NA-AEKF: A NLOS-Aware Adaptive Extended Kalman Filter for Robust Indoor Localization

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***Abstract*—Accurate indoor localization remains challenging due to frequent Non-Line-of-Sight (NLOS) conditions, which degrade the performance of Ultra-Wideband (UWB)-based positioning systems. Traditional filters like the Extended Kalman Filter (EKF) and its variants assume ideal Line-of-Sight (LOS) scenarios and struggle in complex indoor environments. To address this, we propose the NLOS-Aware Adaptive Extended Kalman Filter (NA-AEKF), designed to improve robustness and accuracy under dynamic conditions. NA-AEKF uses machine learning to classify real-time measurements as LOS or NLOS, adjusting filter parameters accordingly. This integration improves adaptability to changing conditions and mitigates NLOS-related errors. Simulations show that NA-AEKF outperforms EKF, the Unscented Kalman Filter (UKF), the Adaptive EKF (AEKF) and the Improved adaptive EKF (I-AEKF) [1], achieving higher precision in complex indoor settings.**

***Index Terms*—AEKF, EKF, NLOS, UWB, Indoor Localization, Machine Learning, NLOS Detection, and Robust Filtering.**

I. Introduction

Key industries like retail, healthcare, and logistics have made indoor localization a strategic priority because operational efficiency and cost reduction are greatly impacted by the accuracy and dependability of positional data. Grand View Research estimates that the global indoor location services market will grow at a compound annual growth rate (CAGR) of 14.1% from its 2022 valuation of USD 15.48 billion to USD 45.16 billion by 2030 [2]. In light of this, Ultra-Wideband (UWB) has become a favored technology because it can provide accuracy down to the centimeter in line-of-sight situations.

However, Non-Line-of-Sight (NLOS) conditions introduce systematic biases and non-Gaussian errors that deteriorate distance measurements and, in turn, positioning accuracy in highly cluttered indoor environments. Even though basic anchor selection can be performed to mitigate these issues [3], Adaptive Kalman Filters (AKFs), which dynamically modify process and observation covariance matrices in real time to reduce external disturbances, have been suggested as a reliable solution to these problems.

Since 2021, a number of significant contributions have shown how effective these filters are. To counteract NLOS effects, Yuan et al. integrated dynamic weighting, directional constraints, and an adaptive EKF (AEKF) with inertial odometry [4]. Yi et al. corrected for statistical noise properties on-line [5] by directly implementing the Sage Husa adaptive algorithm on an embedded UWB system. In order to manage human interference, the Improved Adaptive Kalman Filter (I-AKF) linearized nonlinear noise components, greatly lowering positional drift [6]. In 2024, Ji et al. optimized the observation covariance update in a Cubature Kalman Filter for UWB/IMU fusion [7], while multisensor fusion architectures like UVIO have cleverly integrated UWB, visual SLAM (Simultaneous Localization and Mapping), and inertial measurements, employing RSSI (Received Signal Strength Indicator) to evaluate measurement reliability [8].

Despite these developments, linear and Gaussian assumptions still restrict the applicability of classical Kalman filters to the intricate dynamics of indoor spaces. A promising approach to modeling nonlinearities and deriving contextual information from unprocessed data is the integration of machine learning (ML). Pre-processing measurements using convolutional neural networks (CNNs) to identify NLOS conditions [9], online parameter adaptation through self-supervised networks [10], and even substituting specific filter steps with deep or recurrent neural networks trained to estimate the optimal Kalman gain [11] are examples of recent work.

Here, we present *NLOS-Aware Adaptive Extended Kalman Filter* (NA-AEKF) that incorporates an online classification module to use machine learning to differentiate between Line-of-Sight (LOS) and NLOS measurements. This method improves robustness and positioning accuracy in cluttered indoor environments by allowing dynamic filter behavior adjustment based on measurement quality and continuous modulation of covariance matrices.

The rest of this article is organized as follows. Section II reviews related work on NLOS identification and Kalman-filter approaches. Section III provides a detailed description of the proposed NA-AEKF system and its operational framework. Section IV presents the simulation protocol and test scenarios, comparing our method empirically with EKF, Unscented Kalman Filter (UKF), AEKF and I-AEKF. Finally, Section V concludes the article and outlines future research directions.

