Advanced TDOA-UWB Localization in Complex Environments: Overcoming Multipath and NLOS Challenges

CHRISTIAN TSHIMANGA NKASHAMA[1], MOANDA NDEKO MOSENGO C.M.[1], WITESYAVWIRWA VIANNEY KAMBALE[3], KYANDOGHERE KYAMAKYA[2]

[1]Faculté Polytechnique, Université de Kinshasa (UNIKIN), Kinshasa,
DEMOCRATIC REPUBLIC OF THE CONGO

[2]Institute for Smart Systems Technologies,
Universität Klagenfurt,
AUSTRIA

[3]Faculty of Information and Communication Technology,
Tshwane University of Technology,
Pretoria, SOUTH AFRICA

Abstract: Accurate localization remains a critical challenge in complex environments characterized by multipath propagation, Non-Line-of-Sight (NLOS) conditions, and environmental noise. This paper presents a comprehensive study on enhancing Time Difference of Arrival (TDOA) localization systems utilizing Ultra-Wideband (UWB) signals. The contributions include the development of a robust simulation framework incorporating real-world environmental factors, a comparative analysis of deterministic and statistical approaches, and geometric optimization strategies for anchor placement. The results highlight the capability of TDOA-UWB systems for dependable implementation in industrial sectors, such as logistics, precision agriculture, and mining.

Key-Words: TDOA, UWB, Localization, Multipath, NLOS, Anchor Placement, Statistical Methods

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1 Introduction

Real-time localization in intricate contexts, including logistics sites, agricultural fields, and mining operations, is essential for improving productivity, safety, and operational efficiency. Nevertheless, these surroundings present considerable obstacles, including:

- **Multipath propagation**: Signals reflect off various surfaces, causing interference and delays in measurements.
- **Non-Line-of-Sight (NLOS) conditions**: Physical barriers obstruct or interfere with direct signal pathways, diminishing precision.
- **Environmental noise**: Interference from devices or other sources diminishes the quality of received signals.

The Time Difference of Arrival (TDOA) method, employing Ultra-Wideband (UWB) signals, presents significant benefits among existing localization techniques. It depends on quantifying the temporal discrepancies in signal arrivals at several stationary anchors to ascertain a mobile entity's location precisely. However, its effectiveness can be compromised by the aforementioned challenges, particularly in dynamic environments.

Objectives and Scope of the Study

This research aims to address the challenges of localization in complex environments by exploring the following solutions:

1. Creating a comprehensive modeling framework that integrates real-world environmental variables, including multipath interference and non-line-of-sight circumstances.
2. A comparative analysis of deterministic and statistical techniques utilized in TDOA localization will be performed, emphasizing their various efficiencies.
3. Geometric optimization of anchor placement to minimize errors and maximize accuracy.

Based on simulations and in-depth analyses, this work provides practical recommendations to enhance the robustness of TDOA systems in critical industrial applications.

Novelty of this Work

Unlike previous studies, this work introduces a fully reconfigurable TDOA-UWB simulation framework developed in MATLAB/Simulink. This simulator realistically models multipath propagation, NLOS conditions, and dynamic anchor geometries. A key innovation lies in the integration of a dual-mode localization engine capable of toggling between deterministic and statistical estimation methods (such as weighted least squares and Maximum Likelihood Estimation). This flexibility allows for in-depth performance comparisons. This study evaluates the effects of anchor placement strategies (optimal vs. suboptimal) within both localization paradigms and their influence on Geometric Dilution of Precision (GDOP), Root Mean Square Error (RMSE), and overall error rate, offering a thorough assessment of localization accuracy in realistic conditions.

Author Contributions

Christian Tshimanga Nkashama directed the execution, development of simulations, analysis of data, and the comprehensive composition of the manuscript. Moanda Ndeko Mosengo C.M. and Witesyavwirwa Vianney Kambale equally contributed to the technical validation and critical revision of the manuscript. Kyamakya Kyandoghere was the academic supervisor, providing conceptual guidance and thorough review throughout the research process. All authors have reviewed and endorsed the final version of the text.

2 Background and Related Work

2.1 Overview of UWB Technology and TDOA Localization Principles

Ultra-Wideband (UWB) technology has become a crucial facilitator for high-precision wireless communication systems, due to its extensive bandwidth (surpassing 500 MHz) and minimal power spectral density, [1]. Initially designed for military radar systems, it has subsequently achieved extensive utilization in commercial applications, such as premium cellphones and indoor tracking systems. Its ability to facilitate elevated data rates and exact temporal resolution makes it especially appealing for situations where velocity and spatial precision are essential. A complete analysis of several localization approaches utilizing UWB signals, including TDOA, is presented in [2], emphasizing their benefits and problems in wireless sensor networks.

UWB is distinguished from other wireless technologies by its capability to attain localization precision within the centimeter range, even in situations susceptible to signal attenuation, such as industrial facilities or underground mining tunnels. These qualities are not solely technical benefits; they tackle the operational difficulties encountered in intricate and high-interference settings. Reducing localization error is crucial for real-time tracking and automation in logistics hubs or innovative agriculture systems. Moreover, UWB's minimal power consumption enhances battery longevity in portable devices and diminishes electromagnetic interference with current wireless infrastructure, [3].

The Time Difference of Arrival (TDOA) localization method utilizes the precise temporal resolution of UWB signals to ascertain the location of a target device. TDOA determines position by monitoring the relative time differences of signal arrivals at several anchor nodes, in contrast to approaches that necessitate precise synchronization. The methodology entails resolving hyperbolic equations based on these temporal offsets, yielding a reliable estimating framework applicable to non-line-of-sight (NLOS) and multipath situations, [4]. This technology was selected for its scalability and adaptability to the noisy and blocked settings of logistics and mining activities in Sub-Saharan regions.

When a signal is received by two fixed stations b_1 and b_2, the signals can be modeled as follows:

$$x_{b_1}(t) = s(t - d_{b_1}) + n_{b_1}(t) \tag{1}$$

$$x_{b_2}(t) = s(t - d_{b_2}) + n_{b_2}(t) \tag{2}$$

where:

- $x_{b_1}(t)$ and $x_{b_2}(t)$: Signals received at stations b_1 and b_2.
- $s(t - d_{b_1})$ and $s(t - d_{b_2})$: Transmitted signals delayed by times d_{b_1} and d_{b_2}.
- $n_{b_1}(t)$ and $n_{b_2}(t)$: Noise affecting the received signals.

TDOA localization uses the cross-correlation function to estimate the propagation delay between the two stations:

$$R_{b_1,b_2}(\tau) = \frac{1}{T} \int_0^T x_{b_1}(t) \cdot x_{b_2}(t - \tau)\, dt \tag{3}$$

The value of Δt is defined as:

$$\Delta t = \arg\max_{\tau} R_{b_1,b_2}(\tau), \tag{4}$$

where:

$$\Delta t = t_{b_2} - t_{b_1}, \tag{5}$$

with t_{b_1} and t_{b_2} representing the arrival times of the signals at stations b_1 and b_2, respectively. The peak of this function corresponds to the propagation delay $\Delta t = d_{b_2} - d_{b_1}$ between the two stations, [5].

Conversion from Δt to Geometry The time difference Δt is converted into a distance difference Δd using the propagation speed c (e.g., speed of light):

$$\Delta d = c \cdot \Delta t. \tag{6}$$

This distance difference relates to the positions of the stations b_1 and b_2 and the mobile as:

$$\Delta d = d_{b_2} - d_{b_1}, \tag{7}$$

where:

$$d_{b_1} = \sqrt{(x - x_1)^2 + (y - y_1)^2},$$
$$d_{b_2} = \sqrt{(x - x_2)^2 + (y - y_2)^2}. \tag{8}$$

Hyperbolic Localization The differences in distances Δd define a hyperbola. A hyperbola is the locus of points where the difference of distances to two fixed points (foci) is constant. The general equation for a hyperbola is:

$$\sqrt{(x - x_1)^2 + (y - y_1)^2} - \sqrt{(x - x_2)^2 + (y - y_2)^2} = \Delta d. \tag{9}$$

This equation directly relates the geometric properties of the system to the time difference Δt, providing the foundation for accurate localization. For multiple fixed stations, each pair generates a hyperbola based on Δd. The intersection of these hyperbolas determines the mobile's position (x, y) in 2D or (x, y, z) in 3D, [6].

Multilateration: A Robust Localization Approach Multilateration expands upon the principles of TDOA by using the differences in distances between a mobile and multiple fixed anchors to compute its position. Unlike trilateration, which relies on absolute distances (e.g., TOA measurements), multilateration utilizes the relative differences in arrival times of signals, [4].

