Enhancing UWB Indoor Positioning using Bias-Aware EKF and Anchor Self-Localization

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Abstract

Ultra-Wideband (UWB) technology is gaining attention for indoor positioning due to its high accuracy, low latency and resilience to interference, making it ideal for environments where GNSS (Global Navigation Satellite System) signals are unavailable—such as warehouses, hospitals, and underground facilities. However, UWB systems can suffer from reduced accuracy under Non-Line-of-Sight (NLOS) conditions and dynamic deployments. This paper proposes a novel bias aware EKF (Extend Kalman Filter) model, combined with Anchor Self-Localization method for localization in indoor environments, and enhancing the flexible deployment of anchors. The proposed model demonstrates an overall improvement of 32% and 41% in positioning accuracy compared to traditional methods across both indoor and outdoor environments respectively. The paper demonstrates that the proposed ASL method performs at par with conventional pre-calibrated methods where anchors are to be localized manually. Together, the Bias-Aware filtering and ASL approach enhance the scalability and reliability of UWB-based Indoor Positioning Systems (IPS) for real-world applications.

1. Introduction

Accurate location tracking in indoor environments has become increasingly vital for applications ranging from robotics and augmented reality to healthcare and industrial automation. Traditional satellite-based systems like GNSS (Global Navigation Satellite System) are rendered ineffective in enclosed or obstructed environments due to signal attenuation and multipath effects. This has led to the development of Indoor Positioning Systems (IPS), where technologies such as Wi-Fi (Wireless Fidelity), Bluetooth, and Infrared have been used, but with limitations in terms of accuracy (Syazwani et al., 2022). Among these, Ultra-Wideband (UWB) has emerged as a promising solution, offering high temporal resolution and multipath resistance, thereby achieving sub-meter level positioning accuracy (Dabove et al., 2018). Its short pulse duration and wide frequency spectrum make it ideal for Time of Arrival (ToA) or Two-Way Ranging (TWR) based localization in cluttered indoor spaces (Dabove et al., 2018).

In a typical UWB-based IPS, anchors are static reference nodes placed at known locations, while tags are mobile or target devices whose positions are to be estimated using distance measurements from these anchors. Traditionally, anchor locations are established using precise surveying techniques such as total station measurements or laser scanning (Dabove et al., 2018). While accurate, this setup process can be time-consuming, labor-intensive, and impractical in rapidly changing or large-scale environments. Moreover, in many real-world deployments such as emergency response setups, industrial floors or collaborative robotics the exact anchor positions may be unknown or subject to change. This introduces the need for anchor self-localization, where anchors estimate their own positions using inter-anchor distance measurements (Herbruggen et al., 2023). Simultaneously, UWB ranging data is affected by systematic biases, arising from clock offsets, hardware imperfections, or environmental variations. These biases often vary slowly over time rather than being truly constant (Babjak and Gažovová, 2023). To account for this behavior, bias modeling and compensation become essential, particularly when using filtering techniques such as the Extended Kalman Filter (EKF), which can incorporate domain-aware dynamics into the estimation process for improved performance.

This paper presents a novel UWB-based IPS framework that tackles anchor self-localization and time-varying UWB measurement biases. A key contribution is the integration of a bias decay model into the EKF, where bias evolves with a time-decaying exponential, reflecting realistic sensor behavior. By augmenting the state vector with bias dynamics, the approach improves self-localization accuracy, particularly in long-term or mobile-anchor scenarios. The algorithm is validated by real-world indoor and outdoor experiments, and a performance comparison of proposed adaptive bias-aware EKF, standard EKF and Least Squares methods, especially under slowly varying bias conditions is presented. A brief review of the literature is presented in section 2. Sections 3 and 4 present the anchor self localization and positioning framework using UWBs, respectively. The details of the experiment, results and analysis is presented in section 5. The conclusions of the paper and some ideas for future work are given in section 6.

2. Related Work

Several studies have demonstrated the efficacy of UWB-based indoor positioning systems attributed to their high temporal resolution and resilience to multipath effects. For instance, the authors in (Batstone et al., 2017) proposed a robust localization algorithm leveraging RANSAC and minimal solvers, which effectively filters outliers, achieving an average positioning accuracy of approximately 15 cm through experiments. Similarly, (Alarifi et al., 2016) reviewed UWB-based indoor positioning techniques and highlighted that systems employing two-way ranging (TWR) can consistently attain sub-meter accuracy under controlled conditions. The authors in (Trifunović et al., 2024) implemented an EKF for tag position estimation in 2D and achieved an indoor accuracy of nearly 50

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cm RMSE. The authors in (Gabela et al., 2019) demonstrated a UWB-based cooperative positioning system for pedestrians in GNSS-denied environments achieved decimeter-level accuracy using both Peer-to-Infrastructure and Peer-to-Peer (P2P) measurements, with P2P links significantly enhancing performance in sparse setups. Another study (Retscher et al., 2020) demonstrated multi-platform cooperative positioning (CP) using UWB, Wi-Fi, LiDAR, and inertial sensors, achieving high positioning accuracy and reliability, including 97% room-level detection with Wi-Fi and decimeter-level accuracy with UWB.

