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Evaluation of the applicability of state estimation filters for indoor robot positioning

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Abstract– Indoor robot positioning plays an important role in ensuring autonomous navigation in smart environments where Global Positioning System (GPS) signals are unavailable. Ultra-Wideband (UWB) technology offers high accuracy and multipath interference resistance, providing a suitable foundation for indoor positioning systems. Therefore, this study focuses on evaluating the performance of three state estimation algorithms—the Extended Kalman Filter (EKF), the Unscented Kalman Filter (UKF), and the Particle Filter (PF)—in handling nonlinear models of positioning systems based on UWB. In addition, a ranging bias calibration method is employed to compensate for systematic UWB measurement errors prior to filtering. Experimental results show that the proposed bias calibration method reduces the ranging Root Mean Square Error (RMSE) from 111.6 mm to 72.7 mm (an improvement of approximately 35%). In the filtering stage, the PF achieves its best performance with 10 particles, yielding an RMSE of 56.9 mm while maintaining a high sampling rate of 128 Hz. For nonlinear state estimation, the EKF achieves the lowest RMSE of 44.8 mm after calibration with appropriate tuning of the measurement noise covariance, but it exhibits high sensitivity to parameter selection. The UKF demonstrates more consistent performance, maintaining RMSE values in the range of 55–60 mm across a wide range of noise settings, indicating stronger robustness to model uncertainties. Overall, the EKF is suitable for applications requiring high accuracy with careful tuning; the UKF provides a good trade-off between accuracy and robustness; and the PF offers flexibility in handling non-Gaussian noise at the expense of higher computational cost.

Keywords– UWB, positioning, localization, tracking, Kalman filter, indoor robot positioning.

1 INTRODUCTION

In the context of rapidly growing connectivity technologies, the demand for accurate and reliable Indoor Positioning Systems (IPS) has become increasingly prominent. Global Navigation Satellite Systems (GNSS) [1] perform well outdoors, but their signals degrade severely in enclosed spaces, so they cannot meet indoor positioning requirements. UWB [2, 3] has emerged as a promising solution due to centimeter-level accuracy and strong resistance to interference and multipath, outperforming alternatives such as Wi-Fi, Bluetooth Low Energy (BLE), or Radio Frequency Identification (RFID) [4].

To fully exploit UWB for robot positioning, robust state-estimation algorithms are required. The EKF, UKF, and PF [5] are three widely used approaches that can address nonlinearities that standard Kalman Filter cannot handle.

This paper compares the EKF, UKF, and PF for UWB-based indoor robot positioning using criteria such as accuracy, computational cost, and stability. The results support the selection of appropriate algorithms for low-cost and reliable indoor positioning systems.

This work has three main contributions. Firstly, we build an indoor positioning system consisting of four fixed reference nodes (Anchors) and one mobile target (Tag) using UWB modules with an integrated two-

way ranging (TWR) distance measurement method. Secondly, we talk about implement an anchor-wise error calibration method to compensate for systematic ranging errors of each UWB anchor, thereby improving the reliability of the measured distances. Thirdly, we implement the EKF, UKF, and PF to process the range measurements from the four anchors to the robot-mounted tag and evaluate the positioning accuracy under different initialization settings.

The remainder of this paper is organized as follows. Section 1 presents the context, motivation, and objectives of the study. Section 2 describes the model and architecture of the positioning system. Section 3 presents the principles and implementation of the EKF, UKF, and PF in the proposed system. Section 4 focuses on experimental design and performance evaluation. Finally, Section 5 concludes the article and discusses future directions.

2 RELATED WORK

Indoor positioning has attracted considerable attention for mobile robot localization in GNSS-denied environments. In such settings, satellite signals are frequently blocked or severely attenuated by walls, ceilings, and surrounding structures, making alternative localization technologies essential for autonomous nav-

igation. Existing indoor positioning approaches include Wi-Fi fingerprinting, BLE, RFID, vision-based localization, Light Detection and Ranging (LiDAR)-based localization, and UWB positioning. Wi-Fi- and BLE-based methods are appealing because of their low cost and widespread availability; however, their accuracy is often degraded by signal fluctuations, channel interference, and environmental variations. RFID-based techniques can support reliable identification and short-range localization, but they typically require dense infrastructure deployment. Vision- and LiDAR-based methods provide rich environmental information, yet their performance may be limited by feature degradation, illumination changes, occlusion, or high hardware cost. Among these alternatives, UWB is regarded as a promising solution for indoor robot positioning owing to its fine time-resolution ranging capability, robustness to multipath interference, and high positioning accuracy under line-of-sight conditions.

UWB-based positioning systems commonly estimate the distance between fixed anchors and a mobile tag using time-based ranging techniques such as Time of Arrival (TOA), Time Difference of Arrival (TDOA) or TWR. In a typical anchor–tag configuration, multiple anchors are deployed at known locations, whereas a tag is attached to the mobile robot. The measured anchor–tag distances are then used to estimate the robot position through trilateration or recursive filtering. Although UWB can achieve centimeter-level ranging accuracy under favorable conditions, practical indoor measurements remain affected by both systematic and random errors. These errors may arise from hardware delays, antenna-related timing offsets, clock uncertainties, non-line-of-sight propagation, and multipath effects. Consequently, calibration constitutes an important preprocessing stage prior to localization. By characterizing the relationship between measured and actual distances, bias calibration can compensate for systematic ranging errors and enhance the reliability of the acquired range data. This step is particularly important for low-cost UWB systems, in which uncalibrated measurements may result in substantial positioning errors and unstable filter behavior.

To further improve localization accuracy in the presence of noisy UWB range measurements, recursive state-estimation filters are widely employed in indoor positioning and robot tracking systems. The EKF extends the conventional Kalman filter to nonlinear systems by linearizing the measurement model through the Jacobian matrix. Its relatively low computational complexity makes it suitable for real-time implementation; however, its performance may deteriorate in strongly nonlinear systems or when the process and measurement noise covariance matrices are inadequately tuned. The UKF addresses nonlinear estimation by propagating a set of sigma points through the nonlinear system dynamics, thereby avoiding explicit derivative calculations and often providing greater robustness under nonlinear conditions. In contrast, the PF approximates the posterior distribution using a set of weighted particles and is well suited to nonlinear and

non-Gaussian estimation problems, although its computational burden increases with the number of particles. Accordingly, the selection of EKF, UKF, or PF for UWB-based indoor robot positioning involves a trade-off among estimation accuracy, robustness, parameter sensitivity, and real-time computational efficiency.

Several studies have examined UWB-based indoor positioning and UWB sensor-fusion strategies for mobile robot localization. Some have focused primarily on the effects of Non-Line-of-Sight (NLOS) conditions, multipath propagation, ranging-protocol optimization, or distance-estimation accuracy, whereas others have integrated UWB with complementary sensors such as Inertial Measurement Units (IMUs), LiDAR, red-green-blue-depth (RGB-D) cameras, or visual Simultaneous Localization and Mapping (SLAM) to improve localization robustness. Although such fusion-based approaches can enhance positioning performance, they generally increase hardware complexity, calibration effort, coordinate-frame alignment requirements, and implementation cost. Moreover, while EKF, UKF, and PF have been extensively investigated for nonlinear tracking and localization, their practical trade-offs are not always assessed on a common low-cost, UWB-only indoor robot platform. As a result, the combined impacts of ranging-bias calibration, least-squares initialization, covariance tuning, particle-number selection, sampling rate, and real-time computational cost remain insufficiently explored in the context of UWB-based indoor robot positioning.