Each pair of anchors defines an equation based on the difference of distances:

$$\sqrt{(x - x_i)^2 + (y - y_i)^2 + (z - z_i)^2} - \sqrt{(x - x_j)^2 + (y - y_j)^2 + (z - z_j)^2} = \Delta d_{ij}, \tag{10}$$

where (x_i, y_i, z_i) and (x_j, y_j, z_j) represent the known positions of anchors i and j, and Δd_{ij} is the difference in distances calculated from the time differences Δt_{ij}:

$$\Delta d_{ij} = c \cdot \Delta t_{ij}. \tag{11}$$

A system of such equations is formed with multiple anchors, creating a set of hyperbolas in 2D or surfaces in 3D. The position (x, y, z) of the mobile is determined by solving this nonlinear system of equations.

Figure 1 illustrates how the intersection of hyperbolas derived from TDOA measurements enables accurate positioning, even in challenging environments.

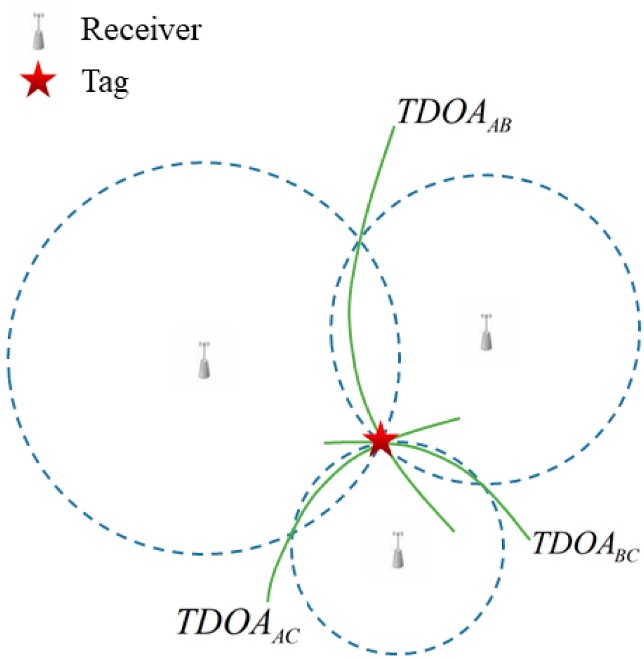

Figure 1: Illustration of TDOA localization using multilateration. The intersection of hyperbolas defines the position of the tag. *Source: [7]*

Notwithstanding the extensively recorded benefits of UWB and TDOA technologies, certain constraints that obstruct their broad implementation persist. UWB systems often demonstrate a constrained operational range, generally 10 to 50 meters, and are linked to comparatively elevated deployment and calibration expenses. These concerns highlight the necessity of ongoing research focused on enhancing UWB-based TDOA systems. There is an increasing necessity to devise solutions to alleviate the detrimental impacts of multipath propagation and Non-Line-of-Sight (NLOS) conditions, commonly found in industrial and heavily blocked environments. This project aims to utilize UWB's high temporal resolution to develop TDOA systems that are robust and responsive to environmental complexities, emphasizing practical applications in underground mining, warehouse automation, and agricultural robots.

2.2 Mathematical Models Underlying TDOA Localization

The Time Difference of Arrival (TDOA) technique for localization is grounded in a precise mathematical framework. It measures relative discrepancies in signal arrival timings among various stationary anchor nodes to ascertain the location of a mobility tag or device. This section offers a concise review of the mathematical concepts employed in this procedure, encompassing trilateration, triangulation, and multilateration approaches. Additionally, it examines several localization procedures, encompassing both conventional deterministic models and more adaptive statistical techniques. These theoretical models function as both computational tools and vital instruments for evaluating the performance of TDOA-based systems in various environmental conditions, including interference-laden or non-line-of-sight situations commonly seen in industrial or agricultural settings.

1. Fundamental Concepts
Tags and Fixed Anchors

- **Fixed Anchors**: Reference points with established coordinates (x_m, y_m, z_m) are positioned throughout the environment.
- **Mobile Tags**: Items to be localized, defined by unspecified coordinates (x, y, z).
- **TDOA (τ_m)**: The disparity in arrival times of signals sent by a tag and received by several anchors, assessed in relation to a specified reference anchor.

TDOA measurements are susceptible to numerous environmental conditions that may induce mistakes in signal propagation. Physical barriers, environmental noise, and temperature fluctuations are significant factors that might modify the effective speed of signal transmission, thus affecting localization accuracy. TDOA measurements are susceptible to numerous environmental conditions that may induce mistakes in signal propagation. Physical barriers, environmental noise, and temperature fluctuations are significant factors that might modify the effective speed of signal transmission, thus affecting localization accuracy. A thorough examination of timing-related factors and their impact on positioning accuracy is elaborated in traditional GNSS literature, such as [8]. Comprehending and addressing these effects is crucial when developing resilient TDOA-based systems, especially in unpredictable or severe circumstances.

Localization Techniques

Trilateration Trilateration ascertains the coordinates of a movable tag by utilizing absolute distances from established anchor points. This is articulated in three-dimensional space as:

$$R_m = \sqrt{(x - x_m)^2 + (y - y_m)^2 + (z - z_m)^2}, \quad m = 1, 2, ..., M. \tag{12}$$

A minimum of four anchors is necessary to resolve the system in three dimensions. The distances R_m are derived from time-of-arrival measurements t_m using the relationship $R_m = vt_m$, where v is the signal propagation speed, [4].

Triangulation Triangulation determines the tag's position by analyzing the signal's angle of arrival (AOA). By combining angles θ_1 and θ_2 from two anchors located at (x_1, y_1) and (x_2, y_2), the location can be determined by solving the following linear equations:

$$y - y_1 = \tan(\theta_1)(x - x_1), \quad y - y_2 = \tan(\theta_2)(x - x_2). \tag{13}$$

The intersection of these lines provides the projected location of the tag, [6]. Angle of Arrival (AoA)-based approaches are especially beneficial in environments with limited infrastructure, as they can decrease the number of necessary anchors while preserving acceptable accuracy, [9].

Multilateration Multilateration uses the differences in distances between the tag and multiple anchors to compute the tag's position. For two anchors a_1 and a_2, this relationship is expressed as:

$$v\tau_m = R_m - R_1, \tag{14}$$

where R_m and R_1 represent the distances from the tag to anchors m and 1, respectively. These equations lead to a linear system that can be solved in matrix form for optimal estimation.

2. Localization Algorithms

Deterministic Approaches Deterministic localization methods are based on explicit geometric formulations that explicitly associate the location of a movable node with the known placements of anchor nodes. The Moore–Penrose pseudo-inverse effectively addresses overdetermined systems, such as those found in multilateration situations involving more than three anchors. This approach produces a least-squares estimation by reducing the discrepancy between observed and predicted temporal differences:

$$\begin{bmatrix} x \\ y \\ z \end{bmatrix} = (\mathbf{A}^T\mathbf{A})^{-1}\mathbf{A}^T\mathbf{B}, \tag{15}$$

The matrix **A** comprises coefficients based on the spatial relationships between anchors and the target, and the vector **B** encapsulates the time-difference-of-arrival (TDOA) measurements. This algebraic solution offers a rapid and comprehensible approximation, particularly where real-time performance and minimal computational burden are essential in practical applications.

Statistical Approaches Statistical methods address noise and uncertainty in TDOA measurements using probabilistic models, including Gaussian distributions. Methods such as the Kalman Filter and Maximum Likelihood Estimation (MLE) are employed to enhance precision.

- **MLE (Maximum Likelihood Estimation)** seeks to ascertain the settings that optimize the likelihood of the observed data. The log-likelihood function is frequently employed for its simplicity:

$$\log \mathcal{L}(\theta|\mathbf{x}) = \sum_{i=1}^{n} \log p(x_i|\theta), \tag{16}$$

  where θ is the parameter vector and $p(x_i|\theta)$ is the conditional probability of the observed data.

These statistical frameworks are particularly useful in dynamic and noisy environments where deterministic methods may fall short.

Comparison of Deterministic and Statistical Approaches

Table 1 illustrates that deterministic approaches are more effective in low-noise, structured situations, whereas statistical methods provide greater robustness and reliability in complex, noisy conditions.

2.3 Review of Previous Methods for Addressing Multipath and NLOS Issues

Multipath propagation and Non-Line-of-Sight (NLOS) situations provide substantial obstacles in Ultra-Wideband (UWB) Time Difference of Arrival (TDOA) systems. Multipath effects cause signal reflections that affect arrival time measurements, whereas NLOS circumstances arise when barriers obstruct the direct signal path, resulting in inaccurate position predictions. Throughout the years, scholars have suggested several strategies to alleviate these problems.