Traditionally, UWB systems rely on manual surveying using precise geodetic instruments to fix anchor positions. Although this method ensures high accuracy, it is labor-intensive, time-consuming, and impractical for large, frequently changing indoor environments. To overcome this, recent research has explored anchor self-localization, where the system estimates anchor positions using mutual distance measurements or mobile tag trajectories. The authors in (Vashistha et al., 2018) proposed a differential time-difference-of-arrival (DTDOA) technique requiring only two anchors and demonstrated 20–30 cm RMSE. However, this method assumes time synchronization, which is difficult to maintain. Similarly, (Taner, 2020) presented a graph-based optimization framework for anchor self-localization, which achieved accuracies below 25 cm but is sensitive to initial estimates and noise. The authors in (Sarkka et al., 2013) used Bayesian filtering for anchor and tag co-localization, but did not model biases explicitly, allowing measurement errors to propagate into both anchor and tag estimates. These studies highlight that bias in UWB measurements, if not modeled, can significantly degrade system performance—even when self-localization techniques are applied effectively.

Bias in UWB-based range measurements can result from hardware imperfections, antenna delays, or environmental factors, and often changes gradually over time. Early work like (Dardari et al., 2009) acknowledged this challenge but only treated the bias as part of measurement noise. More recent studies (Yogesh et al., 2024) have tried to consider bias as a fixed offset and performed calibration before operation, making it unsuitable for long-term dynamic scenarios. The authors in (Yi et al., 2021) proposed a Kalman filter with adaptive noise tuning but did not distinguish between noise and slowly varying bias, limiting its ability to model real-world behavior. To the best of author’s knowledge, limited work has been done in modeling the varying nature of the bias in real time. The proposed bias-aware EKF with exponential decay dynamics proposes to capture gradual changes in measurement errors. This enhances robustness and accuracy after self-localization, especially in long-duration or mobile anchor deployments where traditional bias models fall short.

3. Anchor Self Localization

UWB is a radio technology that measures distance using Time of Flight (ToF)—the time a signal takes to travel between devices. In a UWB setup, fixed anchors serve as reference points, while the mobile tag estimates its position by measuring two way ToF-based distances to multiple anchors. The tag stores these distances and transmits the data via a serial interface. In UWB-based positioning system while the tag is used for localization, accurate initialization of anchor coordinates is essential in a defined coordinate frame. This section presents a method for automatically estimating anchor positions without conventional surveying.

The process begins with the establishment of a base network using three anchors. The first anchor is fixed at the origin at [0, 0, 0] and the second is positioned along the x-axis at [d_{12}, 0, 0] where d_{12} is the measured distance averaged between the first two anchors. The third anchor is placed on the xy-plane using its measured distances d_{13} and d_{23}, from the first two anchors. These three anchors define the reference coordinate system. The positional ambiguity of the third anchor can be easily resolved by defining the positive y axis. Each pair of anchors performs n range measurements, and the average distance is used to account for random errors in distance observations. After establishing the base, additional anchors with unknown positions (x_i, y_i, z_i) are sequentially added to known anchor network (x, y, z). For each anchor position estimation, distances to known anchors are used to form a system of equations. The new position is estimated by minimizing residuals between measured and computed distances using nonlinear least squares, The proposed algorithm for self-localization is given in figure 1. This iterative procedure continues until all anchor positions are estimated within the local coordinate frame. The next section presents the complete methodology for tag positioning using Least Squares, EKF and a novel bias aware algorithm.

Algorithm 1: Self Localization of Anchor network

Input: D_i (pairwise distance matrix), n (number of anchors)
Output: Anchor positions $A = \{a_1, a_2, ..., a_n\}$

Initialize $A_1 = (0, 0, 0)$
Initialize $A_2 = (d_{12}, 0, 0)$
Estimate A_3 using nonlinear LS with distances d_{13}, d_{23}
$A = \{A_1, A_2, A_3\}$
while size(A) < n do
  for anchor a_k not in A do
    Select all anchors $a_i \in A$
    minimize$\sum (\sqrt{(x_i - x)^2 + (y_i - y)^2 + (z_i - z)^2} + r_i)$
    Define residuals: $r_i = d_i - D_i$
    Compute covariance matrix from Jacobian
    Add estimated a_k to A
  end for
end while
return A

Figure 1. Proposed algorithm for self localization of anchors in the UWB network.

4. Positioning Model

In this study, anchors are assumed to lie on the same horizontal plane, reducing the localization problem to 2D. The z-coordinate is constant across anchors and tag, hence only (x, y) are estimated for positioning. Once the anchor coordinates are initialized in a coordinate system and the network is set up, the next step is to estimate the position of the mobile tag. The following section outlines the methodology for tag position estimation using various approaches, including Least Squares, a standard Extended Kalman Filter (EKF) and the proposed Bias-Aware EKF model. The impact of each method on positioning accuracy is discussed in detail in section 5.