II. Related Work

A. UWB NLOS identification

The ability to distinguish between LOS and NLOS paths is crucial for accurate UWB localization, as NLOS conditions introduce significant positive biases in range estimation [12]. Consequently, consistent LOS/NLOS identification has become a key preprocessing step in modern UWB-based systems. Early research focused on conventional methods categorized as range-based and channel-based techniques. Range-based methods analyze statistical properties of repeated measurements, such as Time of Arrival (TOA) or Time Difference of Arrival (TDOA), using features like mean and variance [13], but often lack robustness in complex environments. In contrast, channel-based methods extract features from the Channel Impulse Response (CIR), including Root Mean Square Delay Spread (RMS-DS), Kurtosis, Skewness, and signal energy distributions, combined with statistical classifiers or hypothesis testing [14]. Although more physically interpretable, their dependence on environment-specific thresholds limits generalization [15].

To address these limitations of traditional LOS/NLOS identification, research shifted towards ML, employing algorithms like Support Vector Machines (SVM) [12] and Random Forests (RF) [15] on handcrafted features, achieving accuracies above 93%. Building on this, deep learning (DL) approaches, including convolutional neural networks (CNNs) [16], long short-term memory (LSTM) networks, and hybrid 1D-ConvLSTM models [17], have surpassed 95% accuracy by operating directly on raw or minimally processed CIR data. Advances such as Capsule Networks [18] and wavelet-transformed feature models [16] further capture multi-scale temporal dependencies.

Despite these advances, challenges persist, including the cost of labeled data acquisition, computational demands on embedded systems, the need for interpretable decisions, and maintaining robustness in dynamic environments [15]. Addressing these issues remains central to advancing scalable and reliable LOS/NLOS identification for next-generation UWB localization systems.

B. Kalman filtering for indoor localization

Kalman filtering significantly enhances UWB-based indoor localization by addressing measurement noise, environmental dynamics, and system non-linearities. The standard Kalman Filter (KF) is commonly applied to reduce range measurement noise, particularly in LOS conditions using protocols such as double-sided two-way ranging (DS-TWR) [19]. Its integration with methods such as the Taylor algorithm improves initial position estimates [20]. However, KF's linearity assumptions and sensitivity to outliers limit its performance in cluttered environments [21]. To manage non-linear models, the Extended Kalman Filter (EKF) linearizes around the current estimate and is widely adopted in UWB systems, proving effective in fusing UWB with IMU or pedestrian dead reckoning (PDR) data to counteract sensor drift and transient errors [22]. Variants like the Biased EKF address low-cost IMU inaccuracies [23], while low-pass filtering further refines precision [21].

Adaptive Kalman Filters (AKF) dynamically adjust noise parameters based on residuals or contextual cues, improving robustness in real-world indoor environments [24]. Techniques using range variance or RSSI are effective under NLOS conditions and in SLAM or visual odometry fusion [8]. Robust adaptive EKF variants further mitigate outliers and PDR drift [25], with recent advances addressing unknown anchor positions and credibility-driven adaptation [26].

Thus, advances in adaptivity, robustness, sensor fusion, and ML integration continue to drive progress in reliable and accurate UWB indoor localization.

III. Proposed Method

The proposed NA-AEKF method is illustrated in Figure 1 and consists of three main components: the input module, the NLOS identification module, and the Kalman filtering module. The system takes two types of inputs. The first input is a set of CIR features, represented as a matrix of dimensions $n \times m$, where n denotes the number of anchors in the localization system and m is the number of CIR features selected for NLOS identification. The second input consists of localization measurements, typically Time of Arrival (TOA) in UWB-based systems, formatted as a vector of size $n \times 1$.

These inputs are processed by the NLOS identification module, which employs a machine learning classifier to label each measurement as LOS or NLOS. The output is a binary vector IS_NLOS $\in \{0,1\}^{n\times 1}$, where IS_NLOS$_i = 0$ indicates a LOS condition between the tag and anchor i, and IS_NLOS$_i = 1$ indicates a NLOS condition.