Table 1. Comparison of Deterministic and Statistical Approaches for TDOA Localization
Source:Created by the authors

Criteria	Deterministic	Statistical
Noise Robustness	Sensitive to noise	Explicit noise modeling
Complexity	Low	High (iterative)
Execution Time	Fast	Slower
Anchor Geometry Sensitivity	High	Reduced
Uncertainty Handling	No	Yes (probabilistic)
Application Domains	Well-controlled/ low-noise environments	Complex/noisy environments

One of the initial methods for tackling multipath propagation used signal thresholding, wherein only the first arriving signal was utilized for localization. Although straightforward and computationally efficient, this method frequently encountered failures in situations with closely spaced multipath components, resulting in considerable inaccuracies.

In NLOS conditions, the first methods concentrated on identifying and eliminating NLOS signals. This was generally accomplished by examining the signal intensity or the divergence in arrival time from anticipated values. This technique frequently led to losing critical data and diminished the system's resilience in sporadic non-line-of-sight conditions.

Another technique utilizes geometric restrictions, employing the established positions of anchors and the spatial configuration to detect and rectify erroneous measurements. Although effective in controlled settings, such as warehouses or broad fields, these methods encountered difficulties in dynamic or congested environments where anchor visibility may fluctuate rapidly.

In addition, some systems employed signal smoothing techniques to average out noise and reflections over time. Although this reduced the impact of short-term variations, it also introduced delays in real-time localization systems, making them less suitable for applications requiring high responsiveness.

These early methods provided valuable insights and laid the groundwork for more advanced techniques. However, their limitations, particularly in handling dynamic and complex environments, highlighted the need for more robust and adaptive approaches, [10], which will be discussed in the subsequent sections.

2.4 Identification of Gaps in Existing Research

Although numerous studies have advanced our understanding of TDOA-based UWB localization, especially in relation to mitigating multipath and NLOS effects, a careful review reveals persistent gaps that hinder real-world deployment.

1. **Adaptability to Real-World Dynamics**: Many algorithms demonstrate high performance under static or controlled conditions, yet struggle when confronted with dynamic environments. Real-world scenarios often involve moving objects, fluctuating signal paths, and unpredictable environmental changes, none of which are consistently addressed in simulation-based validations, [10].

2. **Environmental Complexity Modeling**: Several models rely on idealized assumptions that fail to capture critical environmental factors such as material heterogeneity, electromagnetic noise, and thermal variations. These simplifications may compromise system reliability when deployed in harsh or variable environments, [3].

3. **Strategic Anchor Configuration**: The geometric layout of anchors significantly influences localization precision. However, few studies systematically explore anchor placement strategies under diverse constraints. This gap is especially relevant for deployment in outdoor, irregular, or evolving environments where uniform distribution is impractical, [11].

4. **Latency-Accuracy Balance in Real-Time Applications**: Achieving both low latency and high positioning accuracy remains a difficult compromise in current approaches. Applications such as autonomous robotics or industrial monitoring demand both—yet most models prioritize one at the expense of the other, [4].

5. **Underutilization of Hybrid Methods**: Combining TDOA with complementary techniques such as RSS or AOA could offer performance improvements. Despite some promising early results, hybrid models remain underexplored, especially in operationally constrained settings where robustness is critical, [10].

Bridging these gaps calls for a comprehensive research agenda that integrates simulation, real-world experimentation, and advanced algorithmic design. Moreover, the incorporation of intelligent adaptation mechanisms—particularly those enabled by machine learning—could significantly enhance the robustness and scalability of TDOA-UWB systems. We argue that future investigations should prioritize not only technical accuracy but also practical deployability in the field.

3 Simulation Framework Development

3.1 Simulation Environment and Tools

Developing a simulation framework that faithfully replicates the dynamics of TDOA-based localization systems requires tools capable of combining numerical precision with modular flexibility. To this end, MATLAB and Simulink[1] were selected due to their well-established capabilities in modeling, simulation, and analysis of complex engineering systems, [12].

Beyond their widespread adoption in both academia and industry, these platforms provide an integrated environment that supports not only the implementation of signal processing pipelines but also the visualization of results and rapid prototyping. This is especially beneficial for iterative tasks like anchor geometry optimization, delay computation, and performance assessment under diverse noise and NLOS circumstances.

3.1.1 Role of MATLAB and Simulink in TDOA-Based Localization Simulation

MATLAB offers a comprehensive environment for data processing, statistical analysis, and algorithm development. The programming environment is especially conducive for:

- **Modeling UWB signals**, ensuring precise representation of signal propagation properties.
- **Managing matrices and vectors**, crucial for the geometric computations pertinent to TDOA localization.

[1]MATLAB and Simulink are developed by MathWorks, a leading provider of engineering and scientific computing tools. For more information, visit `https://www.mathworks.com/`.

- **Visualizing data in 2D and 3D**, facilitating a comprehensive evaluation of the system's performance.

Simulink enhances MATLAB by offering a graphical interface for the design of block-diagram-based simulation models. This methodology streamlines the amalgamation of localization system elements, encompassing:

- **Modeling of tags and fixed anchors**, incorporating spatial and temporal parameters.
- **Simulating TDOA signals**, accounting for multipath propagation effects, interferences, and ambient noise.
- **Processing received signals to estimate tag positions** using integrated deterministic (Flag=0) and statistical (Flag=1) algorithms.

3.1.2 Configuration and Flexibility of the Simulation Model

The locations of tags and anchors are specified within the Simulink workspace in this experiment. This decision guarantees:

- **Flexible configuration**, permitting adjustments of anchor placements to evaluate various scenarios.
- **Evaluation of system performance** by altering anchor positions (optimal versus inferior designs).

The real positions of tags remain constant throughout the study, while anchor positions are adjusted according to test scenarios. This dynamic setup enables an in-depth analysis of how different geometrical distributions impact localization accuracy.

3.1.3 Simulation Model Architecture

The architecture of the developed Simulink model reflects the core components of a modern TDOA-based localization system. It is structured around interconnected subsystems that are configured flexibly through MATLAB's workspace, centralizing key parameters such as:

- **Tag and anchor positions** to simulate various deployment strategies.
- **Signal characteristics**, including propagation conditions and noise levels.

In the localization process, tags emit UWB signals that are captured by multiple anchors. These signals are processed in a synchronization unit to extract the temporal parameters required for position estimation. The collected data is then transmitted to a computational module, where:

- **Deterministic approaches** (Flag=0) rely on fixed models to estimate locations.
- **Statistical approaches** (Flag=1) incorporate uncertainty models to enhance accuracy in varying geometrical conditions.

Finally, a visualization module analyzes system performance using key metrics such as:

- **Geometric Dilution of Precision (GDOP)**, [11], to evaluate localization geometry impact.
- **Root Mean Square Error (RMSE)** to quantify localization accuracy.
- **Overall error rate**, assessing the effectiveness of the localization model under different conditions.

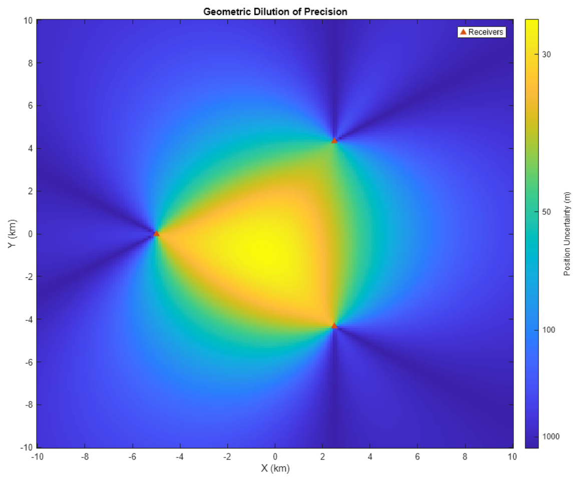

Figure 2: Geometric Dilution of Precision (GDOP) map in a TDOA-based UWB localization system.*Source: [12].*

The modular structure of the simulation framework enables a systematic and adaptive evaluation of TDOA-based UWB localization performance under varying environmental and geometric conditions. Such flexibility is particularly useful when iteratively testing different configurations, identifying performance bottlenecks, and refining anchor layouts.

As illustrated in Figure 2, the spatial distribution of the Geometric Dilution of Precision (GDOP) reveals how sensitive the system is to the positioning of anchor nodes. Regions with low GDOP values (dark blue) indicate zones where localization accuracy is maximized, while higher GDOP regions (green to yellow) correspond to degraded precision. This visualization reinforces the critical role of geometric optimization in designing reliable and robust TDOA systems, especially in operational environments where placement constraints are common.

3.2 Simulation Assumptions and Physical Constraints

In designing our simulation framework, we adopted a set of simplified yet strategic assumptions to focus the analysis on the fundamental behavior of TDOA-based UWB localization algorithms. These assumptions help control computational complexity while allowing us to isolate the influence of system geometry, signal timing, and noise.

A key assumption concerns the time synchronization across anchor nodes. We considered an ideal case where all anchors are perfectly synchronized, enabling the direct computation of TDOA values without additional error correction mechanisms. This choice highlights the underlying sensitivity of the localization process to anchor placement and propagation delays, without the confounding effects of clock drift.