Based on the comparison in Table I, the main research gap can be stated more clearly as follows. Existing studies usually emphasize *one* of three aspects: (i) UWB channel/ranging behavior such as NLOS influence or TWR optimization [2, 6], (ii) ranging-error calibration or statistical error modeling [7], or (iii) sensor-fusion-based localization using additional modalities such as BLE or IMU [8, 9]. However, there is still limited experimental evidence on how the three widely used nonlinear filters—EKF, UKF, and PF—compare *under the same low-cost UWB-only robot platform* after bias calibration and with the same initialization framework. Therefore, this paper fills the gap by providing a controlled end-to-end evaluation that links anchor-wise bias calibration, least-squares initialization, covariance tuning, particle-number selection, positioning RMSE, and real-time sampling performance in a single experimental study.

3 INDOOR POSITIONING SYSTEM MODEL

3.1 System overview

3.1.1 UWB system: The positioning system is built using compact DWM1001 modules integrating a UWB transceiver, an ARM Cortex-M4 processor, and BLE. The modules are configured as fixed reference nodes (Anchors) and a mobile target (Tag): four anchors are deployed at known locations and a mobile robot is equipped with a UWB tag. The complete system model is shown in Figure 1. The anchors and tag perform continuous TWR [6] by exchanging timestamped packets to

Table I
COMPARISON OF REPRESENTATIVE RELATED STUDIES AND THE RESEARCH GAP ADDRESSED IN THIS WORK

Reference	Main focus	System/setup	Main strength	Limitation relative to this work
[2]	NLOS impact analysis for UWB indoor positioning	Multi-anchor UWB positioning under challenging propagation conditions	Clarifies how NLOS degrades UWB localization performance	Focuses on channel effects; does not compare EKF, UKF, and PF on the same calibrated low-cost robot platform
[6]	Double-Sided Two-Way Ranging (DS-TWR) ranging and localization optimization	UWB ranging with protocol-level improvement	Improves ranging procedure and distance-estimation reliability	Emphasizes ranging optimization rather than end-to-end comparison of nonlinear state-estimation filters for robot localization
[7]	Statistical modeling of UWB distance error	UWB localization with error modeling and calibration	Shows that calibration can reduce systematic ranging bias	Does not study how calibrated measurements affect EKF, UKF, and PF performance, parameter sensitivity, and real-time behavior
[8]	High-precision indoor positioning using UWB/BLE fusion	Multi-sensor fusion in indoor localization	Achieves high accuracy through complementary sensing modalities	Requires additional sensing infrastructure and fusion complexity, making it less suitable for an isolated assessment of UWB-only filtering trade-offs
[9]	Kalman-filter-based UWB/Inertial Measurement Unit (IMU) integration	Tight fusion of UWB and inertial sensing	Strong accuracy and continuity for navigation	Focuses on fused sensing rather than a fair same-platform comparison among EKF, UKF, and PF using only UWB ranges
[10]	Experimental validation of low-cost UWB positioning and tracking	Low-cost UWB hardware implementation	Demonstrates practical feasibility of UWB-based tracking	Does not provide a detailed comparative analysis of calibration, initialization, filter tuning, particle selection, and sampling-rate trade-offs across EKF, UKF, and PF
This work	Bias-calibrated UWB-only indoor robot positioning with comparative filter evaluation	Four-anchor, one-tag low-cost UWB robot platform with least-squares estimation (LSE) initialization	Provides a unified experimental comparison of EKF, UKF, and PF in terms of accuracy, robustness, sensitivity, and computational efficiency	Addresses the gap by jointly analyzing calibration effect, initialization, covariance tuning, particle count, RMSE, and achievable sampling rate

estimate distances from time-of-flight information. All anchors interact with the tag simultaneously, enabling robust range measurements even in dynamic environments. In each ranging cycle, the tag receives distance measurements from four anchors, which are then used as inputs for position estimation.

Both the tag and the anchors run the *DWM1001_PANS_R2.0.hex* firmware, which supports a ranging update rate of up to 160 Hz, enabling fast distance measurements suitable for real-time mobile robot positioning. With this high update frequency and appropriate estimation methods, the system can achieve high positioning accuracy.

3.1.2 Main processing unit: The hardware includes a four-wheel indoor mobile robot equipped with a Raspberry Pi 4 as the main processing unit. The Pi reads continuous range data from the tag via a serial connection. The EKF, UKF, and PF are implemented as separate Python modules and executed directly on the Pi 4.

3.2 Calibration model

UWB range can achieve centimeter-level accuracy and a maximum measurable range of more than 100 m in outdoor environments. However, both of them have been significantly degraded when UWB is operated in indoor environments. Therefore, the preliminary calibration is necessary to use UWB for indoor environ-

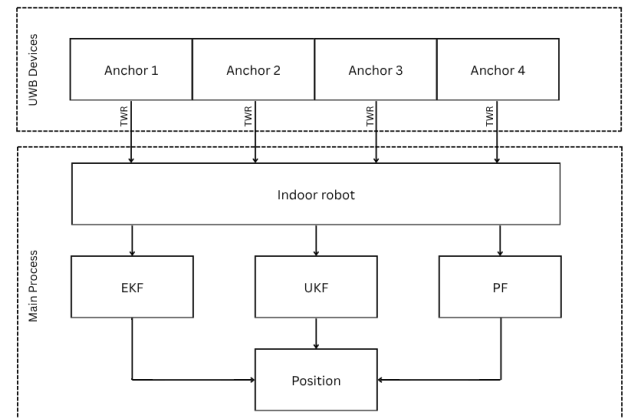


Figure 1. System architecture.

ments. The UWB calibration procedure for distance measurements using the Symmetric Double-Sided Two-Way Ranging (SDS-TWR) method is bias calibration.

We assumed that the relationship between measured distance, what we called d , and the actual distance, d' , can be expressed as equation follow

$$d' = md + c, \quad (1)$$

where m and c denotes the parameters of the bias calibration which can be obtained by taking multiple measurements at different distances [7].

3.3 Mathematical model

When initializing the system, we assume that the initial velocity components are zero, i.e., $v_{x,0} = v_{y,0} = 0$. The system uses four fixed anchors and one mobile tag. The coordinates of the i -th anchor are denoted by $\mathbf{a}_i = (x_{a_i}, y_{a_i})^\top$, for $i = 1, \dots, 4$. The measurements are distances from the tag to each anchor: $z_{i,k}$ is the measurement from the tag to anchor i at sample k , and the measurement vector at time k is $\mathbf{z}_k = [z_{1,k}, \dots, z_{4,k}]^\top$.

The sampling interval between two consecutive samples is determined from the tag update characteristics; in this system, $dt = 0.1$ s. The process-noise matrix $\mathbf{Q}$ and measurement-noise matrix $\mathbf{R}$ are assumed under different cases to analyze convergence. The values of σ_a^2 are adjusted in different experimental scenarios to study filter response to tag dynamics and sensitivity to noise levels.