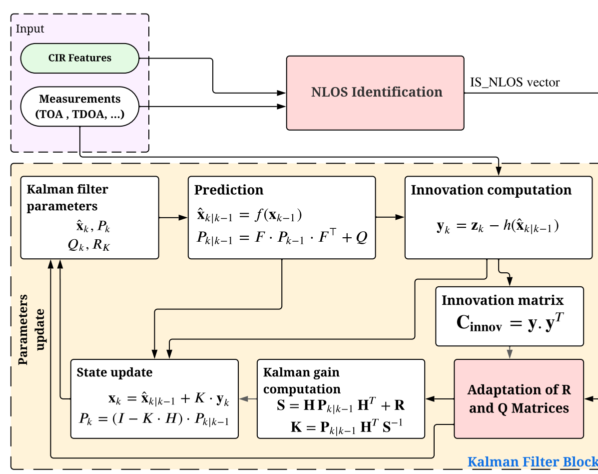

Fig. 1. Architecture of NA-AEKF (NLOS-Aware Adaptive Extended Kalman Filter)

The Kalman filtering module takes into account the system state vector $\mathbf{x}$, the prediction covariance matrix $\mathbf{P}$, the process noise covariance $\mathbf{Q}$, and the measurement noise covariance $\mathbf{R}$. A key innovation of the NA-AEKF architecture lies in how the IS_NLOS vector is integrated into the adaptive mechanism of the filter. Specifically, this vector is used to dynamically adjust the $\mathbf{Q}$ and $\mathbf{R}$ matrices in real time, enabling the filter to maintain robust performance under varying NLOS conditions. The following sections detail the design of the NLOS identification mechanism and the strategy for adaptive adjustment of the filter parameters.

A. NLOS identification Module

As discussed in Section II-A, identifying NLOS conditions is critical due to their impact on indoor localization accuracy. Given the energy and computational constraints of such systems, this study focuses on channel-based methods using features extracted from the CIR, which have shown effectiveness in NLOS detection.

We evaluated traditional machine learning classifiers SVM, RF, K-Nearest Neighbors (KNN), Classification and Regression Trees (CART), and Naïve Bayes (NB), for their favorable trade-off between accuracy and efficiency. These are compared with deep learning models, including deep Neural Networks (NN) and Convolutional Neural Networks (CNN), to assess their suitability in resource-limited scenarios. The results are presented in Section IV.

The machine learning models were implemented using the Scikit-learn Python library, while the deep learning models (NN and CNN) were developed using the TensorFlow framework. The hyperparameter definitions and notations used in Table I follow the conventions and API specifications of these respective packages.

TABLE I
MODELS AND KEY PARAMETERS

Model	Key Parameters
SVM	$C = 10.0$, RBF kernel, γ = scale
KNN	$k = 7$
RF	$N = 100$, depth = 10, min samples = 10/4
NB	Gaussian model, default parameters
CART	Max depth = 8, min split = 10, min leaf = 5, features = $\surd$
NN	Dense(64) $\rightarrow$ Dropout(0.2) $\rightarrow$ Dense(32) $\rightarrow$ Dropout(0.2) $\rightarrow$ Dense(1), activation: ReLU
CNN	Conv1D(12,32) $\rightarrow$ Max-pooling1d(6,32) $\rightarrow$ Conv1D(6,64) $\rightarrow$ Max-pooling1d(3,64) $\rightarrow$ Conv1D(3,128) $\rightarrow$ Flatten $\rightarrow$ Dense(256) $\rightarrow$ Dropout(0.4) $\rightarrow$ Dense(128) $\rightarrow$ Dropout(0.3) $\rightarrow$ Dense(128) $\rightarrow$ Dropout(0.2) $\rightarrow$ Dense(1), activation: ReLU

The experimental dataset was collected using the SNPN-UWB board [27] equipped with a DWM1000 UWB module across seven indoor environments. Each location includes 3,000 LOS and 3,000 NLOS samples, totaling 42,000 randomized samples. Measurements were taken using two UWB nodes, one anchor and one tag, recording only CIR traces without reference positioning. The dataset was originally introduced by Bregar et al. [27].

The key Channel Impulse Response (CIR) features used in this study were extracted from the DW1000 Ultra-Wideband (UWB) transceiver. These features are defined and described in [28]. To optimize our classification models and reduce redundancy, we initially discarded features that did not exhibit significant statistical correlation with others, based on a preliminary correlation analysis.