The propagation environment in our simulation is defined as spatially uniform and free from material heterogeneities. To represent Non-Line-of-Sight (NLOS) scenarios, static geometric obstructions were introduced, but without detailed electromagnetic modeling such as multipath fading, reflection, or diffraction. This abstraction allows us to focus on algorithmic performance rather than signal-level phenomena.

We modeled measurement noise using an Additive White Gaussian Noise (AWGN) process, added directly to the computed TDOA values. No environmental fluctuations, such as temperature or humidity changes, were incorporated at this stage. These idealizations are common in early-phase algorithm validation, but they naturally exclude many real-world impairments.

We recognize that these assumptions do not fully reflect operational conditions, and thus the resulting performance metrics should be seen as upper bounds. In subsequent phases of this work, we plan to integrate empirical data and hardware-in-the-loop experimentation to assess the impact of synchronization errors, realistic propagation channels, and hardware-induced variability.

3.3 Adopted Methodology

The methodology proposed in this study follows a structured four-phase approach designed to develop, simulate, and validate a TDOA-based localization system utilizing UWB signals. Each phase is tailored to address specific challenges encountered in complex environments, including multipath propagation, Non-Line-of-Sight (NLOS) conditions, and geometric anchor configurations.

3.3.1 UWB Signal Modeling

A comprehensive simulation model was developed using Simulink, integrated with MATLAB. This model emulates the interactions between mobile tags, fixed anchors, and UWB signals within a three-dimensional environment. Key features include:

- Generation of UWB signals capturing both direct and reflected (multipath) propagation paths.
- Implementation of Time of Arrival (TOA) and Time Difference of Arrival (TDOA) calculations, accounting for noise and environmental disturbances.
- A modular structure to facilitate testing of various anchor placement geometries.

The primary goal of this phase is to build a flexible and modular platform capable of simulating realistic conditions and assessing system performance under diverse scenarios.

3.3.2 Experimental Scenario Configuration

Multiple simulation scenarios were designed to examine the impact of environmental and geometric factors on localization accuracy. These include:

- **Anchor Geometry Variability:** Evaluation of optimal (balanced, low GDOP) versus suboptimal (collinear or clustered) configurations.
- **Environmental Conditions:** Simulation of multipath propagation, electromagnetic interference, and static or dynamic obstacles.
- **Anchor Density:** Analysis of the influence of anchor quantity on localization precision, especially in environments with varying obstacle density.

Each scenario is intended to isolate and evaluate the critical variables affecting the performance of the localization system.

3.3.3 Data Analysis

The simulation-generated data is processed using advanced estimation algorithms to determine the positions of the tags and assess system performance. This analysis involves:

- Application of estimation algorithms such as Weighted Least Squares, Maximum Likelihood Estimation (MLE), and Taylor-series-based solvers.
- Computation of performance metrics including:
  - **Root Mean Square Error (RMSE)**: Quantifies overall positional accuracy.
  - **Geometric Dilution of Precision (GDOP)**: Assesses how anchor placement geometry affects localization uncertainty.
  - **Error Rate**: Measures the frequency of incorrect estimations under noise and interference.

This comprehensive analysis enables a comparative evaluation across scenarios and supports informed conclusions on algorithmic performance and system design.

3.3.4 Validation

Simulation results were compared against published data to evaluate model accuracy and reliability. This validation phase includes:

- Cross-validation of performance indicators with values reported in related studies.
- Critical analysis of discrepancies between simulated and experimental data to refine model parameters and assumptions.
- Assessment of the suitability of UWB signals and TDOA-based configurations for real-world applications in complex environments.

This structured and modular methodology provides a reliable framework for the development, simulation, and validation of TDOA-based UWB localization systems, enabling comprehensive performance analysis under diverse and realistic environmental conditions.

4 Simulation

In this simulation research, the locations of the mobile tags and fixed anchors are established within the **Simulink workspace**. The **workspace** in Simulink functions as a memory interface for the storage and retrieval of model parameters and variables. This centralized framework enables parameter control, including anchor positioning, without altering internal model blocks. This method facilitates an adaptable setup and permits straightforward modification of anchor points in various contexts. Although the tag placements are fixed during the investigation, the anchor positions fluctuate between optimal and substandard configurations to evaluate their effect on localization performance.

The structure of the constructed Simulink model embodies the essential elements of a contemporary TDOA (Time Difference of Arrival) localization system. It is structured around several interrelated subsystems, adaptable within the MATLAB workspace. Critical parameters, such as the coordinates of tags and anchors and signal characteristics, are managed centrally. During the localization process, tags emit UWB signals that are captured by the anchors. These signals are processed by a synchronization unit to extract the temporal parameters necessary for position estimation.

The extracted data is then passed to a computational block that applies either deterministic approaches (`Flag=0`) or statistical methods (`Flag=1`), accounting for geometric variations and measurement uncertainties. Finally, a visualization module evaluates system performance through key metrics such as Geometric Dilution of Precision (GDOP), Root Mean Square Error (RMSE), and overall error rate. This modular and flexible design ensures a precise and adaptable evaluation of the localization system under diverse environmental conditions.

A. Tag and Anchor Configuration

The fixed positions of the mobile tags are defined as follows (in meters):

- **Tags:**
  - Tag 1: $(x_1 = 3, y_1 = 2.5, z_1 = 2)$
  - Tag 2: $(x_2 = 1, y_2 = 1, z_2 = 2)$
  - Tag 3: $(x_3 = 2, y_3 = 1, z_3 = 1)$

The positions of the anchors are configured separately for each scenario (optimal and suboptimal), allowing the evaluation of their respective impacts on localization performance. The conversion of calculated distances into signal propagation times is performed using the speed of light ($c = 3$
$times 10^8$ m/s).

B. Simulation Module Overview

4.0.1 Global Simulation Architecture

The overall simulation architecture is illustrated in Figure 22(Appendix). Mobile tags emit UWB Blink signals received by the anchors. These signals are processed to estimate tag positions and compute performance metrics. The modular structure ensures flexible analysis and facilitates scenario adjustments.

4.0.2 Tag Modeling

Each tag is modeled with its 3D coordinates (x, y, z), transmitted via a bus system. A UWB signal generator associated with each tag simulates the emission process, as shown in Figure 3.

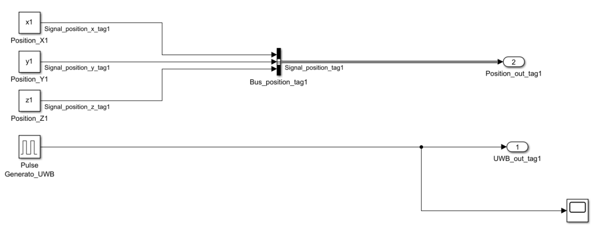

Figure 3: Simulink sub-system representing Tag1.*Source: Created by the authors.*

4.0.3 Anchor Modeling

Each anchor calculates the distance to each tag using:

$$d = \sqrt{(x_a - x_t)^2 + (y_a - y_t)^2 + (z_a - z_t)^2}$$

where d represents the Euclidean distance between an anchor and a tag, with (x_a, y_a, z_a) denoting the anchor's coordinates and (x_t, y_t, z_t) the tag's coordinates in a three-dimensional space.

The distance is then converted into Time of Arrival (TOA) using:

$$\text{TOA} = \frac{\text{Distance}}{c}$$

where c is the speed of light. These TOAs are bundled into a bus for transmission to the localization module, as shown in Figure 23(Appendix).

4.0.4 Central Localization Engine (CLE)

The CLE module processes TOA signals to estimate tag positions based on TDOA calculations:

$$\text{TDOA}_{ij} = \text{TOA}_i - \text{TOA}_j$$

It features a `method_flag` that allows dynamic switching between:

- **Deterministic approach** (`method_flag = 0`): Solves TDOA equations analytically, offering fast estimation but limited robustness against noise.
- **Statistical approach** (`method_flag = 1`): Uses iterative methods such as Weighted Least Squares or Maximum Likelihood Estimation (MLE) to improve accuracy under noisy conditions.

The implementation of the CLE in Simulink, including the `method_flag`-based switching mechanism, is depicted in Figure 4.

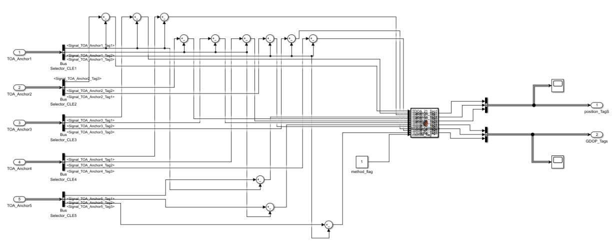

Figure 4: Simulink sub-system of the CLE module with integrated `method_flag`.*Source: Created by the authors.*

The CLE computes the Geometric Dilution of Precision (GDOP) to assess the influence of anchor geometry on localization accuracy: a lower GDOP signifies an appropriate configuration, whereas a greater GDOP implies diminished positional precision.