4.1 Positioning using Least Squares

The Least Squares method estimates the tag's position by minimizing the difference between measured and calculated distances to known anchors. The measurement model is nonlinear. At least three non-collinear observations are required to uniquely determine a tag's 2D position; two range observations can yield two symmetric solutions, the detailed approach for LS solution is mentioned in (Welsch, 1979). Given measured distances D_i between tag and known anchor positions $(x_i,\, y_i)$, the tag's position $(x,\, y)$ is estimated by solving the system of equations as given below:

$$D_i = \sqrt{(x_i - x)^2 + (y_i - y)^2} + v_i \tag{1}$$

4.2 Positioning using EKF

The Extended Kalman Filter (EKF) is an adaptation of the standard Kalman Filter, specifically designed to handle nonlinear systems like those encountered in UWB-based positioning. In such systems, the relationship between measured distances and tag coordinates is nonlinear, making linear filtering approaches inadequate. EKF overcomes this by linearizing the system around the current estimate using Jacobian matrices. It recursively predicts the tag's position and then updates it using incoming range measurements, making it effective for real-time tracking. The Following are the assumptions made in this EKF:

The state space models are given below (Simon, 2006).
State transition model:

$$x_k = x_{k-1} + v_{x_{k-1}}\Delta t + \epsilon_p \tag{2}$$

$$y_k = y_{k-1} + v_{y_{k-1}}\Delta t + \epsilon_p \tag{3}$$

$$v_{x_k} = v_{x_{k-1}} + \epsilon_v \tag{4}$$

$$v_{y_k} = v_{y_{k-1}} + \epsilon_v \tag{5}$$

$$b_k = b_{k-1} + \epsilon_b \tag{6}$$

Here, x_k and y_k are the current positions of the tag, predicted using the previous positions x_{k-1}, y_{k-1}, respective velocities $v_{x_{k-1}}$, $v_{y_{k-1}}$ and a time step Δt. The terms ϵ_p and ϵ_v represent process noise associated with position and velocity, respectively. The velocity components $v_{x_{k-1}}$ and $v_{y_{k-1}}$ are updated based on their previous values and process noise. The term b_k is the bias at the current step, assumed to change slowly over time and affected by a small noise term ϵ_b. These equations capture both motion and bias dynamics under the assumption of slow-changing velocity and constant bias.
Measurement Model :

$$z_i = \sqrt{(x - x_i)^2 + (y - y_i)^2} + b_k + \epsilon_R \tag{7}$$

Here z_i is the observed distance between the tag and the i^{th} anchor. The term (x_i,y_i) represents the known position of the i^{th} anchor, and (x,y) is the estimated position of the tag. The term b_k denotes the bias at time step k amd ϵ_R is the measurement noise, assumed to be Gaussian, with zero mean and known measurement covariance R_k.

The state covariance matrix $P_{k-1|k-1}$ denotes the uncertainty in the estimated state vector, including the tag's position, velocity, and bias. Larger values imply higher initial uncertainty and $P_{k-1|k-1}$ is iteratively refined through the prediction and correction phases. The matrix $P_{k-1|k-1}$ is given as,

$$P_{k-1|k-1} = \begin{bmatrix} \sigma_x^2 & 0 & 0 & 0 & 0 \\ 0 & \sigma_y^2 & 0 & 0 & 0 \\ 0 & 0 & \sigma_{v_x}^2 & 0 & 0 \\ 0 & 0 & 0 & \sigma_{v_y}^2 & 0 \\ 0 & 0 & 0 & 0 & \sigma_b^2 \end{bmatrix} \tag{8}$$

The process noise covariance matrix Q_k models the uncertainty arising from unmodelled dynamics or assumptions in the motion model. It consists of variances associated with the state and these values are selected based on the experimental observation of the system's motion and are tuned to ensure smooth and stable performance of the filter. The measurement noise covariance matrix R_k captures the uncertainty in UWB range measurements, with diagonal elements representing the variance of distance observations from at least three anchors. These values are empirically derived from multiple sample observations. Proper estimation of R_k ensures balanced trust between model prediction and sensor observations. The full EKF workflow is summarized in figure 2.