3.3.1 State model: We choose a 2D constant-velocity (CV) model with state

$$\mathbf{x}_k = \begin{bmatrix} x_k \\ y_k \\ v_{x,k} \\ v_{y,k} \end{bmatrix}. \quad (2)$$

The discrete-time dynamics are linear

$$\mathbf{x}_{k+1} = \mathbf{F} \mathbf{x}_k + \mathbf{w}_k, \quad \mathbf{w}_k \sim \mathcal{N}(\mathbf{0}, \mathbf{Q}). \quad (3)$$

The state-transition matrix $\mathbf{F}$ (with sampling period dt) is

$$\mathbf{F} = \begin{bmatrix} 1 & 0 & dt & 0 \\ 0 & 1 & 0 & dt \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}. \quad (4)$$

If the process noise is modeled as zero-mean white acceleration with variance σ_a^2 , the discrete-time process noise covariance matrix for CV motion model is given by

$$\mathbf{Q} = \sigma_a^2 \begin{bmatrix} \frac{dt^3}{3} & 0 & \frac{dt^2}{2} & 0 \\ 0 & \frac{dt^3}{3} & 0 & \frac{dt^2}{2} \\ \frac{dt^2}{2} & 0 & dt & 0 \\ 0 & \frac{dt^2}{2} & 0 & dt \end{bmatrix}, \quad (5)$$

where dt denotes the sampling interval and σ_a^2 represents the variance of the continuous-time acceleration noise.

The CV model assumes that acceleration is not explicitly included in the state vector but is treated as a random disturbance. The structure of $\mathbf{Q}$ in (5) results from integrating white acceleration noise over the sampling interval dt , which propagates uncertainty into both position and velocity states. In practical tuning, only the scalar parameter σ_a^2 is adjusted, while the matrix structure remains unchanged.

3.3.2 Measurement model: Since DWM1001 provides direct distances (TOA/TWR) from the tag to each anchor, the nonlinear measurement model is

$$z_{i,k} = h_i(\mathbf{x}_k) + v_{i,k}, \quad v_{i,k} \sim \mathcal{N}(0, \sigma_{r,i}^2), \quad (6)$$

with measurement function

$$h_i(\mathbf{x}_k) = \sqrt{(x_k - x_{a_i})^2 + (y_k - y_{a_i})^2}. \quad (7)$$

The measurement vector is

$$\mathbf{z}_k = h(\mathbf{x}_k) + \mathbf{v}_k, \quad h(\mathbf{x}) = \begin{bmatrix} h_1(\mathbf{x}) \\ \vdots \\ h_m(\mathbf{x}) \end{bmatrix}, \quad \mathbf{v}_k \sim \mathcal{N}(\mathbf{0}, \mathbf{R}), \quad (8)$$

where $\mathbf{R}$ is diagonal and $\sigma_{r,i}^2$ is the assumed variance of the range measurement error to anchor i

$$\mathbf{R} = \text{diag}(\sigma_{r,1}^2, \sigma_{r,2}^2, \dots, \sigma_{r,m}^2). \quad (9)$$

4 POSITIONING ALGORITHM MODEL

4.1 LSE

LSE is used to estimate the initial coordinates from the first four TWR measurements in order to initialize the EKF, UKF, and PF with a reliable starting state, improving convergence speed. The LSE formulation [8] is

$$\mathbf{A} \mathbf{x}_{\text{LS}} = \mathbf{b}, \quad (10)$$

where

$$\mathbf{A} = \begin{bmatrix} x_2 - x_1 & y_2 - y_1 \\ x_3 - x_1 & y_3 - y_1 \\ \vdots & \vdots \\ x_n - x_1 & y_n - y_1 \end{bmatrix}, \quad \mathbf{x}_{\text{LS}} = \begin{bmatrix} x_{\text{LS}} \\ y_{\text{LS}} \end{bmatrix}, \quad (11)$$

$$\mathbf{b} = \frac{1}{2} \begin{bmatrix} x_2^2 + y_2^2 - d_2^2 - (x_1^2 + y_1^2 - d_1^2) \\ x_3^2 + y_3^2 - d_3^2 - (x_1^2 + y_1^2 - d_1^2) \\ \vdots \\ x_N^2 + y_N^2 - d_N^2 - (x_1^2 + y_1^2 - d_1^2) \end{bmatrix}.$$

The LSE estimate is computed by solving the linear system

$$\mathbf{x}_{\text{LS}} = (\mathbf{A}^\top \mathbf{A})^{-1} \mathbf{A}^\top \mathbf{b}. \quad (12)$$

4.2 Filter implementations

4.2.1 Extended Kalman Filter: EKF extends the Kalman filter to nonlinear systems by first-order linearization using a Taylor expansion. For UWB positioning, the nonlinearity mainly appears in the measurement model. The state model and measurement model are initialized as above, and the initial state is set from the LSE estimate.

The EKF linearizes the measurement function $h(\mathbf{x}_k)$ by computing the Jacobian

$$\mathbf{H}_k = \left. \frac{\partial h}{\partial \mathbf{x}} \right|_{\mathbf{x}=\hat{\mathbf{x}}_{k|k-1}}. \quad (13)$$

For UWB positioning, the Jacobian of the measurement function is

$$\mathbf{H}_k[i, :] = \begin{bmatrix} \frac{\hat{x}_{k|k-1} - x_{a_i}}{\hat{d}_{i,k}} & \frac{\hat{y}_{k|k-1} - y_{a_i}}{\hat{d}_{i,k}} & 0 & 0 \end{bmatrix}, \quad (14)$$

where $\hat{d}_{i,k} = \sqrt{(\hat{x}_{k|k-1} - x_{a_i})^2 + (\hat{y}_{k|k-1} - y_{a_i})^2}$ is the estimated distance from the tag to anchor i .

Algorithm 1: EKF

Input : Range measurements $d_1, \dots, d_4$;
anchor positions; sampling
interval Δt

Initialization: State: $\mathbf{x} = [x, y, v_x, v_y]^\top$ (initial
position from LSE, initial velocity
assumed zero)
Transition matrix: $\mathbf{F}(\Delta t)$
Initial covariance: $\mathbf{P}_0$ (tunable)
Process noise : $\mathbf{Q}$
Measurement noise : $\mathbf{R}$

while measurement $\mathbf{z}$ available **do**

if not init **then**
 initialize $\mathbf{x}$ by LSE; set $v = 0$
 // predict
 $\mathbf{x} \leftarrow \mathbf{F}\mathbf{x}$; $\mathbf{P} \leftarrow \mathbf{F}\mathbf{P}\mathbf{F}^\top + \mathbf{Q}$
 // update
 Evaluate $\mathbf{H}$ at $\mathbf{x}$; $\hat{\mathbf{z}} = \mathbf{h}(\mathbf{x})$ $\mathbf{S} \leftarrow \mathbf{H}\mathbf{P}\mathbf{H}^\top + \mathbf{R}$;
 $\mathbf{K} \leftarrow \mathbf{P}\mathbf{H}^\top \mathbf{S}^{-1}$ $\mathbf{x} \leftarrow \mathbf{x} + \mathbf{K}(\mathbf{z} - \hat{\mathbf{z}})$;
 $\mathbf{P} \leftarrow (\mathbf{I} - \mathbf{K}\mathbf{H})\mathbf{P}$