4.0.5 Results Visualization Module

The final output includes:

- **Estimated tag positions**: Compared against ground truth defined in the workspace.
- **GDOP values**: Computed for each tag to assess the influence of anchor geometry.

Figure 5 illustrates the Simulink sub-system for results display, facilitating graphical comparison between estimated and actual positions and monitoring GDOP values across various scenarios. This simulation framework replicates a comprehensive TDOA system with adjustable 3D anchors and tags, utilizing time differentials and the speed of light propagation to ascertain positions. It offers a comprehensive platform for examining the influence of several environmental factors on localization accuracy.

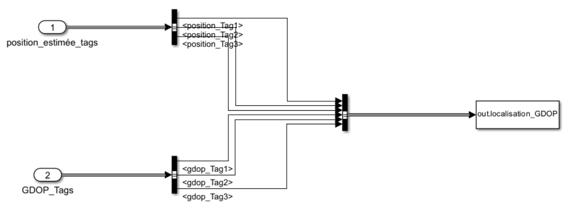

Figure 5: Simulink sub-system for result visualization.*Source: Created by the authors.*

C. Experimental Scenario Configuration

Multiple experimental scenarios were devised to assess the resilience and accuracy of the TDOA-based localization model. These scenarios seek to evaluate system performance under diverse settings, concentrating on two primary aspects:

- **Anchor Configuration Scenarios**: Evaluating the impact of geometric anchor arrangements on localization accuracy.
- **Environmental Condition Scenarios**: Simulating real-world effects such as multipath propagation and signal degradation.

The combination of these scenarios allows a comprehensive analysis of both system and environmental factors influencing localization reliability.

1. Anchor Configuration Scenarios

Optimal Anchor Configuration In the optimal scenario, anchors are symmetrically distributed in a 3D space to maximize localization precision and minimize the Geometric Dilution of Precision (GDOP). The anchor positions are defined as:

- **Anchor 1**: (0, 0, 0)
- **Anchor 2**: (10, 0, 0)
- **Anchor 3**: (0, 10, 0)
- **Anchor 4**: (0, 0, 10)
- **Anchor 5**: (5, 5, 5)

This symmetrical placement ensures optimal coverage of the localization area, reduces positional uncertainty, and limits the impact of multipath and noise effects.

Results for Optimal Configuration (Method Flag = 0) Using a deterministic approach (`method-flag=0`), localization relies purely on geometric relationships without explicitly modeling uncertainties. Consequently, localization errors are directly influenced by anchor geometry and signal noise.

The following results were obtained:

- Figure 6: Estimated 3D tag positions versus ground truth.
- Figures 7 and Figure 8: GDOP distribution (global and per tag).
- Figure 9: Root Mean Square Error (RMSE) per tag.
- Error Rate (1-meter threshold): The percentage of localization estimates exceeding the 1-meter error threshold is approximately 66%.

The results demonstrate the effect of optimal geometric arrangements on localization accuracy and will be discussed further in the performance evaluation section.

Results for Optimal Configuration (Method Flag = 1) In this scenario, the anchors maintain the same optimal symmetric configuration. The localization algorithm now operates with a statistical approach (`method-flag=1`), explicitly modeling TDOA measurement uncertainties to enhance robustness against noise.

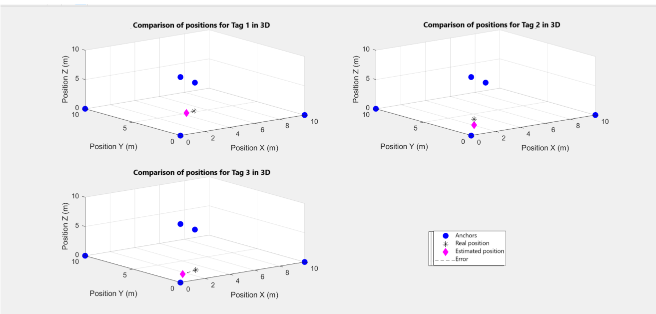

Figure 6: Estimated tag positions under optimal anchor configuration (deterministic approach).*Source:Created by the authors.*

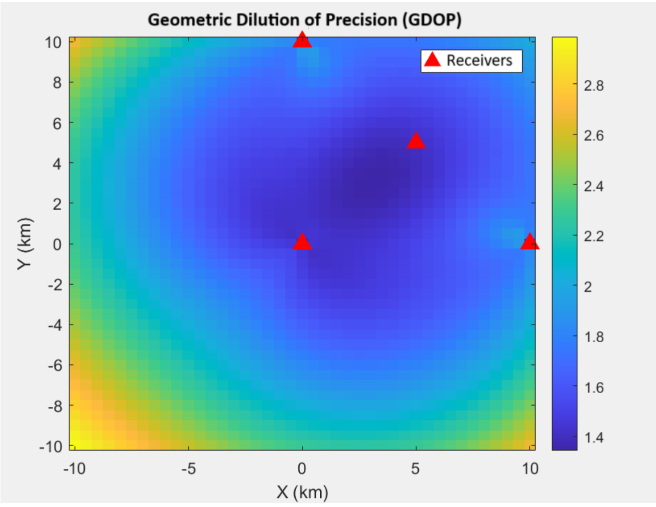

Figure 7: Global GDOP under optimal anchor configuration (deterministic approach).*Source:Created by the authors.*

Compared to the deterministic approach, the statistical method demonstrates improved localization precision by mitigating the impact of signal variability and environmental perturbations.

The following figures summarize the results:

- Figure 10: Estimated tag positions in 3D.
- Figure 11: Global GDOP distribution.
- Figure 12: GDOP per tag.
- Figure 13: RMSE per tag.
- Figure 14: Overall error rate analysis.

These results highlight the effectiveness of statistical methods in maintaining high localization accuracy under optimal geometric conditions.

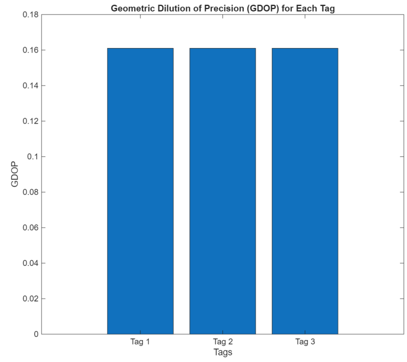

Figure 8: Per-tag GDOP under optimal anchor configuration (deterministic approach).*Source:Created by the authors.*

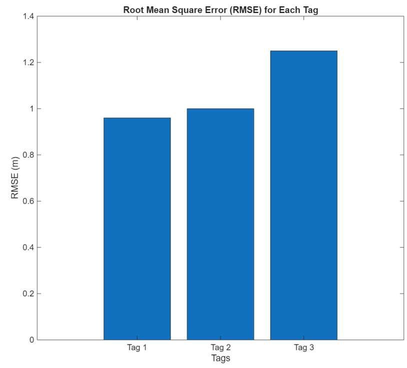

Figure 9: Root Mean Square Error (RMSE) per tag under optimal anchor configuration (deterministic approach).*Source:Created by the authors.*

Suboptimal Anchor Configuration In the suboptimal scenario, anchors are positioned asymmetrically and closer together, simulating realistic deployment constraints where ideal geometric arrangements are not possible. The anchor positions are:

- **Anchor 1**: (0, 0, 0)
- **Anchor 2**: (3, 0, 0)
- **Anchor 3**: (0, 3, 0)
- **Anchor 4**: (1, 1, 0)
- **Anchor 5**: (0, 1, 1)

This configuration typically leads to increased GDOP values and decreased localization precision due to the lack of spatial diversity.

