

Indoor Positioning System via Bluetooth Low Energy and mmWave Radar Sensor Fusion

Jayme de Queiroz, Jamil de Araujo Farhat, Guilherme Luiz Moritz, Ohara Kerusauskas Rayel, João Luiz Rebelatto, Richard Demo Souza, and Glauber Brante

Abstract—Indoor positioning is vital for many applications such as asset tracking, context-aware automation, and human-machine interaction, yet achieving sub-meter accuracy remains challenging. This paper proposes a sensor fusion approach that integrates Bluetooth Low Energy (BLE) and millimeter-wave (mmWave) radar to improve positioning performance. We show that, due to the high variance of the BLE measurements, sensor fusion alone does not considerably improve position accuracy over either BLE-only or mmWave-only localization. To mitigate that issue, a sliding window median filter is applied to BLE measurements to enhance stability, and the refined data are fused with mmWave estimates using a track-to-track method. Experimental results demonstrate that the proposed approach reduces positioning error by 42.83% and 25.40% compared to BLE and mmWave alone, respectively.

Keywords— Indoor Positioning, Sensor Fusion, BLE, mmWave.

I. INTRODUCTION

The ability to accurately locate people and objects indoors is becoming as essential as the Global Positioning System (GPS) is for outdoor localization [1]. The integration of sensing and communications is envisioned as a key pillar of 6G [2], while the relationship between Indoor Positioning Systems (IPS) and the Internet of Things (IoT) is symbiotic, as IPS adds spatial awareness to the network, enabling IoT devices to know not only *what* but also *where* [3]. IPS supports critical applications in healthcare (monitoring patient flows and tracking medical equipment) [4], logistics and warehousing (real-time inventory visibility) [4], and autonomous systems and robotics (self-localization in GPS-denied environments) [5]. These use cases highlight the need for IPS solutions that are accurate, robust, and scalable. However, achieving high-accuracy indoor positioning remains challenging, motivating ongoing research on more reliable and precise approaches.

Among many sensing technologies, Bluetooth Low Energy (BLE) and millimeter-wave (mmWave) radar emerge as promising candidates due to their complementary strengths [6]. BLE offers ubiquity, low cost, and minimal power consumption, making it attractive for large-scale deployments [7]. The

BLE 5.1 specification introduced the Constant Tone Extension (CTE), which is appended at the end of the BLE packet to allow for Angle of Arrival (AoA) estimation [8]. As a result, an increasing use of BLE technology in indoor localization within the IoT is observed [7], [9]–[11]. However, BLE AoA is vulnerable to multipath propagation and interference in the crowded 2.4 GHz band, leading to unstable measurements and noisy estimates [6], [7]. In contrast, mmWave radar provides centimeter-level range resolution, enabling high-fidelity sensing even in complex environments [12]–[14]. Nevertheless, mmWave radar suffers from severe path loss, limited operational range, and strong sensitivity to occlusion, often requiring a clear line-of-sight (LOS) to the target [6], [15]. The complementary characteristics of BLE and mmWave sensors form the key motivation for a fusion-based strategy.

Sensor fusion is widely recognized as a means to overcome the limitations of individual modalities [16]. In the context of IPS, Bayesian filtering frameworks, such as the Kalman Filter (KF) and its variants, are commonly applied to track moving objects by recursively combining prediction and measurement updates. For instance, the authors in [17] fused BLE-based trilateration with dead-reckoning data from smartphone sensors, using a KF to achieve a positioning accuracy of less than one meter. Similarly, in the context of mmWave systems, the work in [17] employed a recursive KF for high-precision people tracking, highlighting the filter's efficiency and ability to produce reliable tracks from radar point clouds. In addition, while classical filtering techniques are well-established, recent work has also explored learning-based fusion. Notably, the work in [6] fused BLE and mmWave data using a deep neural network (DNN), achieving high accuracy by jointly training the model on measurements from both sources. This highlights a key branching point in current fusion strategies: the choice between model-based filters and learning-based approaches.