Algorithm 2: EKF Based Position Estimation

Input:
Initial state estimate: $\hat{x}_0$
Initial covariance: P_0
Process noise covariance: Q
Measurement noise covariance: R
Anchor coordinates: (x_i, y_i) for i = 1 to M
UWB measurements: $z_k = [z_1, z_2, ..., z_M]$
Time step: Δt
Output:
Estimated tag position: (x, y) from $\hat{x}_k|_k$
Initialization:
Set initial $\hat{x}_0$ and P_0
For each time step k = 1, 2, ...
1: Prediction Step:
$\hat{x}_k|_{k-1} = F \cdot \hat{x}_{k-1}|_{k-1}$
$P_k|_{k-1} = F \cdot P_{k-1}|_{k-1} \cdot F^T + Q$
2: Measurement Prediction:
For each anchor i = 1 to M:
$\hat{z}_i = \sqrt{(x - x_i)^2 + (y - y_i)^2} + b + \epsilon_R$
Form $z_k = [z_1, z_2, ..., z_M]$
3: Compute Jacobian H_k based on partial derivatives of $\hat{z}_k$
4: Update Step:
- Innovation: $y_k = z_k - \hat{z}_k$
- Innovation covariance: $S_k = H_k \cdot P_k|_{k-1} \cdot H_k^T + R$
- Kalman Gain: $K_k = P_k|_{k-1} \cdot H_k^T \cdot S_k^{-1}$
- State update: $\hat{x}_k|_k = \hat{x}_k|_{k-1} + K_k \cdot y_k$
- Covariance update: $P_k|_k = (I - K_k \cdot H_k) \cdot P_k|_{k-1}$
End For

Figure 2. Algorithm for EKF based position estimation.

4.3 Positioning with proposed Bias Aware EKF

In practical indoor environments, the bias affecting UWB range measurements is not strictly constant. It may originate from transient phenomena such as multipath reflections, clock drift, or hardware delays, which typically vary in magnitude over time. The assumption of a constant bias in the standard EKF model limits its adaptability and can lead to persistent localization errors. To overcome this, we introduce a Bias Aware EKF model where the bias is allowed to decay exponentially, improving estimation performance in dynamically changing conditions. The Bias Model is derived under the assumption that the rate of change of bias is proportional to its current value, expressed as:

$$\frac{db}{dt} = -\lambda b \tag{9}$$

where $\lambda > 0$ is the decay rate constant. Solving this first order differential equation yields the analytical solution:

$$b_k = b_0 e^{-\lambda t} \tag{10}$$

Discretizing over time with time step Δt gives the recursive form suitable for EKF integration and is expressed as,

$$b_k = b_{k-1} e^{-\lambda \Delta t} + \epsilon_b \tag{11}$$

Here, $\epsilon_b \sim N(0, \sigma_b^2)$ represents Gaussian process noise associated with bias uncertainty. This bias model is embedded into the EKF state transition model, while the rest of the filtering framework including the state vector, Jacobian computation and measurement update remains consistent with the standard EKF structure outlined previously in section 4.2. By modeling the temporal decay of bias, the proposed approach dynamically adjusts the influence of the bias term, enabling more accurate and robust localization. Although the current bias model assumes a common bias term b_k for simplicity, in practice each anchor may exhibit individual biases. Extending the model to a vector form $b_k = [b_{1,k}, b_{2,k}, ., ., ., .b_{n,k}]$ would account for anchor-dependent effects, but this work focuses on the dominant temporal bias component observable across all ranges. This methodology is inspired by the estimation of state varying with time from (Decawave, 2025).

5. Experiments, Results and Analysis

To evaluate the performance of the proposed positioning algorithm, experiments are conducted in both outdoor and indoor environments as shown in figures 3 and 4, respectively. The outdoor tests are performed in an open 20×20 m, while the indoor experiments are carried out in a typical office environment. In the indoor setup, tests are specifically designed to include non-line-of-sight (NLOS) scenarios while the tag is in motion. A total of 8 anchors are used in the outdoor setup and 9 anchors in the indoor setup. The ground truth data is obtained by Total Station survey. The results are compared across three methods: Least Squares (LS), Standard Extended Kalman Filter (EKF) and the proposed Bias-Aware Extended Kalman Filter. All positioning measurements are obtained using Decawave R DWM1001 UWB sensors (Decawave, 2025), ranging data are collected directly at the tag device through serial communication, with a sampling rate of approximately 10 Hz.

5.1 Performance Evaluation Metrics

To assess the accuracy of the positioning algorithms, three key metrics are used: Deviation Error (Δ_e), Root Mean Square Error (RMSE) and Horizontal Dilution of Precision (HDOP). Deviation Error is calculated as the Euclidean distance between the estimated position and the true position of the tag at each

Figure 3. Experiment setup in outdoor environment. Ground truth is estimated by total station survey.