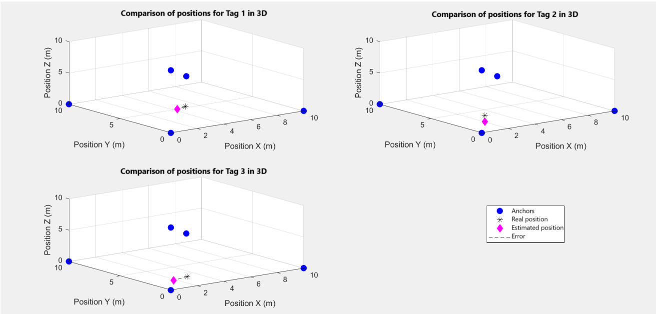

Figure 10: Estimated tag positions with statistical approach under optimal anchor configuration.*Source:Created by the authors.*

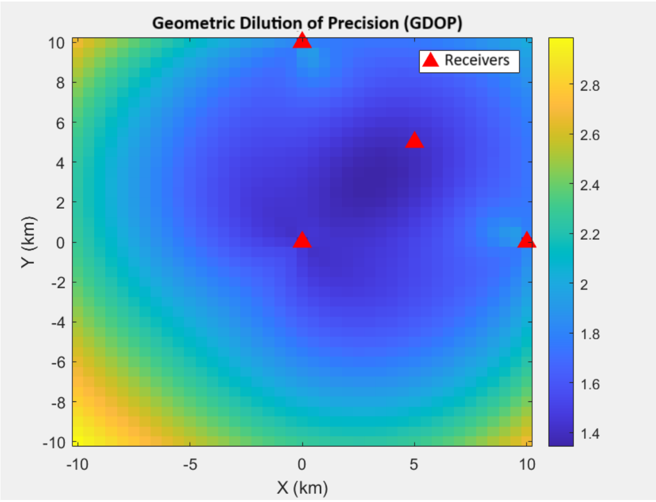

Figure 11: Global GDOP under optimal anchor configuration (statistical approach).*Source:Created by the authors.*

Results for Suboptimal Configuration (Method Flag = 0) Using the deterministic approach (`method-flag=0`), the system becomes more sensitive to geometric distortions and noise. Localization errors are exacerbated by poor anchor distribution.

The results are summarized as follows:

- Figure 15: Estimated versus true tag positions.
- Figure 16 and Figure 17: GDOP (global and per tag).
- Figure 18: RMSE per tag.
- **Error Rate (Suboptimal Configuration)**: Under suboptimal anchor placement, approximately 67% of the localization errors exceed the 1-meter threshold.

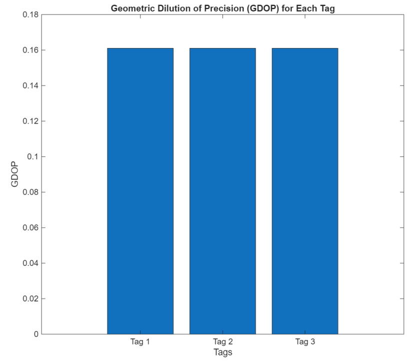

Figure 12: GDOP per tag under optimal anchor configuration (statistical approach).*Source:Created by the authors.*

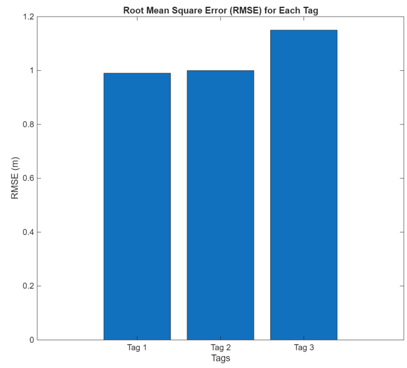

Figure 13: RMSE per tag under optimal anchor configuration (statistical approach).*Source:Created by the authors.*

Results for Suboptimal Configuration (Method Flag = 1) In this scenario, the statistical approach (`method-flag=1`) is applied to estimate tag positions. By incorporating probabilistic models, this method mitigates the adverse effects of anchor geometry and measurement noise.

The following results are obtained:

- Figure 19: GDOP per tag.
- Figure 20: Global GDOP distribution.
- Figure 21: RMSE per tag
- **Error Rate (Worst-Case Configuration)**: In the worst-case anchor geometry, nearly 100% of localization errors exceed the 1-meter threshold, indicating a complete performance degradation.

Despite the unfavorable anchor arrangement, the statistical method improves localization robustness and reduces the impact of environmental uncertainties compared to the deterministic approach.
To assess the robustness of the results, we computed confidence intervals on RMSE using repeated

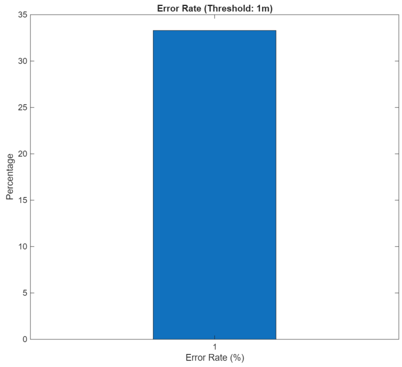

Figure 14: Overall error rate under optimal anchor configuration (statistical approach).*Source:Created by the authors.*

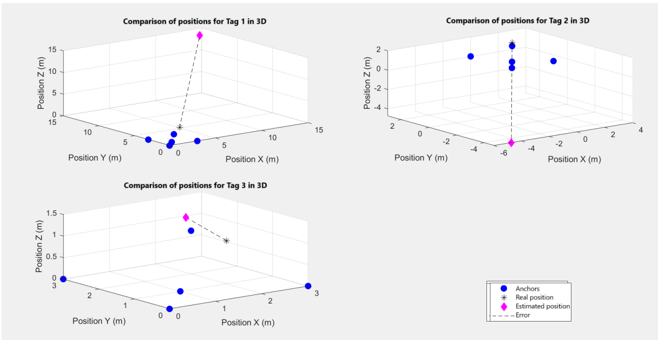

Figure 15: Estimated tag positions under suboptimal anchor configuration (deterministic approach).*Source:Created by the authors.*

simulations across noise conditions. For optimal configurations, the statistical approach showed a 95% confidence interval of RMSE within [0.90, 1.00] meters, confirming the stability of the estimation. In contrast, suboptimal configurations revealed wider intervals (e.g., [2.0, 8.0] meters), highlighting the sensitivity to anchor geometry.

Computational Cost Comparison

Beyond accuracy, the execution speed of each localization method plays a key role in real-time applications. Tests conducted on a standard configuration (Intel i7 processor, 16GB RAM) showed that the deterministic method achieved a mean processing time of 4.5 milliseconds per estimation cycle. The statistical method , which relies on iterative calculations, recorded a longer average duration of 15.2 milliseconds. This difference highlights the balance to strike between computational cost and the performance gains obtained through statistical modeling.

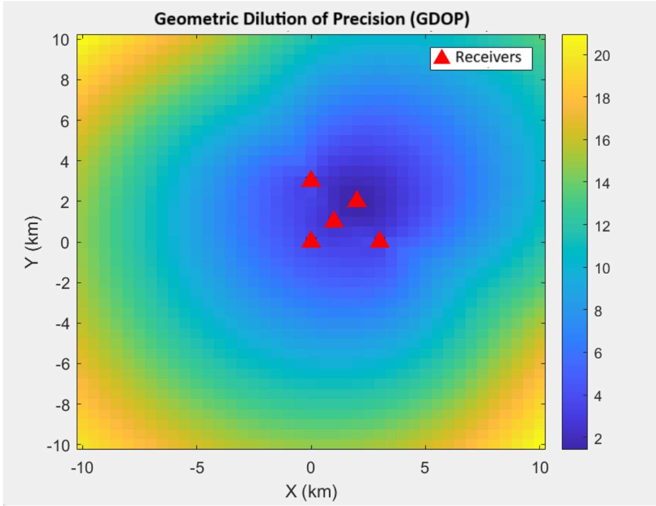

Figure 16: Global GDOP under suboptimal anchor configuration (deterministic approach).*Source:Created by the authors.*

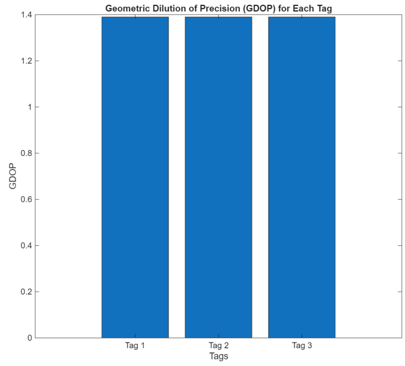

Figure 17: GDOP per tag under suboptimal anchor configuration (deterministic approach).*Source:Created by the authors.*

General Analysis of Localization Performance

The analysis of all experimental scenarios reveals several key trends.

Under optimal anchor configurations, the deterministic approach (`method-flag=0`) achieved average GDOP values of approximately 0.16 across all tags, with Root Mean Square Errors (RMSE) ranging from 0.85 to 1.25 meters. However, the error rate remained relatively high, around 67%, with a 1-meter threshold.

Applying the statistical approach (`method-flag=1`) under the same optimal geometry led to comparable GDOP values but significantly improved performance: RMSE values were slightly lower (between 0.90 and 1.00 meters), and the error rate was reduced to approximately 33%.