When integrating multiple sensors, Track-to-Track Fusion (T2TF) is a promising approach in which each sensor generates its own independent track that is later combined into a global estimate [7]. In addition, the complexity of T2TF is very low compared to learning-based approaches, avoiding long training endeavors. However, significant differences in measurements of the different sensors will result in inconsistent association decisions for T2TF [18]. Indoor localization measurements are inherently uncertain, with errors appearing due to noise, inconsistent LOS, and physical characteristics of the indoor environment. As a consequence, it is unlikely that sensor fusion will compensate for poor sensor data [19]. When comparing the reliabilities of BLE and mmWave localization

J. Queiroz, J. Farhat, G. L. Moritz, O. K. Rayel, J. L. Rebelatto, and G. Brante are with the Federal University of Technology - Paraná (UTFPR), Brazil. E-mails: jaymequeiroz@alunos.utfpr.edu.br, {jamilfarhat, moritz, oharakr, jlrebelatto, gbrante}@utfpr.edu.br. R. D. Souza is with the Federal University of Santa Catarina (UFSC), Brazil. E-mail: richard.demo@ufsc.br. This work was partially supported by CAPES, Finance Code 001, CNPq (300705/2026-3, 317368/2025-7, 307222/2023-3, 403124/2023-9, 306359/2025-1), Agência Nacional de Energia Elétrica (ANEEL) and Celesc Distribuição S.A. under the research and development program (project PD05697-1323/2023).

approaches, while mmWave degrades performance when the distance of the target object with respect to the radar increases, BLE is known for a higher variability in the AoA estimates due to multipath propagation. As depicted in [20], it is crucial to evaluate the accuracy of the obtained BLE-based AoA estimates to ensure a minimum quality level. Importantly, high variance in BLE AoA-based position estimates significantly limits the effectiveness of direct T2TF without preprocessing: sensor fusion alone yields only marginal improvements over standalone sensors when BLE measurements carry significant outliers caused by nonlinear error propagation from the AoA domain. This motivates a preprocessing step that stabilizes BLE position estimates before fusion, allowing the T2TF engine to operate on cleaner, more reliable inputs.

In the literature, a few approaches have been proposed to classify the quality of the BLE estimates as, *e.g.*, in [9], [20]. In [20] the authors propose a classification method that calculates a Rician K -factor to evaluate AoA measurements. The proposed algorithm discards estimates with low precision, reducing the mean AoA error. However, despite important performance improvements, the proposed method relies on transmitting CTEs at multiple frequencies, which is not readily available in all BLE hardware. In [9], the authors propose a Sliding Window Median Filter (SWMF) to remove outliers as the measurements are processed, so that every new AoA estimate is compared to the median of the W previous valid estimates. If the measurement quality does not fit the predefined threshold, it is considered an outlier and is discarded. The results show important performance improvements, at the cost of discarding an amount of AoA samples.

In this work, we propose a sensor fusion method that integrates BLE and mmWave radar estimates through a T2TF strategy. Due to the high variance of the BLE measurements, a simple use of the T2TF is not enough to significantly improve overall performance. Then, to further stabilize the BLE inputs, we employ a SWMF strategy similar to [9], but with the threshold calculated over the position estimates rather than the AoA estimates as in the original method. This filtering reduces noise and improves the consistency of BLE measurements prior to fusion. Furthermore, the high percentage of discarded BLE samples inherent to the method in [9] is mitigated in our approach, since mmWave estimates are used as a basis for the localization method, with high reliable BLE estimates used to further improve accuracy. As a result, by conducting an experimental evaluation using a mmWave radar and a few BLE anchors, we show that the proposed approach substantially improves positioning performance, reducing the average error by 42.83% compared to BLE alone and 25.40% compared to mmWave alone.