Output: $[x, y]$

4.2.2 *Unscented Kalman Filter:* UKF addresses nonlinearities via the unscented transform, avoiding explicit derivative computation as in the EKF. The UKF uses a carefully chosen set of *sigma points* to represent the state distribution. With state dimension $n_x = 4$, the UKF uses $2n_x + 1 = 9$ sigma points:

$$\begin{aligned}\chi_k^{(0)} &= \hat{\mathbf{x}}_{k|k}, \\ \chi_k^{(i)} &= \hat{\mathbf{x}}_{k|k} + \left(\sqrt{(n_x + \lambda) \mathbf{P}_{k|k}} \right)_i, \quad i = 1, \dots, n_x \\ \chi_k^{(i)} &= \hat{\mathbf{x}}_{k|k} - \left(\sqrt{(n_x + \lambda) \mathbf{P}_{k|k}} \right)_{i-n_x}, \quad i = n_x + 1, \dots, 2n_x.\end{aligned} \quad (15)$$

The parameter $\lambda = \alpha^2(n_x + \kappa) - n_x$, where α controls the sigma-point spread (we use 10^{-1}) and $\kappa = 1.0$ is kept positive to ensure positive definiteness and avoid overly wide sigma-point dispersion.

The sigma-point weights are

$$\begin{aligned}w_m^{(0)} &= \frac{\lambda}{n_x + \lambda} \\ c^{(0)} &= w_m^{(0)} + (1 - \alpha^2 + \beta) \\ w_m^{(i)} &= w_c^{(i)} = \frac{1}{2(n_x + \lambda)}, \quad i = 1, \dots, 2n_x,\end{aligned} \quad (16)$$

with β incorporating prior information (set to $\beta = 2$ for Gaussian distributions). UKF is particularly effective for UWB positioning systems due to its ability to handle nonlinearities without requiring derivative computations while maintaining high accuracy even under strong nonlinear dynamics.

4.2.3 *Particle Filter:* PF is a Monte Carlo filtering approach using a set of particles to approximate the posterior distribution. Each particle represents a hypothesis about the system state and is assigned a weight reflecting the likelihood of that hypothesis.

Algorithm 2: UKF

Input : Range measurements $d_1, \dots, d_4$;
anchor positions; sampling
interval Δt

Initialization: State: $\mathbf{x} = [x, y, v_x, v_y]^\top$ (initial
position from LSE, initial velocity
assumed zero)
Initial covariance: $\mathbf{P}_0$ (tunable)
Sigma-point parameters: α, β, κ
Process noise : $\mathbf{Q}$
Measurement noise : $\mathbf{R}$

while measurement $\mathbf{z}$ available **do**

if not init **then**
 initialize $\mathbf{x}$ by LSE; set $v = 0$
 // predict
 Form sigma points; propagate via $\mathbf{f}(\cdot, \Delta t)$;
 recover $\mathbf{x}^-, \mathbf{P}^-$; $\mathbf{P}^- \leftarrow \mathbf{P}^- + \mathbf{Q}$
 // update
 Propagate through $\mathbf{h}(\cdot)$; compute
 $\hat{\mathbf{z}}, \mathbf{P}_{zz} + \mathbf{R}, \mathbf{P}_{xz}$ $\mathbf{K} \leftarrow \mathbf{P}_{xz}(\mathbf{P}_{zz} + \mathbf{R})^{-1}$
 $\mathbf{x} \leftarrow \mathbf{x} + \mathbf{K}(\mathbf{z} - \hat{\mathbf{z}})$; $\mathbf{P} \leftarrow \mathbf{P} - \mathbf{K}\mathbf{P}_{zz}\mathbf{K}^\top$

Output: $[x, y]$

The posterior distribution is approximated as

$$p(\mathbf{x}_k | \mathbf{z}_{1:k}) \approx \sum_{i=1}^N w_k^{(i)} \delta(\mathbf{x}_k - \mathbf{x}_k^{(i)}), \quad (17)$$

where N is the number of particles, $\mathbf{x}_k^{(i)}$ is the state of particle i , and $w_k^{(i)}$ is its weight. Weights are updated using the measurement likelihood

$$w_k^{(i)} \propto w_{k-1}^{(i)} p(\mathbf{z}_k | \mathbf{x}_k^{(i)}),$$

assuming Gaussian range errors

$$p(\mathbf{z}_k | \mathbf{x}_k^{(i)}) = \prod_{j=1}^4 \mathcal{N}(z_{j,k}; \hat{z}_{j,k}^{(i)}, \sigma_{r,j}^2),$$

with $\hat{z}_{j,k}^{(i)} = \sqrt{(x_k^{(i)} - x_{a_j})^2 + (y_k^{(i)} - y_{a_j})^2}$.

PF provides a flexible solution for UWB positioning, especially in complex multipath environments. However, PF requires significant computational resources, and the number of particles must be tuned to balance accuracy and real-time performance.

5 EXPERIMENTAL DESIGN AND EVALUATION

5.1 Bias Calibration

The experiments were carried out at fixed distances from 1.2 m to 5.4 m in line-of-sight (LOS) environment, with 0.6 m increments. For each distance, 5000 measurement samples were collected to compute the RMSE, and calibration was performed using the method described in Section 3.

To evaluate the effectiveness of the proposed calibration method, the measured data are recalibrated using the estimated parameters m and c for each anchor,

Algorithm 3: Particle Filter

Input : Range measurements $d_1, \dots, d_4$;
anchor positions; sampling
interval Δt ; number of particles N

Initialization: Particles $\mathbf{p}_i = [x_i, y_i]^\top$ initialized
around the LSE position estimate
according to a chosen spatial
spread;

Weights initialized uniformly: $w_i = 1/N$;
Process noise $\mathbf{Q}_{\text{pf}}$ (tunable, consistent with
position units);
Measurement noise parameter(s) defining the
likelihood model (tunable);

while measurement $\mathbf{z}$ available **do**
 if not initialized **then**
 Compute initial position using LSE;
 Distribute particles around this position;
 Mark initialized;
 end
 // prediction
 Propagate each particle using a motion
 model and add noise $\sim \mathcal{N}(0, \mathbf{Q}_{\text{pf}})$;
 // update
 Compute importance weights from
 measurement likelihood;
 Normalize weights;
 // resampling
 Compute $N_{\text{eff}} = 1 / \sum_i w_i^2$;
 if N_{eff} below threshold **then**
 Resample particles; reset $w_i = 1/N$;
 end
end

Output : Estimated position $[x, y]^\top$

and the results are visualized through RMSE graph. Moreover, the cumulative distribution function (CDF) of LSE before and after calibration is also presented to evaluate the impact of the proposed method on the overall system performance.

5.2 System evaluation

The system uses four fixed UWB anchors and one mobile tag. The anchor coordinates (mm) are: $\mathbf{A}_1 = (0, 0)$, $\mathbf{A}_2 = (5470, 0)$, $\mathbf{A}_3 = (5420, 5050)$, and $\mathbf{A}_4 = (770, 5050)$. With this layout, the test area is approximately $5.5 \text{ m} \times 5 \text{ m}$ under LOS conditions.