We then tested various models, and the results are presented in Figure 2. It is evident that model performance varies between approaches, but it is noteworthy that classical classifiers, such as the RF classifier, with a precision of 90% and recall

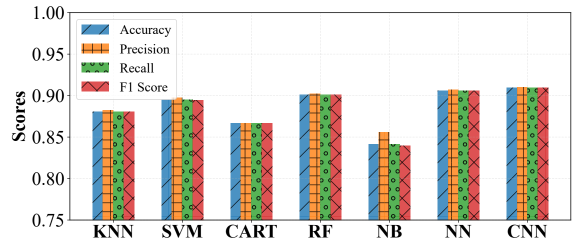

Fig. 2. Model Performance Comparison

of 90.5%, yield results comparable to those obtained using NN and CNN. Specifically, the CNN achieved slightly better results, with a precision and recall of 91.4%, suggesting that deep learning may not be necessary for this task to achieve satisfactory performance.

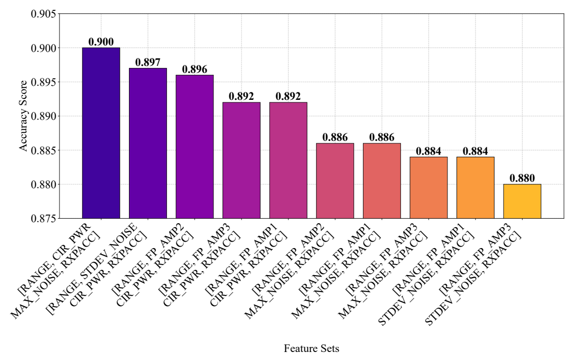

Fig. 3. Classification Accuracy Across Feature Sets

Besides, we noticed that some features were weakly correlated with the NLOS flag, which encouraged us to explore the effect of the reduction of the feature set without compromising the performance of the model. To do this, we used the Sequential Forward Selection (SFS) technique, which enabled us to select the most pertinent features. Note that the feature selection was done only for the model of the RF Classifier and not for every model of classification. The result presented in Figure 3 reveals that incorporating just four features and the first set being [RANGE, CIR_PWR (total channel impulse response power), MAX_NOISE (maximum value of noise), RXPACC (received RX preamble symbols)], the performance was similar to what was obtained when the whole set of features was used. This reduction demonstrates the potential for simplifying the model without sacrificing much accuracy.

However, it should be noted that the error rate in identifying NLOS cases is still 10%. This limitation should be taken into account in future developments of the method, especially when comparing our method with other methods.

B. Kalman Filtering Module

In order to include our NLOS adaptation technique, we employ the Extended Kalman Filter (EKF) framework due to its nice balance between performance and computational overhead. Its dependency on Jacobian linearization is typically less intensive than the sampling method used in UKF or CKF and is more suitable for probable real-time implementation constraints.

We consider a 2D motion model with a state vector and evolving under a constant velocity model:

$$\mathbf{x}_k = \begin{bmatrix} x_k & y_k & v_{x,k} & v_{y,k} \end{bmatrix}^\top, \mathbf{x}_k = \mathbf{F}\mathbf{x}_{k-1} + \mathbf{w}_{k-1}, \quad (1)$$

where $\mathbf{w}_{k-1}$ is the process noise with covariance $\mathbf{Q}$.
UWB anchors provide range measurements modeled as:

$$\mathbf{z}_k = \mathbf{h}(\mathbf{x}_k) + \mathbf{v}_k, \quad (2)$$

where $\mathbf{v}_k$ is measurement noise, and each range measurement is:

$$h_i(\mathbf{x}_k) = \|\mathbf{p}_k - \mathbf{p}_i\|, \quad \mathbf{p}_k = \begin{bmatrix} x_k & y_k \end{bmatrix}^\top. \quad (3)$$

To handle the nonlinearity, we apply the AEKF using Jacobian $\mathbf{H}_k$ and covariance update:

$$\hat{\mathbf{R}}_k = \operatorname{diag}\left(\left|\operatorname{diag}\left(\mathbf{y}_k\mathbf{y}_k^\top - \mathbf{H}_k\mathbf{P}_{k|k-1}\mathbf{H}_k^\top\right)\right|\right), \quad (4)$$

Process noise is adapted using innovation magnitude:

$$\gamma_k = \max\left(1, \frac{\|\mathbf{y}_k\|}{\sqrt{\operatorname{trace}(\mathbf{S}_k)}}\right), \quad (5)$$

$$\mathbf{Q}_k = (1-\beta)\mathbf{Q}_{k-1} + \beta\,\gamma_k\,\mathbf{I}. \quad (6)$$