II. SYSTEM SETUP

The experiments were conducted in a controlled office environment with typical indoor challenges, such as multipath propagation and partial shadowing. Fig. 1 illustrates the physical layout, radar, BLE anchors, and placement of the objects. The hardware setup consisted of: (i) one Texas Instruments IWR6843ISK operating in the 60 GHz band with

Frequency-Modulated Continuous-Wave (FMCW) signaling, mounted at fixed reference position with clear LOS to the central hallway, generating real-time 3D point clouds via on-chip DSP processing; (ii) four Silicon Labs BG22-RB4191A Anchor Boards, equipped with dual-polarized antenna arrays for high-resolution AoA estimation, positioned to provide geometric coverage for triangulation; and (iii) one Silicon Labs BG22-EK4108A Explorer Kit broadcasting BLE beacons at regular intervals, received by all four anchors.

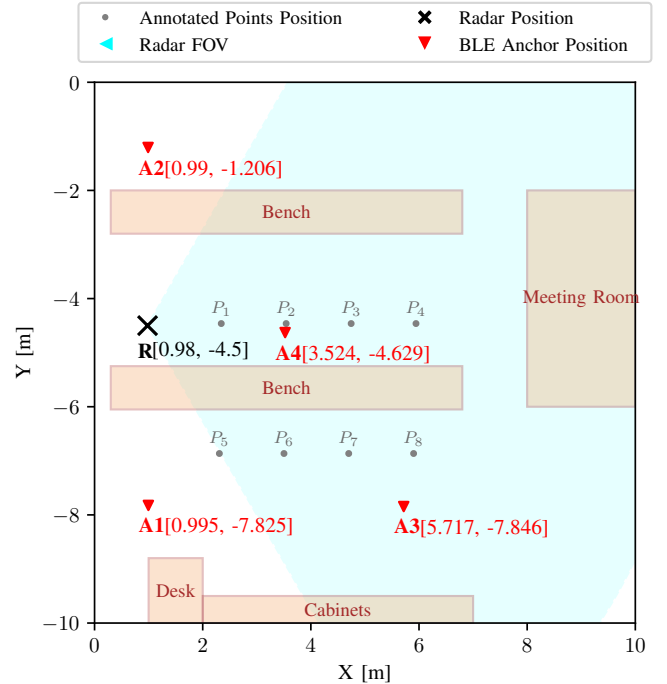


Fig. 1. 2D representation of system setup, showing BLE anchors, radar position and FOV, and ground truth points P_i .

The BLE anchors were deployed in different positions of the environment to ensure geometric coverage, represented by the red triangles in Fig. 1, while the mmWave radar was placed at a fixed reference point with LOS to the primary tracking area, represented by a black cross in the figure. The radar field of view (FOV) is shown in blue. Ground-truth positions were manually measured and annotated at 8 reference points, denoted as P_i , where $i \in [1, 8]$ represents the point ID.

III. PROPOSED METHOD

In the proposed T2TF framework, raw data streams from each sensor are processed independently to generate local position estimates (tracks), which are then aligned and fused¹.

¹Our choice of SWMF and T2TF is motivated by their simplicity and computational efficiency. The SWMF exhibits a complexity of $\mathcal{O}(W \log W)$, while T2TF relies on low-order (2×2) matrix operations, resulting in effectively constant-time processing. This efficiency is a key advantage for real-time embedded system deployment, where low computational complexity is often a more critical design requirement than model sophistication.

Algorithm 1 Sliding Window Median Filter

Require: T, W

```

1: for CTEcount = 1, ..., numCTE do
2:   Compute the new position estimate  $\hat{P}_{\text{BLE}}(\text{CTEcount})$ 
3:   Calculate the median of the  $W$  previous position esti-
     mations:  $\text{estimate} = \text{median}(\hat{P}_{\text{BLE}}(\max\{0, \text{CTEcount} - 1\}), \dots, \hat{P}_{\text{BLE}}(\max\{0, \text{CTEcount} - W\}))$ 
4:   Calculate deviation =  $|\text{estimate} - \hat{P}_{\text{BLE}}(\text{CTEcount})|$ 
5:   if deviation >  $T$  then
6:     Discard  $\hat{P}_{\text{BLE}}(\text{CTEcount})$  estimate
7:     numCTE = numCTE - 1
8:   end if
9: end for
    
```