The robot moves sequentially at 0.5 m/s through points $\mathbf{A} = (1200, 2710)$, $\mathbf{B} = (1200, 600)$, $\mathbf{C} = (4800, 600)$, $\mathbf{D} = (4800, 2710)$, and returns to $\mathbf{A}$, forming a closed rectangular trajectory.

Overview of scenarios: Two complementary scenarios are executed.

Scenario 1 — PF computational cost vs. particle count.

This scenario evaluates how the number of particles N affects PF runtime and positioning performance. The robot repeats the fixed trajectory while N is varied across trials. For each configuration we record:

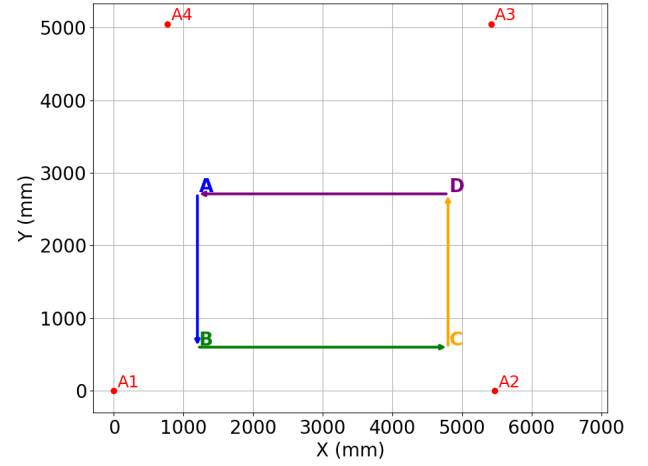


Figure 2. Experimental trajectory.

- per-step processing time (averaged and median),
- achieved sampling rate (Hz),
- estimation error samples and empirical CDF,

Scenario 2 — Sensitivity of EKF/UKF to $\mathbf{Q}$ and $\mathbf{R}$.

We analyze how process and measurement noise affect EKF and UKF performance. Both filters share the same initialization and baseline noise settings before sweeping

$$\text{Baseline: } \sigma_{a,0}^2 = 1, \quad \sigma_{r,0}^2 = 1.$$

A two-stage, one-at-a-time sweep is performed:

- 1) Fix $\mathbf{R} = \sigma_{r,0}^2 \mathbf{I}$ and sweep $\sigma_a^2 = s_Q \cdot \sigma_{a,0}^2$ over $s_Q \in \{10^{-5}, 10^{-4}, \dots, 10^4\}$ (logarithmic grid).
- 2) Fix $\mathbf{Q} = \sigma_{a,0}^2 \mathbf{Q}_{\text{cv}}(\Delta t)$ and sweep $\sigma_r^2 = s_R \cdot \sigma_{r,0}^2$ over $s_R \in \{10^{-5}, 10^{-4}, \dots, 10^4\}$.

The LSE (bias-calibrated) and the PF benchmark from Scenario 1 are included in all comparisons.

Parameter initialization and pragmatic prescriptions: For reproducibility and clarity we follow these prescriptions:

- **Initial state:** initial position from LSE trilateration; initial velocity set to zero.
- **Initial covariance $\mathbf{P}_0$:** diagonal matrix with variances that reflect the expected LSE spread and prior velocity uncertainty.
- **Process noise $\mathbf{Q}$ (EKF/UKF):** use the structured CV matrix $\mathbf{Q}_{\text{cv}}(\Delta t)$ and sweep only the scalar multiplier σ_a^2 as described above.
- **Measurement noise $\mathbf{R}$:** modeled as diagonal; when anchors share similar characteristics use $\mathbf{R} = \sigma_r^2 \mathbf{I}$ and sweep via the scalar multiplier σ_r^2 .
- **PF settings:** particle spread σ_{init} , resampling threshold (e.g., N_{eff} threshold), and $\mathbf{Q}_{\text{pf}}$ are selected and documented; these are tuned in Scenario 1.
- **Reproducibility:** fix and record random seeds; save exact $\mathbf{Q}$ and $\mathbf{R}$ matrices used for each run.

Metrics and reporting: For each trial and configuration we compute and report:

- **RMSE, MAE** over the whole trajectory,

- **Empirical CDF** of per-sample Euclidean positioning error with key percentiles (50%, 90%, 95%),
- **Convergence traces:** error vs. time to assess transient behaviour,
- **Computational metrics** (PF: per-step runtime and achieved sampling rate; EKF/UKF: average update time).

Selection of PF benchmark (N^* , Q_{pf}^*): From Scenario 1 choose the smallest particle count N^* that achieves RMSE within a tolerance within 5% of the best observed RMSE while maintaining per-step runtime compatible with real-time operation. Use this tuned PF as the benchmark in Scenario 2.

The above setup ensures unit consistency, isolates the effect of process vs. measurement noise, and produces statistically robust comparisons between EKF, UKF, LSE and PF.

5.3 Results

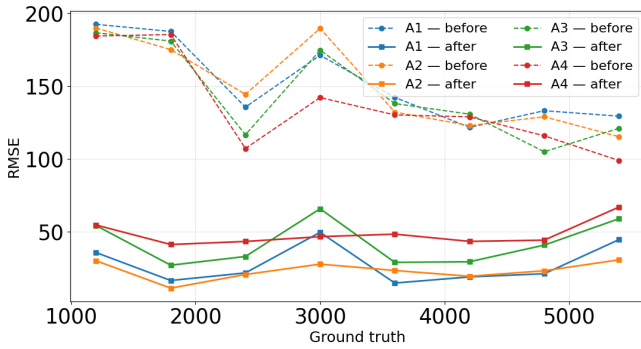


Figure 3. Bias calibration

5.3.1 Calibration results: Figure 3 shows the RMSE values of four anchors at different ground-truth distances under LOS conditions, comparing results before and after calibration. Before calibration, the RMSE is relatively high (around 100 – 190 mm) and varies significantly with distance, indicating systematic bias and measurement noise in the raw UWB data. After calibration, the RMSE decreases considerably to about 15 – 65 mm and becomes more stable. This result demonstrates that the calibration process effectively reduces systematic errors, such as hardware delays and antenna-related timing offsets in the SDS-TWR process, thereby improving the overall accuracy of the system.

Figure 4 presents the CDF of the positioning errors obtained using the conventional LSE method and the calibrated LSE approach.

It can be observed that the CDF curve of the calibrated LSE consistently lies above and to the left of the raw LSE curve. This indicates that, for any given error threshold, a larger proportion of samples exhibit smaller positioning errors after calibration.

At an error threshold of approximately 100 mm, the calibrated method achieves a cumulative probability of about 0.8 – 0.85, whereas the raw LSE only reaches around 0.65 – 0.7. This demonstrates that nearly 80% of

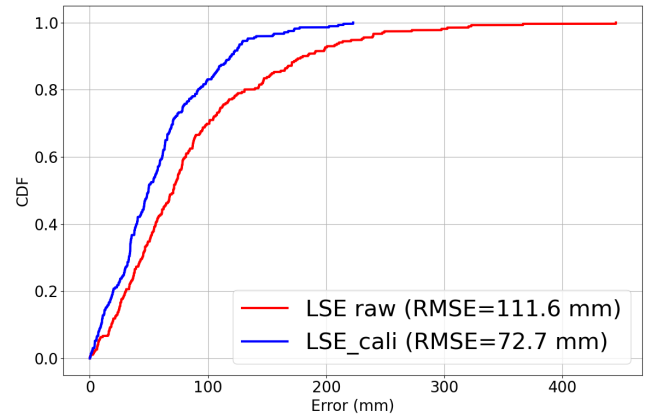


Figure 4. CDF LSE raw and calibrated

the calibrated estimates fall below 100 mm, compared to roughly 65% for the uncalibrated case.