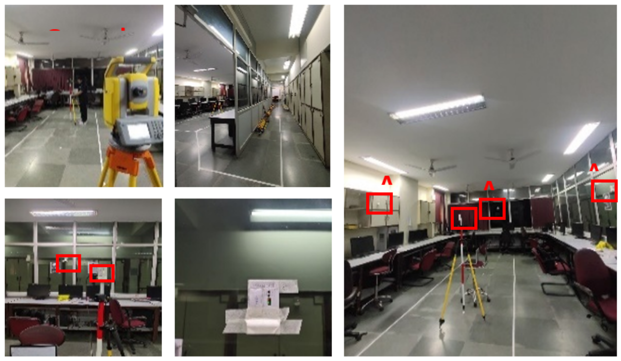

Figure 4. Experiment setup in indoor environment. Ground truth is estimated by total station survey.

timestamp:

$$\Delta_e^i = \sqrt{(x_{true}^i - x_{est}^i)^2 + (y_{true}^i - y_{est}^i)^2} \tag{12}$$

RMSE (R_e) provides a single-value summary of the overall positioning error across all observations:

$$R_e = \frac{1}{n}\sqrt{\sum_{i=1}^{n} \Delta_e^i} \tag{13}$$

HDOP (H_d) is a geometry-based metric that reflects the effect of anchor placement on the accuracy of the estimated horizontal position; lower HDOP values indicate better geometry and more reliable positioning. It is derived from the variance-covariance matrix of the position estimates as:

$$H_d = \sqrt{\sigma_x^2 + \sigma_y^2} \tag{14}$$

Where $\sigma_x^2$and σ_y^2 are the variances of the estimated x and y coordinates, respectively. These are obtained from the diagonal elements of the variance-covariance matrix, typically computed during LS and EKF-based estimation.

5.2 Parameter selection and metrics in proposed model

In this study, Q and R are empirically tuned based on initial test runs conducted in both indoor and outdoor environments. The values are selected such that the filter maintains stability while accurately tracking the tag position under varying conditions, including indoor NLOS scenarios.

The variance of UWB distance measurements varies across anchors, ranging from approximately 0.09 m^2 to 0.15 m^2 in table 1. To ensure a balanced treatment of the measurement un-

Anchor ID	Variance (m^2)
A(DA02)	0.118
B(54A9)	0.135
C(DD0E)	0.149
D(8D13)	0.122
E(C79A)	0.094
F(C1A6)	0.106
G(C1BB)	0.091
H(DA1C)	0.111

Table 1. Distance data statistics of UWB sensor.

certainty across all anchors, the measurement noise covariance matrix R is chosen as a diagonal matrix with 0.1 m^2 on the diagonal. The process noise covariance matrix Q is empirically tuned to reflect the expected motion dynamics of the tag and to balance responsiveness with stability in the proposed EKF.

5.3 Outdoor Experiments - LOS condition

The first phase focuses on the self-localization of anchors, the anchor placement is mentioned. Each anchor estimates its position through the proposed localization explained in figure 1. The results in table 2 show varying levels of accuracy across anchors. The average localization error ranges from 0.072 m to 0.224 m, the accuracy can be improved if the algorithm is further tuned to select the appropriate anchor addition in the system, rather than randomly adding it. The second phase

Anchor ID	Error (m)
A(DA02)	0.161
B(54A9)	0.127
C(DD0E)	0.224
D(8D13)	0.154
E(C79A)	0.072
F(C1A6)	0.131
G(C1BB)	0.073
H(DA1C)	0.081

Table 2. Accuracy analysis of anchor self localization.

Figure 5. Moving tag trajectory estimated in outdoor environment using LS.

focuses on tag positioning in the moving case, the results are demonstrated in figures 5 - 7, where the Bias Aware EKF model demonstrates the best performance in modeling localization errors under outdoor LOS conditions. Slight deviations are observed near the far-end of the path, corresponding to regions of higher HDOP, where anchor geometry temporarily degrades.

The results are mentioned in table 3, which demonstrates positions estimated with LS, Standard EKF and Proposed EKF, the

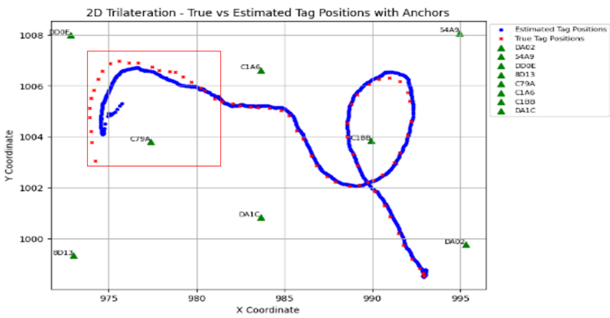

Figure 6. Moving tag trajectory estimated in outdoor environment using EKF.

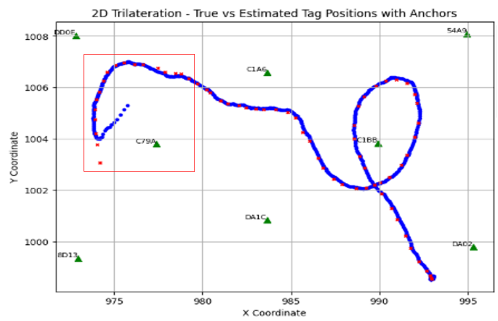

Figure 7. Moving tag trajectory estimated in outdoor environment using proposed bias aware EKF.

results are compared, also for base anchor network established using Total Station (TS) survey and Anchor Self-Localization (ASL).