A. mmWave Track

For the mmWave track, the radar transmitted FMCW signals, which propagate toward the target². Part of this signal is reflected and subsequently received by the radar receiver antennas. After undergoing mixing and low-pass filtering, the reflected signal produces an intermediate frequency signal with a constant frequency, which is further sampled, and the processor performs range and Doppler FFT operations, followed by non-coherent detection using the constant false alarm rate (CFAR) algorithm [12]. Finally, using a 3D-FFT technique, the system generates detected points known as point-cloud data. Static clutter was filtered, and the cluster corresponding to the target was identified. The geometric centroid of the cluster is then calculated in each frame to provide the position estimate $\hat{\mathbf{P}}_{\text{mmWave}} = (\hat{x}_{\text{mmWave}}, \hat{y}_{\text{mmWave}})$.

B. BLE Track

For the BLE track, the BG22-EK4108A tag broadcasts BLE packets with a CTE. Each anchor performed IQ sampling to estimate azimuth and elevation angles. By knowing the anchor positions, the estimated position $\hat{\mathbf{P}}_{\text{BLE}} = (\hat{x}_{\text{BLE}}, \hat{y}_{\text{BLE}})$ is obtained via least-squares triangulation.

Then, in order to mitigate noise and outliers common in BLE data [7], a variant of the SWMF algorithm proposed in [9] was applied. Here, every new position estimate obtained by the least-squares triangulation method is compared to the median of the W previous valid estimates. If the absolute value of the difference between the new position estimate and the median is smaller than a predefined threshold, the new estimate is considered as *valid*; otherwise, it is considered an *outlier* and it is discarded.

Algorithm 1 details the method. By denoting CTEcount as the index of the received CTE, we first compute the new position estimate $\hat{P}_{\text{BLE}}(\text{CTEcount})$ using least-squares triangulation (line 2). To determine if $\hat{P}_{\text{BLE}}(\text{CTEcount})$ is reliable we calculate the median of the W previous position estimations, denoted by the indexes $(\text{CTEcount} - 1)$ and $(\text{CTEcount} - W)$ in line 3 of the algorithm. Based on the median, we calculate the absolute value of the difference between variables estimate and $\hat{P}_{\text{BLE}}(\text{CTEcount})$. If the

difference is larger than an established threshold (T), then $\hat{P}_{\text{BLE}}(\text{CTEcount})$ is discarded (line 6).

C. Track-to-Track Fusion

At each known ground-truth location depicted in Fig. 1, position estimates from both sensors were collected, denoted as $\hat{\mathbf{P}}_{\alpha} = (\hat{x}_{\alpha}, \hat{y}_{\alpha})$, where $\alpha \in \{\text{BLE}, \text{mmWave}\}$ indicates the sensor type.

Then, for each ground-truth distance of the experiment, a 2×2 covariance matrix is computed to characterize sensor uncertainty, given by [7]

$$K_{\alpha}(d) = \begin{bmatrix} \text{Var}[\hat{x}_{\alpha}] & \text{Cov}[\hat{x}_{\alpha}, \hat{y}_{\alpha}] \\ \text{Cov}[\hat{x}_{\alpha}, \hat{y}_{\alpha}] & \text{Var}[\hat{y}_{\alpha}] \end{bmatrix}. \quad (1)$$

This process yields lookup tables of covariance matrices, K_{BLE} and K_{mmWave} , that model how the uncertainty of each sensor varies with distance and environmental conditions, enabling adaptive weighting during fusion.