The improvement is further confirmed by the RMSE values, which decrease from 111.6 mm (raw) to 72.7 mm (calibrated), corresponding to an error reduction of approximately 35%. Additionally, the maximum observed error is significantly reduced after calibration, indicating that the proposed calibration model effectively mitigates systematic bias and suppresses large-error outliers.

Overall, the results clearly demonstrate that bias calibration substantially enhances the accuracy and robustness of the LSE-based positioning system.

5.3.2 Evaluation results:

Scenario 1:

Table II
SAMPLING RATE

Number of particles	10	30	50	70	90
Number of samples	4112	3688	3247	2800	2595
Sampling rate (Hz)	128	119	108	94	87

Table III
RMSE COMPARISON

	Particle number	RMSE (mm)	Improvement vs. LSE
Raw	10	83.1	25.53%
	30	106.6	4.48%
	50	100.8	9.67%
	70	107.5	3.67%
	90	109.8	1.61%
Calibrated	10	56.9	21.73%
	30	64.5	11.28%
	50	73.8	−1.51%
	70	76.3	−4.95%
	90	63.9	12.1%

From Table II and Table II, it can be observed that the number of particles significantly affects both computational efficiency and localization accuracy. As

shown in Table II, when the particle number increases from 10 to 90, the sampling rate gradually decreases from 128 Hz to 87 Hz. Moreover, the number of generated samples is reduced considerably (from 4112 to 2595). This indicates that increasing the number of particles increases computational complexity, thereby reducing the update frequency of the system.

Regarding localization accuracy, Table II presents the RMSE results for both raw and calibrated data. In the raw scenario, the best performance is achieved with 10 particles, resulting in an RMSE of 83.1 mm. When the particle number increases to 30, 50, 70, and 90, the RMSE increases to 106.6 mm, 100.8 mm, 107.5 mm, and 109.8 mm, respectively. This demonstrates that increasing the particle number does not improve accuracy in the raw case; instead, it may even degrade the estimation performance.

In the calibrated scenario, the overall RMSE values are significantly reduced. The lowest RMSE is again obtained with 10 particles, reaching 56.9 mm. When the particle number increases, the RMSE rises to 64.5 mm (30 particles), 73.8 mm (50 particles), and 76.3 mm (70 particles), before slightly decreasing to 63.9 mm at 90 particles. However, none of these configurations outperform the 10-particle case.

This behavior can be explained by the trade-off between the number of particles and the update speed of the filter. In theory, using more particles can provide a better approximation of the posterior distribution. However, in this experiment, increasing the particle number greatly reduces the sampling rate, which means the filter is updated less frequently within a fixed time period. As a result, when more than 10 particles are used, the particle filter does not have enough updates to converge properly in each motion segment, leading to larger estimation errors and higher RMSE values.

On the other hand, when using 10 particles, the particle filter operates at a much higher update rate. This allows faster weight updates and more frequent resampling. Together with the low-noise environment and the bias-calibrated measurements, the filter can make better use of temporal information and converge more reliably, even with a smaller number of particles.

Overall, the results indicate that increasing the particle number does not necessarily lead to better localization accuracy. On the contrary, a smaller number of particles (10 particles in this scenario) achieves the best trade-off between accuracy and computational efficiency, providing both the highest sampling rate and the lowest RMSE in both raw and calibrated cases.

It should be noted that this result should be interpreted as a consequence of the real-time implementation constraints rather than as an inherent characteristic of the particle filter algorithm. In principle, increasing the number of particles can improve the approximation of the posterior distribution. However, in the proposed implementation on the Raspberry Pi 4 platform, a larger particle set increases the computational burden of the prediction, likelihood evaluation, and resampling stages. This additional processing cost reduces the ef-

fective update frequency of the filter. Consequently, the estimated state is propagated over longer intervals before new UWB measurements are incorporated, which allows prediction errors to accumulate more significantly during robot motion. Since the same tendency is observed for both raw and calibrated measurements, the degradation at higher particle numbers is mainly attributed to the limited real-time processing capability of the embedded platform rather than to the calibration procedure or to a general limitation of PF-based localization. Therefore, the 10-particle configuration represents the most suitable practical setting for the tested hardware and experimental conditions, where maintaining a high update rate is more beneficial than increasing particle diversity.

Scenario 2:

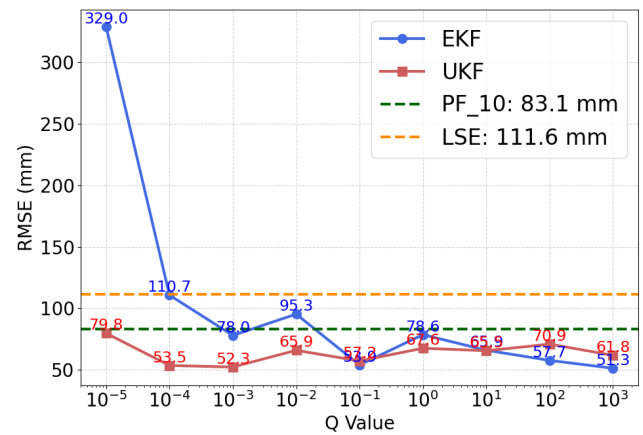


Figure 5. RMSE when varying the process noise covariance Q (raw measurements)

Figure 5 illustrates the RMSE performance of the EKF and UKF under different values of the process noise covariance Q prior to bias calibration. For reference, the dashed horizontal lines represent the RMSE of PF with 10 particles (83.1 mm) and the LSE baseline (111.6 mm).

It can be observed that the EKF is highly sensitive to the selection of Q . When Q is very small (10^{-5}), the RMSE reaches 329.0 mm, indicating severe model mismatch due to underestimation of process uncertainty. As Q increases, the EKF performance improves significantly, reaching a minimum RMSE of 51.3 mm at $Q = 10^3$. However, noticeable fluctuations occur across intermediate Q values, demonstrating that improper tuning may degrade stability.

In contrast, the UKF exhibits more stable behavior across the entire Q range. The RMSE remains within a relatively narrow interval between approximately 52 mm and 80 mm. The best performance is achieved at $Q = 10^{-3}$ with an RMSE of 52.3 mm. Compared to EKF, the UKF shows reduced sensitivity to Q variations, indicating stronger robustness against process noise mis-specification.

Furthermore, for most Q values, both EKF and UKF outperform the LSE baseline (111.6 mm) and the PF method with 10 particles (83.1 mm). This con-

firms the advantage of recursive Bayesian filtering over batch least-squares estimation in handling measurement noise and dynamic uncertainty.

Overall, the results highlight the critical importance of proper Q tuning, especially for the EKF. While EKF can achieve competitive accuracy with optimal tuning, UKF provides more consistent performance across a wide range of process noise settings.

