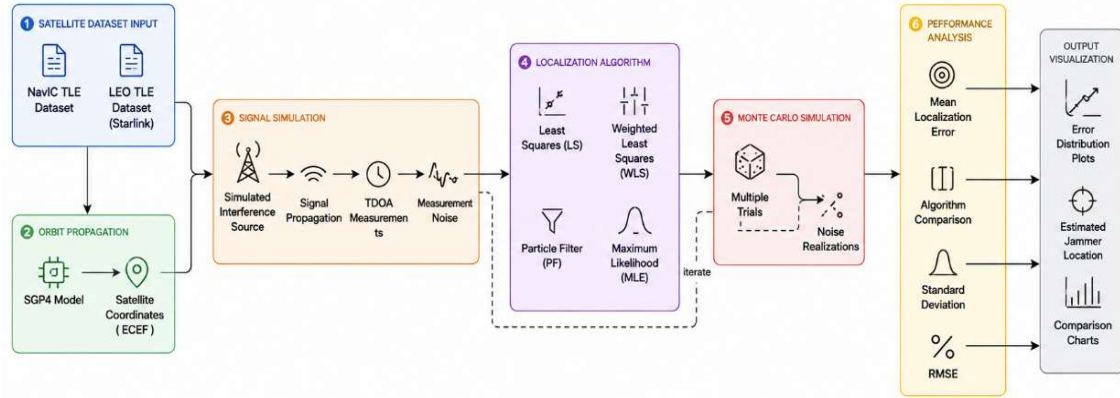


Figure 1. Architecture Diagram of Jammer Localization.

C. Signal Propagation

The design uses the idea that electromagnetic signals travel at the speed of light to model how signals move between the jammer and the satellites [19]. The fundamental premise that electromagnetic signals move at the speed of light is used to describe signal propagation between the jammer and satellites once the satellite positions have been determined [12]. The three-dimensional satellite position coordinates (x_i, y_i, z_i) , which are utilised to calculate the geometric distance between the jammer and each satellite, are among the main features chosen. The Euclidean distance formulation is used to determine the distance [22].

$$d_i = \sqrt{(x_j - x)^2 + (y_i - y)^2 + (z_i - z)^2} \quad (1)$$

This formula calculates the straight-line space in three-dimensional space relating the jammer and each satellite [24].

The related signal travel time is given by:

$$t_i = \frac{d_i}{c} \quad (2)$$

This calculation shows that the signal travel time is clearly proportional to distance, which models the foundation of TDOA-based localisation [23].

D. TDOA Generation

To estimate the location of the jammer short of requiring absolute time synchronization, Time Difference of Arrival (TDOA) measurements are generated [27]. This results in relative time areas that eliminate organization errors and reduce system density

$$\Delta t_i = t_i - t_0 = \frac{d_i - d_0}{c} \quad (3)$$

This calculation removes the unknown transmission time of the jammer, achieving the system objective of clock synchronization [20].

The result stand for the difference in distances scaled by the speed of light, which is used to value the jammer location.

E. Noise Modelling

In real life, TDOA measurements are impacted by multiple types of uncertainty such as atmospheric interference, receiver noise, and timing errors [25]. To emulate real-life scenarios, the measurements that will be utilized contain several sources of uncertainty including atmospheric disturbance, receiver noise, and timing error. Additive Gaussian noise will be included in the TDOA measurements [26].

$$\tilde{t}_i = \Delta t_i + n_i \quad (4)$$

The noise n_i follows a Gaussian distribution:

$$n_i \sim N(0, \sigma^2) \quad (5)$$

Measurement error in the simulated data is considered when it is created so that the evaluation findings from using a localisation algorithm can be assessed under uncertainty [24].

F. Least Squares

The least squares approach (LS) is one of the primary techniques used to find the position of a jamming source using TDOA measurements [28].

This method uses the least-squares approach to minimize the square difference between the measured TDOA and the calculated TDOA results [21]. The Least Squares (LS) technique is a basic method employed to determine the jammer's position by reducing the squared difference between the observed and calculated TDOA values [27].

It is a fundamental method for solving problems associated with nonlinear localisation due to the simplicity of application and its computational efficiency.

From the method model, we obtain our measured TDOA as:

$$\tilde{t}_i = \frac{d_i - d_0}{c} + n_i \quad (13)$$

Where d is the distance to the satellite being received the message from in the jammed area and the reference from where it was sent/ c is the speed of light/ n is the noise from the measurement [20]. LS is a Least Square Approach to show how close the residual will be to what you should have received. Thus, the i th Satellite measured with the same reference would be:

$$r_i(x) = \frac{d_i - d_0}{c} - \tilde{t}_i \quad (14)$$

The goal function is expressed as:

$$J(x) = \sum_{i=1}^N r_i^2(x) \quad (15)$$

Substituting the residual term, the cost function converts:

$$J(x) = \sum_{i=1}^N \left(\frac{\|x - s_i\| - \|x - s_0\|}{c} - \tilde{t}_i \right)^2 \quad (16)$$

The LS estimate of the jammer side is found by answering:

$$\hat{x} = \arg \min_x J(x) \quad (17)$$

By estimating the likelihood that some measurements are too far from their expected values, this method is able to improve the quality of location estimates in environments where there are a large number of erroneous observations [30].