At runtime, the 2D position estimates from both sensors are fused using inverse-covariance weighting, given by [7]

$$\hat{\mathbf{P}}_{\text{f}} = K_{\text{f}} \left(K_{\text{BLE}}^{-1} \hat{\mathbf{P}}_{\text{BLE}} + K_{\text{mmWave}}^{-1} \hat{\mathbf{P}}_{\text{mmWave}} \right), \quad (2)$$

with

$$K_{\text{f}} = \left(K_{\text{BLE}}^{-1} + K_{\text{mmWave}}^{-1} \right)^{-1}. \quad (3)$$

This formulation ensures that the sensor with lower uncertainty contributes more strongly to the fused estimate. The covariance matrices are selected from lookup tables based on the current target distance estimate, enabling dynamic reweighting as the target moves. Consequently, mmWave measurements dominate at short ranges due to their higher precision in LOS conditions, while BLE measurements are prioritized at longer distances where radar precision degrades, effectively leveraging the complementary strengths of both technologies.

In addition, it is important to highlight that, to ensure consistency between the BLE and mmWave measurements, both tracks were first synchronized using a common system clock. This step is critical because the sensors operate at different sampling rates and may introduce timestamp offsets, which can lead to significant errors in dynamic scenarios if uncorrected. Once synchronized temporally, the mmWave and BLE measurements were spatially aligned. Since each sensor operates in its own local coordinate frame, defined by its physical mounting and orientation, the mmWave coordinates were transformed into a global reference frame consistent with the BLE system and the manually annotated ground-truth positions. This transformation involved estimating a rigid-body rotation and translation matrix using reference points within the environment, ensuring that all position estimates lie in a common 2D plane suitable for fusion.

Finally, localization performance is quantified using the Root Mean Squared Error (RMSE), defined as

$$\text{RMSE} = \sqrt{\frac{1}{L} \sum_{i=1}^L \left[(\hat{x}_{\text{f},i} - x_{\text{true},i})^2 + (\hat{y}_{\text{f},i} - y_{\text{true},i})^2 \right]}, \quad (4)$$

²The measurements were carried out with a person carrying the BG22-EK4108A Explorer Kit at the annotated points, so that the person's position is the target for the mmWave radar estimation, while the BG22-EK4108A position is simultaneously captured by the BLE anchors.

where L is the total number of fused position estimates, $(\hat{x}_{f,i}, \hat{y}_{f,i})$ are the coordinated of the fused estimate $\hat{\mathbf{P}}_f$, while $(x_{\text{true},i}$ and $y_{\text{true},i})$ are the ground-truth coordinates.

IV. NUMERICAL RESULTS

This section evaluates the proposed BLE and mmWave sensor fusion framework using real-world experimental data collected in an office environment. The test points (P_1 – P_8) were intentionally designed to explore regions outside the area formed by the BLE anchors and farther from the radar, where the performance of isolated sensors is expected to degrade significantly. This choice validates the robustness of the fusion method precisely in challenging scenarios where individual modalities struggle. For the SWMF (Algorithm 1), the threshold $T = 0.20$ m is physically motivated since at a nominal walking speed of 1.2 m/s with a 10 Hz BLE update rate, a legitimate inter-sample displacement is at most ≈ 0.12 m. A threshold of 0.20 m therefore admits all genuine motion while reliably rejecting outliers caused by multipath and packet loss. Regarding the window size, Fig. 2 illustrates that increasing W beyond 7 yields negligible RMSE improvement (only 1.3 mm from $W = 7$ to 17) with no meaningful change in discard rate. Since SWMF has $\mathcal{O}(W \log W)$ complexity, larger windows significantly increase cost and memory for marginal gains. Thus, the selected configuration represents the optimal operating point on the accuracy-complexity trade-off curve.

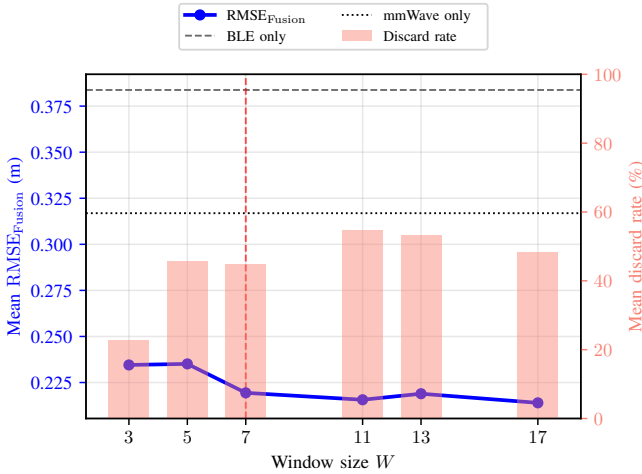


Fig. 2. Mean RMSE_{Fusion} (blue, left axis) and filter discard rate (bars, right axis) vs window size W at the selected threshold; the vertical dashed line marks $W = 7$.