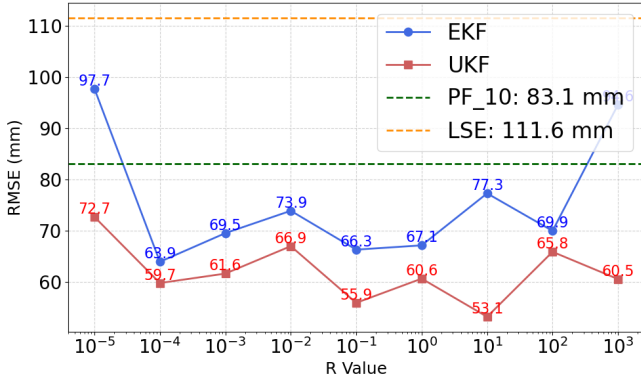


Figure 6. RMSE when varying the measurement noise covariance R (raw measured)

Figure 6 presents the RMSE performance of the EKF and UKF under different values of the measurement noise covariance R prior to bias calibration. The dashed horizontal lines denote the RMSE of PF with 10 particles (83.1 mm) and the LSE baseline (111.6 mm).

It can be observed that both EKF and UKF exhibit relatively stable behavior across a wide range of R values compared to the sensitivity observed with Q tuning. For EKF, the RMSE varies between approximately 63.9 mm and 97.7 mm. The best performance is achieved at $R = 10^{-4}$ with an RMSE of 63.9 mm, while overly small measurement noise ($R = 10^{-5}$) results in degraded performance (97.7 mm), likely due to overconfidence in noisy measurements.

Similarly, the UKF demonstrates consistent performance, with RMSE values ranging from approximately 53.1 mm to 72.7 mm. The optimal performance occurs at $R = 10$, where the RMSE reaches 53.1 mm. Compared to EKF, UKF consistently achieves lower RMSE across most R settings, indicating stronger robustness to measurement noise covariance selection.

Furthermore, for nearly all tested R values, both EKF and UKF outperform the PF benchmark (83.1 mm) and significantly surpass the LSE baseline (111.6 mm). This confirms the effectiveness of recursive filtering methods in mitigating measurement noise.

Overall, the results indicate that proper tuning of R improves estimation accuracy, but both filters remain relatively robust over a broad range of measurement noise settings. Among them, UKF demonstrates superior stability and consistently better accuracy under the non-calibrated condition.

Figure 7 shows the RMSE results of the EKF and UKF for different values of the process noise covariance Q after bias calibration. The dashed horizontal lines rep-

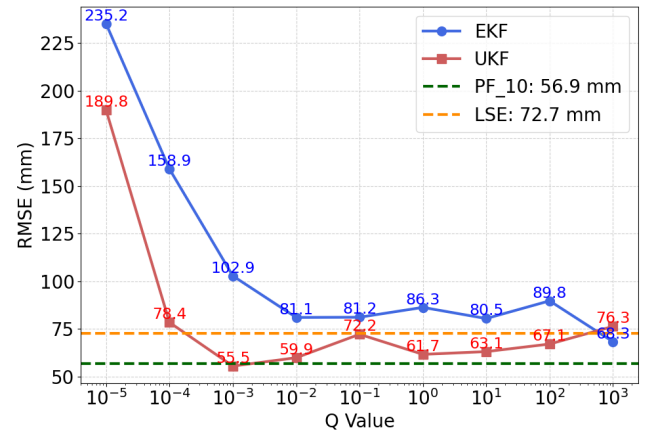


Figure 7. RMSE when varying the process noise covariance Q (calibrated measurements)

resent the calibrated LSE result (72.7 mm) and the PF with 10 particles (56.9 mm).

After calibration, both filters become more stable than in the non-calibrated case. For the EKF, the RMSE is very high when Q is small. At $Q = 10^{-5}$, the RMSE reaches 235.2 mm, and it decreases to 158.9 mm at $Q = 10^{-4}$. When Q increases to moderate values, the EKF performance improves clearly. The RMSE is 102.9 mm at $Q = 10^{-3}$ and drops further to 81.1 mm at $Q = 10^{-2}$. The best EKF result is achieved at $Q = 10$ with an RMSE of 80.5 mm. However, when Q becomes large, the RMSE increases again to 89.8 mm at $Q = 10^2$ before decreasing to 68.3 mm at $Q = 10^3$. This shows that the EKF performance strongly depends on the choice of Q .

The UKF shows more robust behavior across the tested Q range. At very small Q , the RMSE is 189.8 mm for $Q = 10^{-5}$ and decreases to 78.4 mm at $Q = 10^{-4}$. The best UKF performance is obtained at $Q = 10^{-3}$, where the RMSE reaches 55.5 mm. For moderate values of Q , the RMSE remains relatively stable, with values of 59.9 mm at $Q = 10^{-2}$, 72.2 mm at $Q = 10^{-1}$, 61.7 mm at $Q = 1$, and 63.1 mm at $Q = 10$. Even at larger Q values, the RMSE stays below 76.3 mm.

At its optimal point ($Q = 10^{-3}$), the UKF achieves an RMSE of 55.5 mm, which is slightly better than the PF result with 10 particles (56.9 mm) and clearly better than the LSE baseline (72.7 mm). Overall, the UKF is less sensitive to changes in Q than the EKF.

Overall, the results confirm that calibration not only improves absolute positioning accuracy but also enhances filter stability. While EKF requires careful tuning of Q to avoid divergence, UKF provides more consistent and reliable performance across a broad range of process noise settings.

Figure 8 presents the RMSE performance of the EKF and UKF under different values of the measurement noise covariance R after bias calibration. The dashed horizontal lines indicate the calibrated LSE baseline (72.7 mm) and the PF method with 10 particles (56.9 mm).

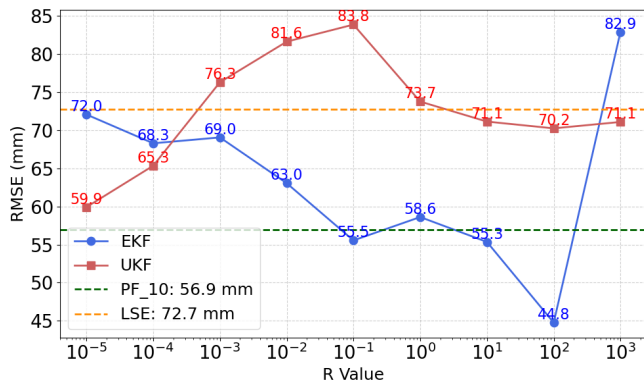


Figure 8. RMSE when varying the measurement noise covariance R (calibrated measured)

It can be observed that both filters demonstrate improved stability compared to the non-calibrated case. For EKF, the RMSE ranges from 44.8 mm to 82.9 mm. The optimal performance is achieved at $R = 10^2$, where the RMSE reaches a minimum of 44.8 mm, significantly outperforming both the calibrated LSE (72.7 mm) and PF (56.9 mm) benchmarks. However, excessively large measurement noise ($R = 10^3$) leads to performance degradation (82.9 mm), indicating overestimation of measurement uncertainty.

In contrast, the UKF exhibits relatively moderate variation across the tested R values. The RMSE ranges between approximately 59.9 mm and 83.8 mm. The best UKF performance is observed at $R = 10^{-5}$ with an RMSE of 59.9 mm. Although UKF does not achieve as low a minimum RMSE as EKF in this case, it maintains more consistent behavior without sharp fluctuations.