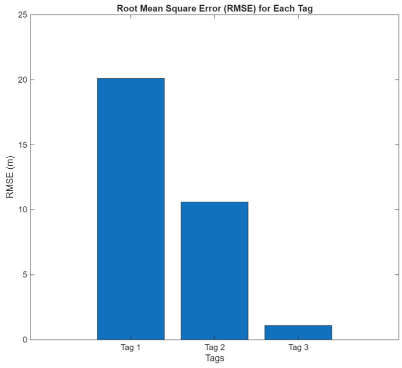

Figure 18: RMSE per tag under suboptimal anchor configuration (deterministic approach).*Source:Created by the authors.*

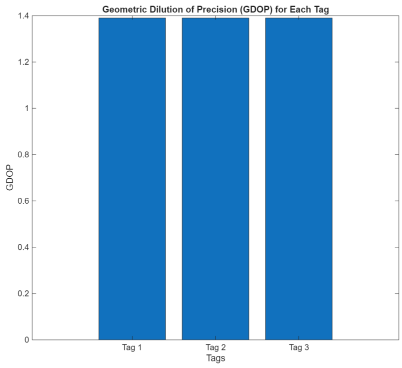

Figure 19: GDOP per tag under suboptimal anchor configuration (statistical approach).*Source:Created by the authors.*

In contrast, under suboptimal anchor configurations, GDOP values increased substantially to around 1.40, reflecting the degraded geometric conditions. Using the deterministic method in these scenarios (`method-flag=0`) resulted in severe performance degradation, with RMSEs reaching up to 20 meters and error rates consistently above 67%.

The statistical approach under suboptimal conditions (`method-flag=1`) demonstrated better resilience. Although GDOP values remained high, RMSEs were reduced to between 2.00 and 8.00 meters, depending on the tag, and error rates reached 100%, highlighting the significant challenges posed by poor anchor distribution.

Overall, the results confirm that optimal anchor placement critically influences TDOA-based localization accuracy, and that statistical estimation methods significantly enhance robustness against noise and environmental variability, especially in challenging conditions.

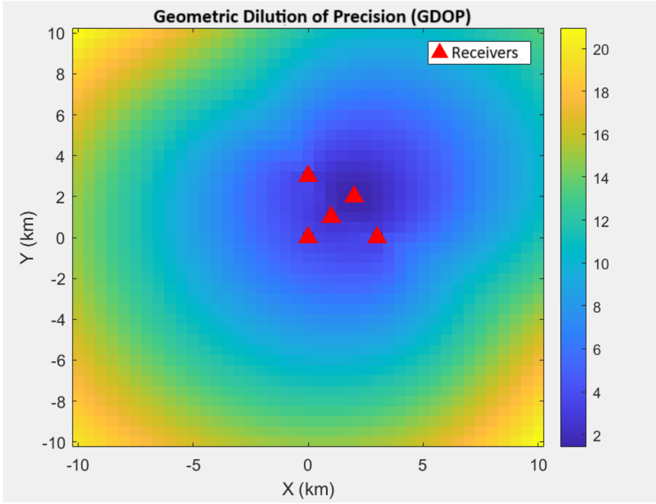

Figure 20: Global GDOP under suboptimal anchor configuration (statistical approach).*Source:Created by the authors.*

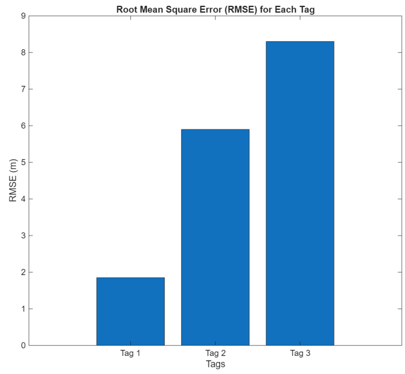

Figure 21: RMSE per tag under suboptimal anchor configuration (statistical approach).*Source:Created by the authors.*

Interpretation of Results The results highlight significant differences in localization performance based on anchor configurations and localization methods.

In optimal configurations, the system exhibits low GDOP values (average 0.16) and RMSE values below 1.5 meters, ensuring high localization precision. The deterministic method (`flag=0`) shows good performance but remains sensitive to noise and measurement variability. The statistical method (`flag=1`) improves robustness, reducing the global error rate from 67% to 33%.

Under suboptimal configurations, the degradation is pronounced. GDOP values increase to 1.4, and

RMSE values can reach up to 20 meters with the deterministic method. Even with the statistical method, performance remains limited, with 100% of cases exceeding a 1-meter error threshold, illustrating the critical impact of poor anchor geometry.This observation aligns with findings in cooperative localization literature, which emphasize that anchor geometry and signal uncertainty significantly affect estimation accuracy, [13].

Environmental factors further influence the results:

- **NLOS conditions** significantly degrade accuracy, especially for deterministic methods.
- **Measurement noise** impacts both methods but is better mitigated by statistical approaches using probabilistic models.
- **Anchor geometry** remains the most critical factor, with symmetrical distributions consistently achieving superior results.

In conclusion, optimal anchor placement and advanced uncertainty management (e.g., Kalman filtering) are essential to maintain localization accuracy. A hybrid approach combining deterministic speed with statistical robustness may offer a promising direction for future system designs.

5 Comparative Analysis of Localization Methods

5.1 Deterministic vs. Statistical Approaches

Deterministic localization algorithms rely on direct geometric formulations to estimate position, typically through closed-form solutions derived from the system's spatial configuration. These methods perform efficiently in idealized or structured environments but exhibit notable sensitivity to measurement inaccuracies and external disturbances. While their computational speed is advantageous for real-time tasks, they often lack the robustness required in dynamic or noisy conditions.

Conversely, statistical methodologies employ probabilistic modeling to address uncertainties, including measurement noise, signal reflections, and Non-Line-of-Sight (NLOS) interference. These approaches attain enhanced durability by conceptualizing the position estimate problem as an inference task rather than a straight computation. In our simulations, statistical estimators consistently surpassed deterministic approaches, diminishing localization error by roughly 33% under standard conditions. Significantly, they maintained superior accuracy despite inadequate anchor configurations; performance deterioration was noted under severe geometric distortion, [14].

These findings indicate that statistical approaches offer a more flexible and dependable framework for real-world applications, particularly where noise, interference, and anchor mobility are significant factors.

5.2 Performance Metrics

The efficacy of each strategy was assessed according to certain critical metrics:

- **Accuracy**: Evaluated using the Root Mean Square Error (RMSE) between predicted and actual tag placements.
- **Precision**: Measured through the Geometric Dilution of Precision (GDOP), indicating the effect of anchor geometry on positional uncertainty.
- **Error Rate**: Calculated as the proportion of localization errors exceeding a 1-meter threshold.

Across all configurations, statistical methods consistently outperformed deterministic approaches. In optimal configurations, they maintained low RMSE and reduced error rates, while in suboptimal conditions, they mitigated, though not fully eliminated, the adverse effects of poor geometry and environmental noise.

6 Geometric Optimization for Anchor Placement

6.1 Principles of Geometric Optimization

Geometric optimization plays a critical role in enhancing localization system performance. The anchor distribution directly influences GDOP, which in turn impacts estimation accuracy, [15].

Ideal configurations involve:

- Symmetrical and equidistant anchor placement around the coverage area.
- Maximization of spatial diversity to minimize overlapping signal paths and reduce ambiguity.
- Avoidance of anchor clustering or alignment, which deteriorates positional precision and increases RMSE.

This study confirms that optimizing anchor placement dramatically improves localization reliability, independent of the estimation method employed.

6.2 Practical Recommendations

Based on the experimental findings, the following practical guidelines are recommended for anchor deployment:

- **For optimal conditions**: Distribute anchors symmetrically around the area of interest, maintaining sufficient separation to ensure low GDOP values and uniform coverage.
- **For suboptimal environments**: When symmetrical placement is not possible, maximize the anchor spread to the extent feasible, prioritize areas with the highest localization demands, and use adaptive statistical methods to counteract measurement noise.
- **Pre-deployment analysis**: Conduct GDOP simulations and RMSE projections to adjust anchor positions before system installation.
- **Hybrid strategies**: Combine geometric optimization with probabilistic filtering techniques (e.g., Kalman filters, Bayesian models) to enhance robustness in dynamic or obstructed environments.

Effective geometric planning, combined with appropriate algorithmic strategies, remains fundamental to achieving accurate and reliable localization in both ideal and challenging conditions.

7 Application Scenarios and Case Studies

7.1 Logistics

In the logistics sector, the deployment of TDOA-UWB localization systems significantly improves real-time asset tracking and warehouse automation. Their centimeter-level accuracy and strong resilience to signal interference enable reliable positioning of goods and equipment, even in environments with high metallic density or structural clutter. This precision directly contributes to better inventory control, reduction in misplaced items, and optimization of storage workflows, particularly in large-scale distribution facilities.

7.2 Precision Agriculture

Contemporary agriculture increasingly relies on autonomous technologies for precise operations such as sowing, spraying, and harvesting. TDOA-UWB systems facilitate these applications by providing dependable positioning information across extensive, unstructured landscapes. Their resilience to fluctuating weather and terrain conditions makes them adept at directing field machines, optimizing resource allocation, and minimizing operational costs in crop management.