Fig. 3 plots the RMSE at each experiment point across different hallways over P_1 to P_8 , comparing: *i*) BLE-alone, *ii*) mmWave-alone, *iii*) T2TF without the SWMF preconditioning, and *iv*) the proposed T2TF scheme with SWMF. Even without the SWMF, fusion alone yields RMSE values slightly better than the best standalone sensor at every point, demonstrating the intrinsic benefit of inverse-covariance weighting. However, this marginal improvement highlights the critical importance of preprocessing: adding the SWMF substantially improves performance by supplying cleaner BLE estimates to the fusion engine.

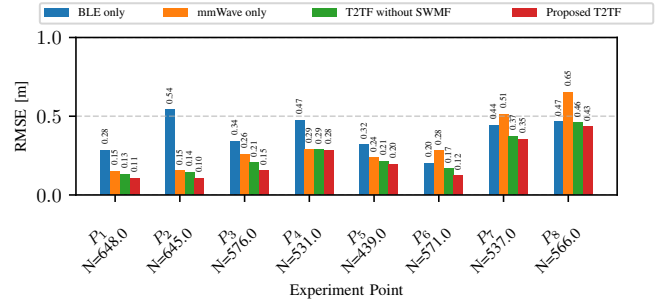


Fig. 3. Comparative analysis of localization RMSE across evaluated experiment points.

Fig. 4 complements the bar chart with a 2D spatial view, overlaying the estimated positions from each method onto the laboratory floor plan. The spatial clustering of the T2TF estimates around the ground-truth markers visually confirms the numerical improvements shown in Fig. 3.

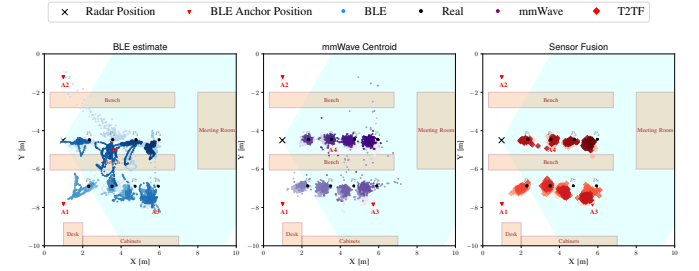


Fig. 4. 2D spatial representation of tracking performance across annotated points.

To further illustrate the spatial dispersion of each sensing modality, Fig. 5 shows the spatial dispersion via convex hulls at close-range (P_1) and far-range (P_8) point. BLE-only shows high variance (RMSE up to 1.241 m) due to multipath and instability in the 2.4 GHz band [6], [7], while mmWave is more consistent but limited by path loss and sparse point-cloud centroiding [12]. The proposed T2TF fusion outperforms both, reducing RMSE by 42.83% relative to BLE-only and 25.40% relative to mmWave-only, validating the hypothesis that combining the high lateral precision of 60 GHz radar with the omnidirectional coverage of BLE yields a complementary sensing system that improves accuracy across all experiment points. Geometrically, at close range (P_1), the fused footprint aligns with the tighter mmWave cluster, reflecting higher trust in radar. At the far range (P_8), where radar degrades along the y -axis due to angular resolution degradation, the fusion shifts trust toward BLE, constraining dispersion.