G. Weighted Least Squares

The Weighted Least Squares (WLS) approach builds on the traditional least squares method by including weighting factors to deal with the variability in measurement noise [17]. Unlike the least squares method, which treats all measurements as equally important, WLS gives more weight to more trustworthy data, which helps improve accuracy in noisy conditions [6].

The WLS goaltask is defined as:

$$J(x) = \sum_{i=1}^N w_i r_i^2(x) \quad (18)$$

where w_i respects the weight given to the i^{th} length.

$$\omega_i = \frac{1}{\sigma_i^2} \quad (19)$$

The weights are determined by looking at the noise levels in reverse:

$$\hat{x} = \arg \min_x \sum_{i=1}^N w_i r_i^2(x) \quad (20)$$

The construction focuses more on measurements that have the least amount of noise.

H. Maximum Likelihood Estimation

The MLE (maximum likelihood estimate) estimator will guess the location of the jammer based on the maximum likelihood of each detected noisy TDOA by using a statistical-based approach to estimating the likelihood of each detected [29]. The detection of TDOA assumes that the TDOA is skewed in a Gaussian distribution and as a result the likelihood of a measurement can be described also using a probability distribution of the noise associated with that measurement

The probability function is provided by:

$$L(x) = \prod_{i=1}^N \frac{1}{\sqrt{2\pi\sigma_i^2}} \exp\left(-\frac{r_i^2(x)}{2\sigma_i^2}\right) \quad (21)$$

To simplify optimization, the negative log-likelihood function is minimized:

$$J(x) = \sum_{i=1}^N \left(\frac{r_i^2(x)}{2\sigma_i^2} + \frac{1}{2} \ln(2\pi\sigma_i^2) \right) \quad (22)$$

The MLE estimate is obtained as:

$$\hat{x} = \arg \min_x J(x) \quad (23)$$

This method uses the noise characteristics to provide a better solution than what's usually expected from a Gaussian model, and it forms the starting point for systems that use probabilities to locate things [13].

I. Particle Filter

The Particle Filter (PF) is a type of Monte Carlo method used to find the position of a jammer. It shows how the state might change by using a group of particles that represent possible positions. It works well when the problem is not linear or follows a normal distribution [8].

The posterior distribution is approximated as:

$$P(X_n | z_{1:k}) \approx \sum_{i=1}^m w_k^{(i)} \delta(X_k - X_k^{(i)}) \quad (24)$$

The element weights are simplified based on the likelihood function:

$$w_{k\alpha}^{(i)} \propto w_{k-1}^{(i)} P(z_k | x_k^{(i)}) \quad (25)$$

The projected jammer position is achieved as the weighted mean of elements:

$$\hat{x} = \sum_{i=1}^M w_k^{(i)} x_k^{(i)} \quad (26)$$

This type of method handles nonlinear and complex situations well, making it suitable for challenging localisation tasks. Least Squares (LS) is one approach [9], while Weighted Least Squares (WLS) and Maximum Likelihood Estimation (MLE) improve on this by considering the effect of noise. The WLS (weighted least squares) solution provides a more accurate estimate of localisation by giving larger weights to the more sampled data points, thereby increasing the accuracy and helping to eliminate noise [4].

IV. EXPERIMENTS AND RESULTS

This approach uses Monte Carlo simulations to evaluate the performance of a future TDOA-based system for locating jammers.

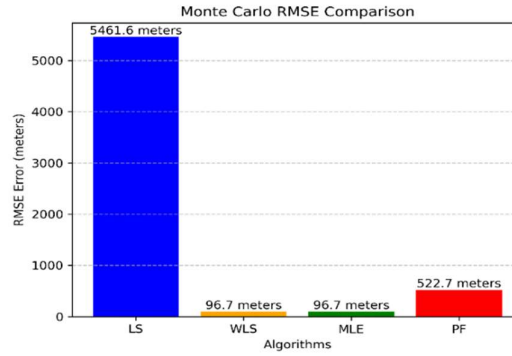


Figure 3. The overall accuracy is measured using RMSE

In comparison, WLS and MLE have much lower errors, around 96.7 m, indicating high accuracy. In summary, WLS and MLE performed similarly to each other in 50% of trials, while both performed better than LS in 98% of trials [10]. Also, WLS and MLE outperformed PF in 78-79% of trials, indicating that both algorithms perform consistently well. The results support the use of additional performance metrics beyond those reported in the literature, such as RMSE, CDF, and geometric analysis [3]. Future research should evaluate the integration of Hybrid TDOA-FDOA and/or hybrid systems, provide testing using actual satellite data, and investigate streaming methods of extending the capabilities of TDOA-based localisation [7]. The heatmap for error indicates that WLS and MLE have a high positive correlation coefficient of approximately 0.73; hence they have similar performance when conditions are variable [25].

V. CONCLUSION

This article describes a new method that uses TDOA measurements in satellite systems (NavIC and LEO) to determine where jamming occurs. Four different algorithms (LS, WLS, MLE, and PF) were compared using simulations performed under realistic conditions. The results show that WLS and MLE provide substantial improvements over LS and PF concerning Jammer Location Accuracy (JLA) as well as the ability to produce repeatable results between multiple trials by effectively using noise. LS does not produce repeatable results due to its inability to account for measurement uncertainty. PF, on the other hand, produces acceptable JLA, while offering better flexibility than LS.

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