We propose the **NA-AEKF**. When an anchor i is detected to be in NLOS condition at time step k, its range measurement variance is adjusted by a penalty factor $\lambda > 1$ as follows:

$$r_{i,k}^{\text{adj}} = \begin{cases} \hat{r}_{i,k}, & \text{if IS\_NLOS}_{k,i} = 0 \\ \lambda \cdot \hat{r}_{i,k}, & \text{if IS\_NLOS}_{k,i} = 1 \end{cases} \quad (7)$$

$$\mathbf{R}_k = (1-\alpha)\,\mathbf{R}_{k-1} + \alpha \cdot \operatorname{diag}(\mathbf{r}_k^{\text{adj}}) \quad (8)$$

The NLOS penalty factor λ adjusts the noise covariance of NLOS measurements to reduce their influence in the Kalman filter. By inflating their covariance, unreliable measurements contribute less to the Kalman gain, minimizing the impact of multipath errors. A small λ treats NLOS data similarly to LOS, while a large λ effectively ignores them, allowing dynamic tuning of the filter's sensitivity to the environment.

This adaptive update mitigates the impact of NLOS-induced errors, improving positioning accuracy and robustness in challenging indoor environments.

IV. Simulation and Results

In this section, the performance of the proposed NA-AEKF is evaluated through comprehensive simulations, comparing it against several established Kalman filtering approaches, namely the EKF, UKF, Adaptive EKF (AEKF), and I-AEKF [1]. The simulation framework models a dynamic UWB-based indoor localization scenario, where ranging measurements are influenced by real-time transitions between LOS and NLOS conditions.

The simulations employ TOA ranging, with LOS/NLOS conditions dynamically determined based on environmental interactions. Although the NA-AEKF framework integrates a machine learning-based LOS/NLOS classifier, to simplify the simulation process, ground-truth environmental knowledge is utilized. Specifically, the presence of obstacles between the tag and anchors is used to establish the LOS/NLOS status. To model realistic classification behavior, two distinct scenarios are introduced: (1) perfect LOS/NLOS identification with 0% classification error, and (2) imperfect identification with a 20% classification error rate, where the system intentionally misclassifies the channel condition in 20% of instances and for the two filters NLOS penalty factor $\lambda = 100$.

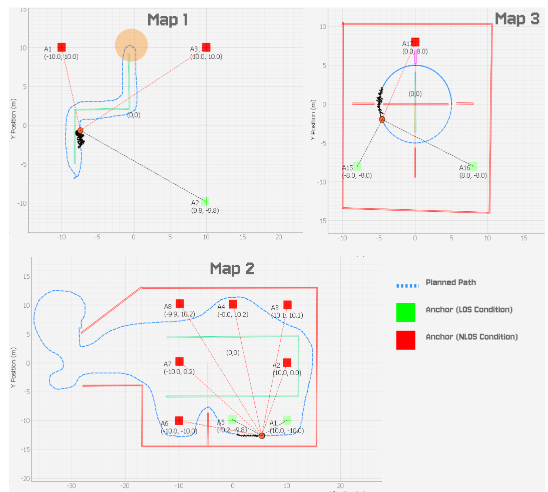

Fig. 4. Simulated Environment Maps for Localization Testing

Figure 4 illustrates the three simulated environments used to assess system performance:

- **Map 1:** Movement around open spaces adjacent to walls, designed to investigate how the number of undetected NLOS conditions impacts localization accuracy.
- **Map 2:** Human movement within an office setting, simulating realistic motion patterns with variable speed and direction, thereby modeling interactive and dynamic mobility behavior.
- **Map 3:** Circular movement inside a building, focusing on transitions between LOS and NLOS conditions throughout the trajectory, with varying classification error rates to emulate fluctuating environmental complexities.