A decoupled analysis of range and azimuth error components using fitted Gaussian models, illustrated in Fig. 6, confirms the complementary nature of the fusion process. At far range (5.5 m), the mmWave radar's precision degrades along the range axis due to path loss, allowing the lower variance of the BLE to actively stabilize the fusion. This complementary dynamic is equally evident along the azimuth axis; whereas the radar exhibits error spread over a higher interval, the BLE maintains a significantly lower variance,

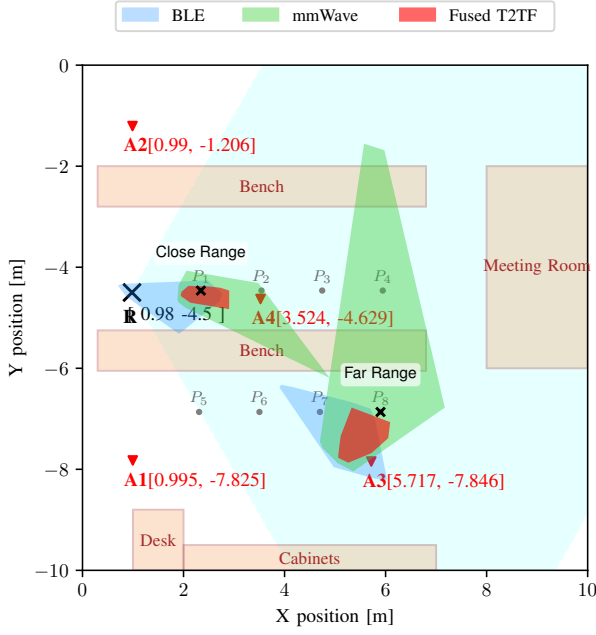


Fig. 5. Footprint of standalone sensors and T2TF fusion estimates in close and far range experiment points.

achieving a consistency similar to T2TF. Consequently, the fused Gaussian profiles remain consistently narrower than those of either standalone sensor on both axes, corroborating the overall RMSE improvements reported in Fig. 3.

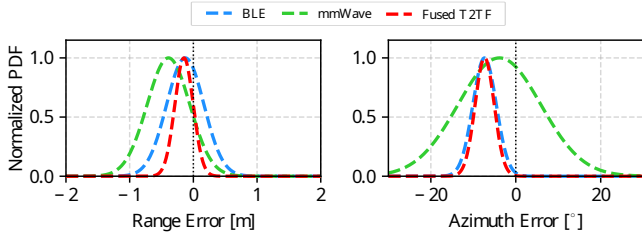


Fig. 6. Decoupled Gaussian error distributions along the range (left) and azimuth (right) axes at far range (5.5 m).

V. CONCLUSION

This paper introduced a sensor fusion framework that integrates BLE and mmWave radar for indoor positioning, leveraging a track-to-track fusion algorithm aided by a sliding window median filter applied in the position domain. Experimental evaluations in an office environment showed that the fused estimates consistently outperformed individual BLE and mmWave results. The core contribution of this work is demonstrating that preprocessing is essential for effective fusion when dealing with high-variance BLE measurements. By applying the SWMF directly to positional estimates rather than raw AoA data, we effectively reject outliers caused by nonlinear error propagation from the AoA domain. This lightweight approach achieves a 42.83% reduction in RMSE

compared to BLE-only and 25.40% compared to mmWave-only, without requiring complex dynamic models or extensive training datasets.