Parameter	LS		EKF		Bias Aware	
	TS	ASL	TS	ASL	TS	ASL
RMSE (m)	0.291	0.293	0.424	0.428	0.224	0.252
Max (m)	0.428	0.436	1.516	1.518	1.340	1.342
Min (m)	0.008	0.009	0.001	0.001	0.001	0.001
95% KDE (m)	0.251	0.259	0.704	0.714	0.135	0.142

Table 3. Tag position analysis in outdoor environments using ASL vs. when anchor position is determined using Total station.

It shows that Bias-Aware EKF achieves the lowest RMSE (0.224 m for TS, 0.252 m for ASL) and the tightest 95% confidence intervals, indicating high accuracy and consistent reliability even when anchor positions are self-localized.

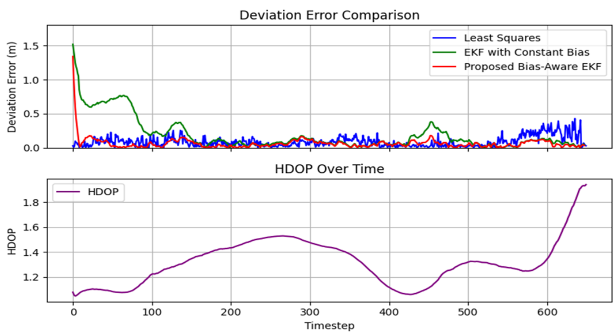

Figure 8. Variation of deviation error, HDOP in all cases vs time.

The deviation error plot in figure 8 further reinforces this advantage, showing that the Bias-Aware EKF maintains the lowest and most stable error profile across all time steps, especially under varying HDOP (in Standard EKF) conditions. Although least squares and standard EKF methods show increased fluctuations—particularly when HDOP values rise—the proposed model remains robust, effectively compensating for geometry-induced uncertainty and temporal drift.

5.4 Indoor Experiments - NLOS condition

The indoor experiment is conducted using 9 anchor positions strategically placed within the test environment. Ground truth data for the tag's position is collected using a Total Station. The setup is designed to evaluate performance under NLOS conditions. The results of tag trajectory in indoor environments are shown in figure 9 to figure 11. The results demonstrate the tag trajectory obtained is much more smoother in case of EKF, as compared to LS. In case of standard EKF, the path is deviated in some NLOS cases and completely gone off-track as highlighted in figure 10, which indicates that the standard bias model cannot model this varying behavior of bias, i.e. as bias is increased in the observations, the value of bias increases in the estimated state but as soon as the input observations have low bias, it cannot immediately decrease, leading to deviation in trajectory, whereas the proposed Bias-Aware EKF has exponentially decaying bias, so when the bias values suddenly drops down, the decay model accounts for it, maintaining correct trajectory (ref figure 11). The bias decay parameter λ in the proposed

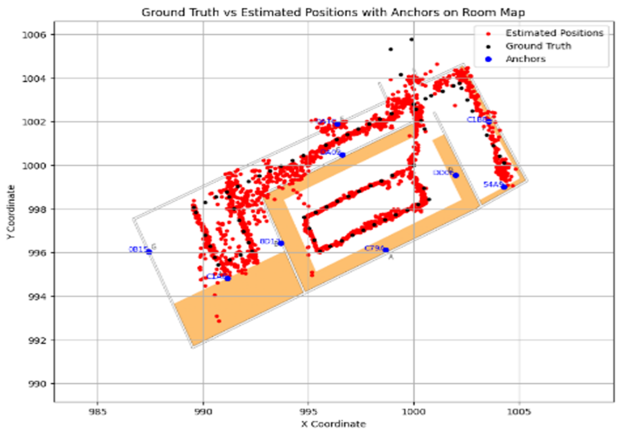

Figure 9. Moving tag trajectory estimated in indoor environment using LS.

Bias-Aware EKF is selected by empirical tuning. As shown in figure 12 RMSE decreases dramatically with increasing λ, stabilizing beyond $\lambda \approx 2$. Based on this trend, a λ value in the range of 2–3 provides an optimal balance between response to bias and localization accuracy.

As summarized in table 4, the proposed Bias-Aware EKF achieved the best performance with an RMSE of $0.317\ m$, compared to $0.419\ m$ for LS and $0.472\ m$ for EKF. Additionally, the 95% CI is narrower ($0.495\ m$) than LS ($0.770\ m$) and EKF ($0.682\ m$), indicating improved consistency. The error peaks correspond to regions with partial NLOS and poor HDOP, where anchor geometry temporarily degrades. Even under these conditions, the proposed Bias-Aware EKF maintains a smoother and more accurate trajectory compared to LS and standard EKF. Figure 13 shows the deviation error and

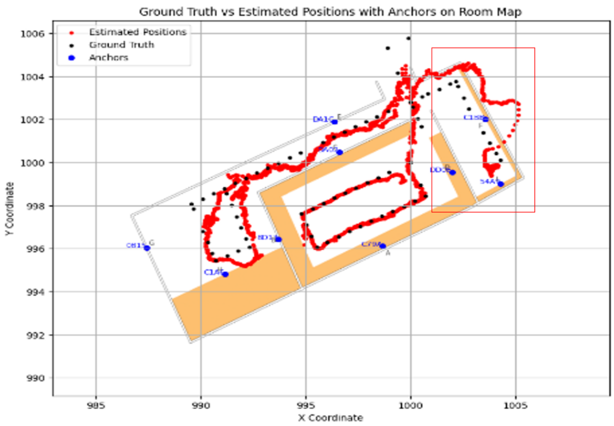

Figure 10. Moving tag trajectory estimated in indoor environment using EKF.