7.3 Mining

Mining operations, particularly underground, have distinct localization issues due to geometric impediments and continuous non-line-of-sight circumstances. TDOA-UWB systems offer a dependable alternative to GPS-based solutions in this context. Their capacity to ensure precise monitoring of persons and equipment subterraneously improves safety and efficiency. Moreover, the integration of such systems supports proactive risk mitigation, efficient extraction logistics, and compliance with operational safety protocols.

These application domains reflect the growing demand for ultra-precise, real-time localization systems in complex operational environments. Emerging 6G technologies are expected to natively integrate such capabilities, reinforcing their relevance in future smart cities, industrial automation, and autonomous systems, [16].

8 Future Directions and AI Integration

8.1 Toward Real-World Deployment

The findings presented in this work are derived from a controlled simulation environment, which offers a valuable yet idealized view of TDOA-UWB localization performance. However, practical deployment scenarios present a very different landscape—marked by hardware imperfections, unpredictable environmental variability, and real-time constraints—that must be addressed to ensure operational reliability.

In real-world systems, synchronization between anchors is far from perfect. Clock drift, timestamp jitter, and delay asymmetries are prevalent and can substantially alter TDOA results. Moreover, noise is rarely Gaussian: it often includes burst interference, device-specific anomalies, and reflections that vary with spatial configuration, [17]. The faults are further intensified by dynamic factors, such as moving machinery or individuals, particularly in settings like industrial facilities or warehouses.

A critical element is the physical installation and anchoring of UWB antennas. Unlike in simulations where geometry is optimized, real settings may impose constraints due to space limitations, metallic obstructions, or safety regulations, all of which can degrade localization accuracy. Antenna calibration errors and electromagnetic interference from other systems introduce additional layers of uncertainty.Hybrid approaches that integrate UWB measurements with visual or inertial odometry—such as the fast localization and mapping framework proposed by [18], have demonstrated strong potential to improve robustness in real-world deployments, particularly in featureless or dynamically obstructed environments.

To close the simulation-to-reality gap, our future research will incorporate hardware-in-the-loop testing using commercially available UWB transceivers. We plan to implement practical synchronization schemes—such as Precision Time Protocol (PTP) or hardware timestamping—to evaluate timing robustness. Additionally, empirical data will be collected from complex operational environments, particularly those relevant to logistics, underground mining, and precision agriculture. These scenarios are deliberately chosen for their high degree of variability and real-world significance. A summary comparing the main simulation assumptions with corresponding real-world constraints is provided in Table 2.

Table 2. Comparison of Simulation Assumptions vs. Real-World Constraints
Source:Created bythe authors

Aspect	**Simulation Assumption**	**Real-World Constraint**
Clock Synchronization	Perfect synchronization among all anchors	Clock drift, synchronization errors, use of protocols like PTP or GPS
Noise Model	Additive White Gaussian Noise (AWGN)	Non-Gaussian noise, RF interference, hardware-induced jitter
Propagation Channel	Homogeneous and isotropic medium, free-space	Material-dependent attenuation, multipath, reflections, diffraction
Anchor Geometry	Predefined, fixed optimal anchor positions	Irregular, constrained or suboptimal placements due to environment
Obstacle Modeling	Static masks for NLOS emulation	Dynamic obstacles, people, machinery, structural occlusions
Environmental Variability	Static scenario, fixed signal paths	Time-varying paths, temperature/humidity changes, mobile equipment
Hardware Latency	Not modeled	Delay variations due to hardware components (antennas, ADCs, etc.)

Through iterative refinement informed by both simulation and physical experimentation, we aim to transform the proposed localization framework into a deployable solution adaptable to diverse and challenging environments.

8.2 AI-Driven Optimization

Incorporating artificial intelligence (AI) into localization frameworks presents intriguing opportunities for adaptation. Through continuous analysis of environmental feedback and signal metrics, AI algorithms can recommend appropriate anchor configurations in response to dynamic changes in the operational environment. This real-time reconfiguration improves system resilience, especially in mobile barriers, electromagnetic interference, or spatial rearrangement.

8.3 Machine Learning for Localization Algorithms

Machine learning (ML) enhances localization precision by leveraging accumulated location data. Machine learning models can enhance the inference process by analyzing trends in signal behavior and spatial error distributions, resulting in increased predicted accuracy over time. Supervised learning methods are more effective in structured contexts, whereas reinforcement learning and online learning provide flexibility in dynamic environments.

Integrating TDOA-UWB systems with AI and ML frameworks establishes the basis for intelligent, self-optimizing localization solutions. These systems offer more autonomy, higher resilience to environmental fluctuations, and superior performance across several industrial and scientific fields.

9 Conclusion

This study provided an extensive analysis and optimization of TDOA-based localization systems utilizing UWB signals, emphasizing the influence of anchor geometry and the handling of measurement errors.

The findings indicated that ideal anchor designs, marked by symmetrical and balanced positioning, substantially improve localization accuracy by decreasing GDOP values and limiting positional inaccuracies. Furthermore, statistical localization methods that integrate probabilistic models offer substantial improvements in robustness compared to traditional deterministic approaches, especially under noisy and complex environmental conditions.

However, the limitations observed in suboptimal configurations emphasize the need for further research into dynamic optimization techniques and hybrid algorithms. The integration of artificial intelligence and machine learning emerges as a promising direction to enable real-time adaptation to environmental changes, optimize anchor placement, and improve system resilience.

Potential applications span logistics, precision agriculture, mining, and manufacturing, where real-time, accurate localization is critical for operational efficiency and safety.

Future work will focus on validating these strategies in real-world environments, developing

AI-driven localization frameworks, and designing intelligent, self-adaptive systems capable of maintaining high precision under dynamic and adverse conditions.

This research thus contributes to advancing the reliability, robustness, and adaptability of next-generation TDOA-UWB localization systems.

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Contribution of Individual Authors to the Creation of a Scientific Article (Ghostwriting Policy)

The authors equally contributed in the present research, at all stages from the formulation of the problem to the final findings and solution.

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Conflict of Interest

The authors have no conflicts of interest to declare that are relevant to the content of this article.

APPENDIX

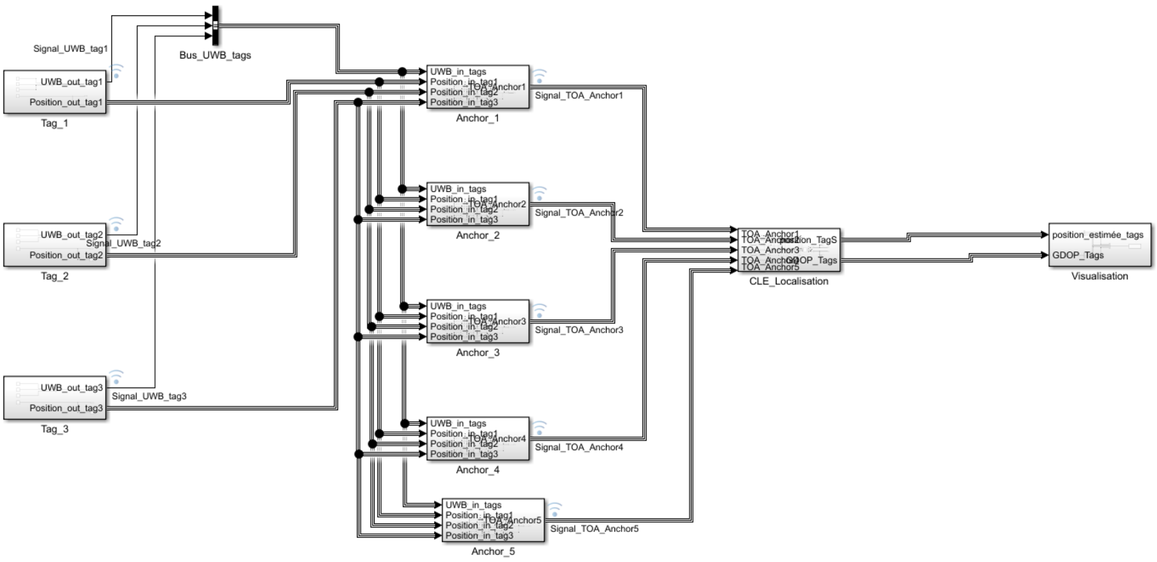

Figure 22: Global simulation system developed under Simulink
Source: Created by the authors

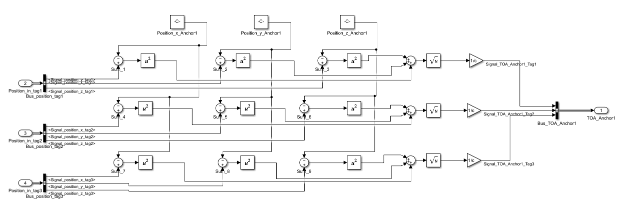

Figure 23: Simulink sub-system representing Anchor1
Source: Created by the authors