REFERENCES

- [1] K. Roohi and A. R. Fekr, "A comparative analysis of indoor localization technologies," *Computer Networks*, vol. 270, p. 111527, 2025.
- [2] J. G. Andrews, T. E. Humphreys, and T. Ji, "6G Takes Shape," *IEEE BITS the Information Theory Magazine*, vol. 4, no. 1, pp. 2–24, 2024.
- [3] P. S. Farahsari, A. Farahzadi, J. Rezazadeh, and A. Bagheri, "A Survey on Indoor Positioning Systems for IoT-Based Applications," *IEEE Internet of Things Journal*, vol. 9, no. 10, pp. 7680–7699, 2022.
- [4] O. Kanhere and T. S. Rappaport, "Position Location for Futuristic Cellular Communications: 5G and Beyond," *IEEE Communications Magazine*, vol. 59, no. 1, pp. 70–75, 2021.
- [5] A. Famili, A. Stavrou, H. Wang, and J.-M. Park, "PILOT: High-Precision Indoor Localization for Autonomous Drones," *IEEE Transactions on Vehicular Technology*, vol. 72, no. 5, pp. 6445–6459, 2023.
- [6] P. Li, J. Singh, H. Cui, and C. Boano, "BmmW: A DNN-based joint BLE and mmWave radar system for accurate 3D localization with goal-oriented communication," *Pervasive and Mobile Computing*, 2024.
- [7] A. Fabris, O. Kerusauskas Rayel, J. Luiz Rebelatto, G. Luiz Moritz, and R. Demo Souza, "AoA and RSSI-Based BLE Indoor Positioning System With Kalman Filter and Data Fusion," *IEEE Internet of Things Journal*, vol. 12, no. 11, pp. 15 348–15 359, 2025.
- [8] S. Bluetooth, "Core specification (amended) version 5.1," 2024.
- [9] E. A. I. Rodriguez, M. E. P. Monteiro, G. Brante, G. L. Moritz, and R. D. Souza, "BLE-Based AoA Estimation Using a Sliding Window Median Filter to Remove Outliers," in *XLIII Brazilian Symposium on Telecommunications and Signal Processing (SBRT)*, 2025, pp. 1–5.
- [10] N. Paulino and L. M. Pessoa, "Self-Localization via Circular Bluetooth 5.1 Antenna Array Receiver," *IEEE Access*, vol. 11, pp. 365–395, 2023.
- [11] H. Ye, B. Yang, Z. Long, and C. Dai, "A Method of Indoor Positioning by Signal Fitting and PDDA Algorithm Using BLE AoA Device," *IEEE Sensors Journal*, vol. 22, no. 8, pp. 7877–7887, 2022.
- [12] A. B. R. C. Mattos, G. Brante, G. L. Moritz, V. D. P. Souto, and R. Demo Souza, "Classifying Small Animals, Standing and Lying Down Humans With Multi-mmWave Radars," *IEEE Sensors Journal*, vol. 25, no. 14, pp. 27 513–27 525, 2025.
- [13] H. Cui and N. Dahmoun, "High Precision Human Detection and Tracking Using Millimeter-Wave Radars," *IEEE Aerospace and Electronic Systems Magazine*, vol. 36, no. 1, pp. 22–32, 2021.
- [14] A. Shastri, N. Valecha, E. Bashirov, H. Tataria, M. Lentmaier, F. Tufveson, M. Rossi, and P. Casari, "A Review of Millimeter Wave Device-Based Localization and Device-Free Sensing Technologies and Applications," *IEEE Communications Surveys & Tutorials*, vol. 24, no. 3, pp. 1708–1749, 2022.
- [15] X. Huang, J. K. P. Tsoi, and N. Patel, "mmWave Radar Sensors Fusion for Indoor Object Detection and Tracking," *Electronics*, vol. 11, no. 14, 2022.
- [16] Y. Zhuang, X. Sun, Y. Li *et al.*, "Multi-sensor integrated navigation/positioning systems using data fusion: From analytics-based to learning-based approaches," *Information Fusion*, 2023.
- [17] X. Huang, H. Cheena, A. Thomas, and J. Tsoi, "Indoor detection and tracking of people using mmWave sensor," *Journal of Sensors*, 2021.
- [18] J. A. Legg, "DSTO-TN-0663: Distributed Multisensor Fusion System Specification and Evaluation Issues," Defence Science and Technology Organisation, Australian Government, Tech. Rep., 2005.
- [19] D. L. Hall and A. K. Garga, "Pitfalls in Data Fusion (and How to Avoid Them)," *International Conference on Information Fusion*, pp. 429–436, 1999.
- [20] P. Lemos, G. Brante, O. Kerusauskas Rayel, and R. D. Souza, "Controlling AoA Estimation Errors in Rician Fading via Measurement Quality Classification," *IEEE Access*, vol. 13, pp. 107 377–107 385, 2025.