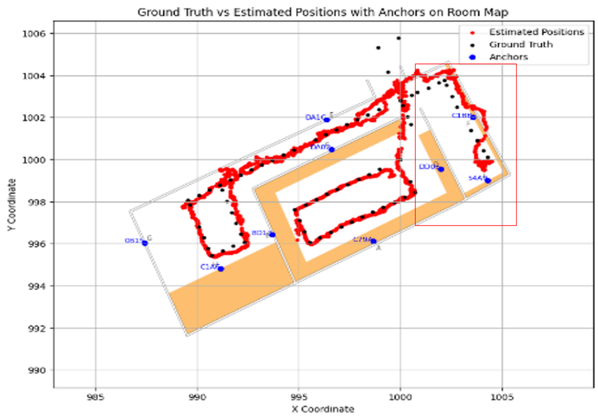

Figure 11. Moving tag trajectory estimated in indoor environment using proposed bias aware EKF.

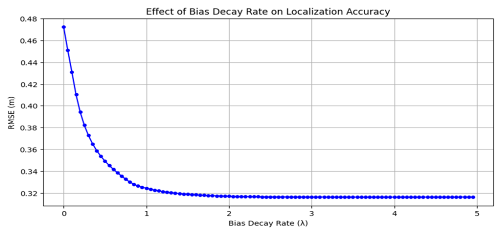

Figure 12. A plot of λ vs RMSE for tuning bias decay.

Parameter	LS	EKF	Bias Aware
RMSE (m)	0.419	0.472	0.317
Max (m)	1.304	2.147	1.102
Min (m)	0.005	0.015	0.001
95% KDE	0.770	0.682	0.495

Table 4. Tag position analysis in indoor experiment.

HDOP (in Standard EKF) over time. The Bias-Aware EKF performs more reliably, especially during intervals with high and low HDOP, highlighting its robustness in dynamic NLOS conditions.

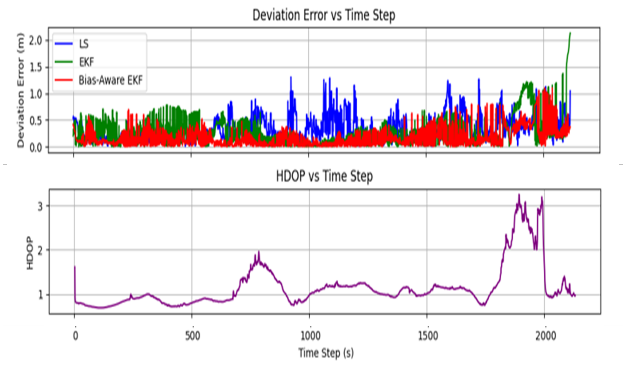

Figure 13. Variation of deviation error, HDOP in all cases vs time; indoors.

6. Conclusions and Future Work

This paper presents a novel Bias-Aware EKF framework for UWB-based Indoor Positioning Systems and evaluates its performance against the standard EKF and Least Squares approaches. The proposed model demonstrated consistent improvements of 32% in RMSE under indoor NLOS and 41% under outdoor LOS conditions, confirming its robustness in varied environments.

An ASL algorithm is also introduced and validated under LOS conditions, achieving comparable accuracy to systems using pre-calibrated anchors—with only a 3 cm increase in RMSE—highlighting its suitability for flexible and rapidly deployable setups.

In future work, the ASL algorithm can be enhanced through geometry-based anchor selection to reduce error propagation and improve network stability. The future work aims to extend the proposed framework to a 3D environment, thus enhancing the applicability of the proposed system. Additionally, modeling individual anchor-specific biases and integrating real-time adaptive noise tuning could make the Bias-Aware EKF more resilient in complex dynamic and multipath indoor environments. Although the paper presented a performance comparison in indoor and outdoor environments, the paper did not consider the impact of environmental factors including humidity and temperature which could potentially affect UWB signals. Further research is recommended to understand and analyze the impact of environmental factors on UWB signals and their effect on the positioning accuracy. Lastly, the decay rate in the proposed bias model is empirically selected in this paper, and no formal tuning mechanism is presented to select the optimal decay rate. Future work will perform a sensitivity analysis of the decay rate and a formal tuning mechanism to estimate optimal decay rate will be developed.