Furthermore, for most moderate R values (10^{-4} to 10^2), the EKF consistently outperforms UKF after calibration. This suggests that once systematic bias is compensated, the EKF can achieve superior accuracy provided that the measurement noise covariance is properly tuned.

The MAE analysis provides an additional interpretation of the localization performance because it reflects the average absolute positioning error without emphasizing large deviations as strongly as RMSE. As shown in Figure 9 to Figure 12, the MAE results exhibit trends that are consistent with the RMSE evaluation. Prior to calibration, the LSE and PF with 10 particles obtain MAE values of 86.6 mm and 64.1 mm, respectively, whereas after calibration these values decrease to 58.4 mm and 45.3 mm. This confirms that bias calibration reduces not only the quadratic error measured by RMSE but also the average absolute localization error. For covariance tuning, the EKF remains highly sensitive to inappropriate parameter selection, particularly for very small Q , while the UKF generally provides more stable MAE values over a wide range of noise settings. After calibration, Figure 10 shows that the best MAE is achieved by the EKF when tuning R , reaching 36.3 mm at $R = 10^2$, which is consistent

with the corresponding RMSE minimum of 44.8 mm. Meanwhile, Figure 12 shows that the UKF achieves its best calibrated MAE of approximately 47.0 mm when tuning Q , close to the PF baseline and consistent with its robust RMSE behavior. Overall, MAE supports the same conclusions as RMSE: calibration improves localization accuracy, UKF offers greater robustness to covariance variations, and EKF can achieve the highest accuracy when the measurement noise covariance is properly tuned. However, because RMSE penalizes large errors more heavily, it remains more suitable for evaluating outlier sensitivity, whereas MAE provides a complementary measure of typical positioning error.

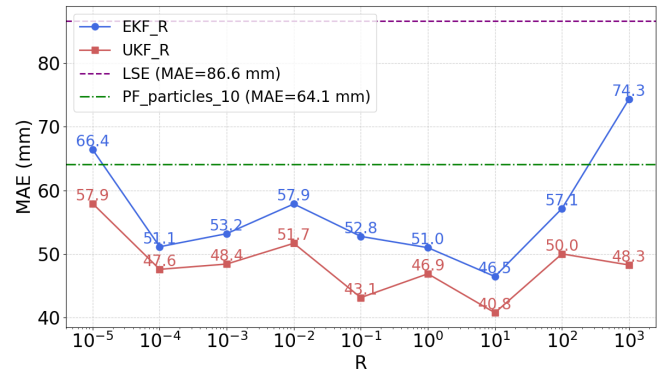


Figure 9. MAE when varying the measurement noise covariance R (raw measured).

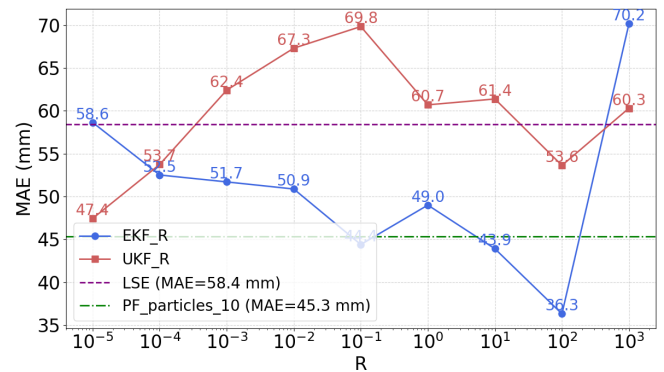


Figure 10. MAE when varying the measurement noise covariance R (calibrated measured).

The results indicate that after calibration, tuning the measurement noise covariance R plays a crucial role in achieving optimal estimation accuracy. While UKF maintains stable performance across a broad range of R settings, the EKF demonstrates the potential for significantly lower RMSE when an appropriate R value is selected.

6 CONCLUSION AND FUTURE WORK

In this study, we have evaluated the applicability of EKF, UKF, and PF for UWB-based indoor robot positioning with four fixed anchors and one

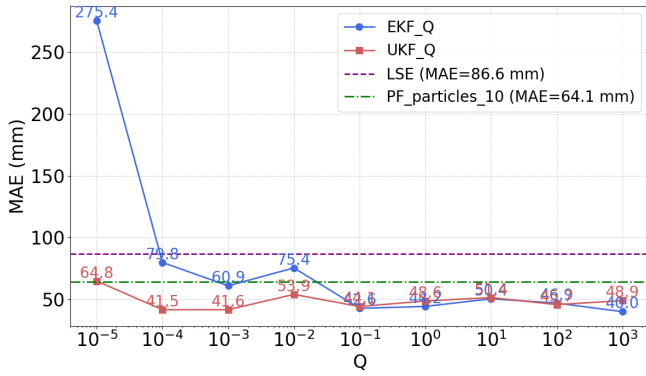


Figure 11. MAE when varying the measurement noise covariance Q (raw measured).

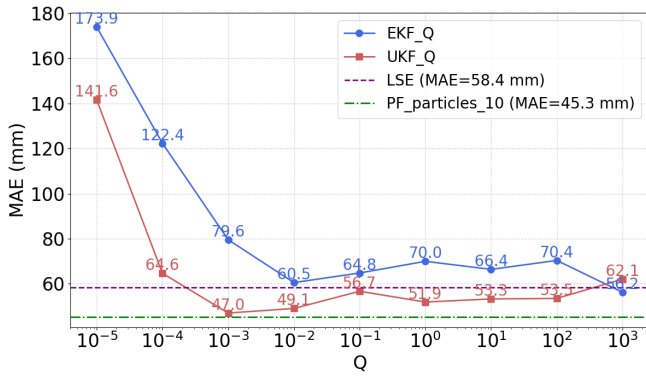


Figure 12. MAE when varying the measurement noise covariance Q (calibrated measured).

mobile tag. The proposed bias calibration effectively removed the dominant systematic ranging offset (approximately -140 mm) and improved the LSE positioning RMSE from 111.6 mm (raw) to 72.7 mm (calibrated), while also reducing large-error outliers. In Scenario 1, PF performance was shown to depend strongly on the number of particles, revealing a clear trade-off between computational cost (sampling rate) and estimation quality. In Scenario 2, varying Q and R significantly affected EKF/UKF convergence; after calibration, both filters consistently outperformed the LSE baseline, with EKF achieving very low RMSE when R was appropriately tuned and UKF providing more robust performance across a wider range of covariance settings.

Although the proposed system demonstrates promising performance under controlled LOS conditions, its robustness in more challenging environments remains an important topic for further investigation. Our future work will focus on extending the framework to operate effectively in NLOS and complex indoor environments, where signal blockage, multipath propagation, and environmental dynamics can significantly affect localization accuracy. To address these challenges, we plan to collect and evaluate extensive datasets under diverse real-world conditions and incorporate adaptive filtering and learning-based techniques to enhance resilience

against NLOS-induced errors. In addition, larger-scale experiments involving more complex trajectories and dynamic obstacles will be conducted to comprehensively assess the scalability, reliability, and practical applicability of the proposed approach.

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