References

Alarifi, A., Al-Salman, A., Alsaleh, M., Alnafessah, A., Al-Hadhrami, S., Al-Ammar, M. A., Al-Khalifa, H. S., 2016. Ultra Wideband Indoor Positioning Technologies: Analysis and Recent Advances. *Sensors*, 16(5). https://www.mdpi.com/1424-8220/16/5/707.

Babjak, M., Gažovová, S., 2023. Temperature impact on clock stability of ultra wideband chip decawave dw1000. *2023 Communication and Information Technologies (KIT)*, 1–5.

Batstone, K., Oskarsson, M., Åström, K., 2017. Towards real-time time-of-arrival self-calibration using ultra-wideband anchors. *2017 International Conference on Indoor Positioning and Indoor Navigation (IPIN)*, 1–8.

Dabove, P., Di Pietra, V., Piras, M., Jabbar, A. A., Kazim, S. A., 2018. Indoor positioning using ultra-wide band (uwb) technologies: Positioning accuracies and sensors' performances. *2018 IEEE/ION Position, Location and Navigation Symposium (PLANS)*, 175–184.

Dardari, D., Conti, A., Ferner, U., Giorgetti, A., Win, M. Z., 2009. Ranging With Ultrawide Bandwidth Signals in Multipath Environments. *Proceedings of the IEEE*, 97(2), 404-426.

Decawave, 2025. Specifications of Qorvo UWB Decawave DWM 1001. https://www.qorvo.com/products/p/DWM1001-DEV.

Gabela, J., Retscher, G., Goel, S., Perakis, H., Masiero, A., Toth, C., Gikas, V., Kealy, A., Koppányi, Z., Błaszczak-Bak, W., Li, Y., Grejner-Brzezinska, D., 2019. Experimental Evaluation of a UWB-Based Cooperative Positioning System for Pedestrians in GNSS-Denied Environment. *Sensors*, 19(23). https://www.mdpi.com/1424-8220/19/23/5274.

Herbruggen, B. V., Luchie, S., Fontaine, J., De Poorter, E., 2023. Multihop Self-Calibration Algorithm for Ultra-Wideband (UWB) Anchor Node Positioning. *IEEE Journal of Indoor and Seamless Positioning and Navigation*, 1, 1-11.

Retscher, G., Kealy, A., Gabela, J., Li, Y., Goel, S., Toth, C. K., Masiero, A., Błaszczak-Bak, W., Gikas, V., Perakis, H., Koppanyi, Z., Grejner-Brzezinska, D., 2020. A benchmarking measurement campaign in GNSS-denied/challenged indoor/outdoor and transitional environments. *Journal of Applied Geodesy*, 14(2), 215–229. https://doi.org/10.1515/jag-2019-0031.

Sarkka, S., Solin, A., Hartikainen, J., 2013. Spatiotemporal Learning via Infinite-Dimensional Bayesian Filtering and Smoothing: A Look at Gaussian Process Regression Through Kalman Filtering. *IEEE Signal Processing Magazine*, 30(4), 51-61.

Simon, D., 2006. *Kalman filter generalizations*. John Wiley Sons, Ltd, chapter 7, 183–227.

Syazwani, N. C. J., Wahab, N. H. A., Sunar, N., Ariffin, S. H. S., Wong, K. Y., Aun, Y., 2022. Indoor Positioning System: A Review. *International Journal of Advanced Computer Science and Applications*, 13(6). http://dx.doi.org/10.14569/IJACSA.2022.0130659.

Taner, A., 2020. Accurate indoor positioning with ultra-wide band sensors. *Turkish Journal of Electrical Engineering and Computer Sciences*, 28(2), 1014-1029. https://doi.org/10.3906/elk-1911-79.

Trifunović, M., Papp, I., Bašičević, I., 2024. Use of extended kalman filter in an uwb based indoor positioning system. *2024 Zooming Innovation in Consumer Technologies Conference (ZINC)*, 204–208.

Vashistha, A., Gupta, A., Law, C. L., 2018. Self calibration of the anchor nodes for uwb-ir tdoa based indoor positioning system. *2018 IEEE 4th World Forum on Internet of Things (WF-IoT)*, 688–693.

Welsch, W., 1979. A Review of the Adjustment of Free Networks. *Survey Review*, 25(194), 167–180. https://doi.org/10.1179/sre.1979.25.194.167.

Yi, C., Da, A. Z., Hui, C., Shan, C., Xuan, Z., 2021. A UWB Location Algorithm—Based on Adaptive Kalman Filter. *Journal of Physics: Conference Series*, 1757(1), 012176. https://doi.org/10.1088/1742-6596/1757/1/012176.

Yogesh, V., Grevinga, L., Voort, C., Buurke, J. H., Veltink, P. H., Baten, C. T., 2024. Novel calibration method for improved UWB sensor distance measurement in the context of application for 3D analysis of human movement. *Engineering Science and Technology, an International Journal*, 58, 101844. https://www.sciencedirect.com/science/article/pii/S2215098624002301.