Figure 5 presents a comprehensive comparison of localization errors across various filtering techniques under three distinct indoor scenarios. For each scenario, simulations were run 10 times with different environmental parameters to account for variability and robustness. The results shown in Figure 5 represent the average localization errors across these 10 simulations for each filtering technique within each scenario

- **Map 1 – Movement near walls in open space:** NA-AEKF significantly outperforms other filters, especially during the initial NLOS phase, by effectively reducing obstruction-induced errors and achieving lower localization error. It also maintains high accuracy in the

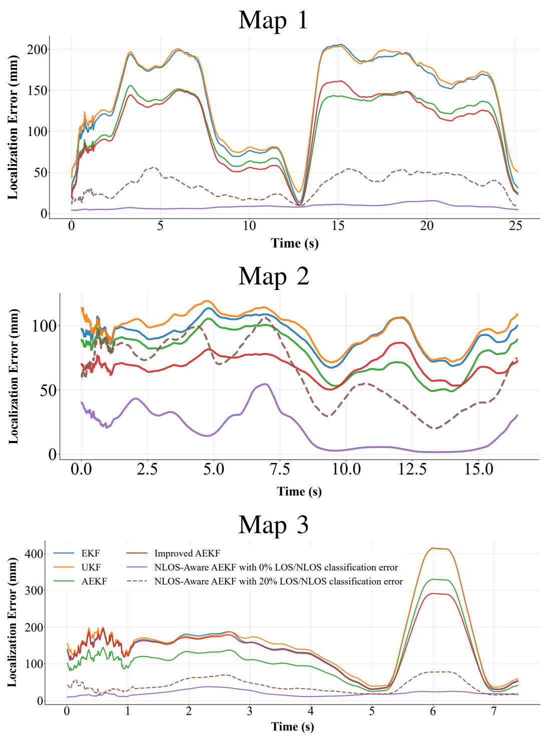

Fig. 5. Time-based analysis of localization error averages for filtering methods on Map1, Map2, and Map3 (legend shown for third curve is identical for the three figures)

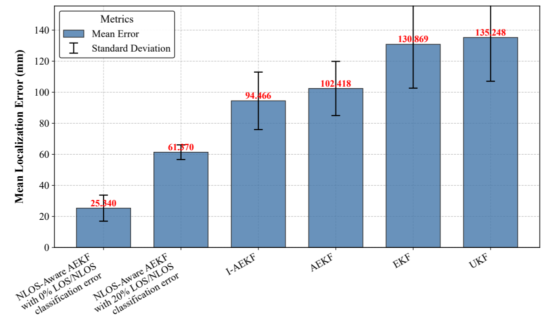

Fig. 6. Overall Localization Filter Performance Evaluation Across All Maps

LOS region ($t \in [12, 14]$s, Map 1), even with a 20% misclassification rate, demonstrating its robustness across varying conditions.

- **Map 2 – Human movement in office-like environment:** NA-AEKF shows strong and consistent performance in dynamic, cluttered indoor environments with varying motion patterns. Despite more pronounced LOS/NLOS classification errors than in Map 1, it outperforms other filters, proving its adaptability to real-world mobility challenges.
- **Map 3 – Circular motion inside a building:** This scenario highlights the weakness of conventional filters during NLOS transitions, notably between $t = 5\,\text{s}$ and $t = 6.5\,\text{s}$. NA-AEKF, on the other hand, retains a low and stable localization error throughout, even with a 20% classification error, affirming its adaptability and environmental responsiveness.

Simulations compared localization filter performance (mean error, standard deviation), with findings summarized in Figure 6. The new NA-AEKF outperformed alternatives by a large margin, thanks to its incorporation of environmental context. In the ideal case of zero-error classification, NA-AEKF provided a benchmark mean error of $25.54\,\text{mm}$. More importantly, it showed robustness by achieving a low $61.87\,\text{mm}$ mean error even under a realistic 20% classification error rate.

This performance is significantly better in comparison to other approaches. Baseline AEKF ($102.42\,\text{mm}$) and Improved AEKF ($94.46\,\text{mm}$) had around **40.2%** and **35.5%** larger mean errors, respectively, that highlight the shortcomings of AEKF derivatives without NLOS awareness. The difference was bigger when compared to traditional filters: EKF ($130.87\,\text{mm}$) and UKF ($135.25\,\text{mm}$) had **111.5%** and **118.6%** larger mean errors, respectively, this validates their weakness under NLOS conditions. In contrast, the NA-AEKF, even when NLOS identification was imperfect, achieved error reductions of **39.6–42.7%** compared to the other AEKFs and **52.7-54.3%** relative to EKF/UKF.

NA-AEKF's context-aware design achieves much higher localization accuracy and robustness. Its fault tolerance against imperfect classification affords it significant error reductions (40-54%) over the traditional methods, rendering it an exceedingly effective solution for dynamic indoor localization under harsh NLOS environments.

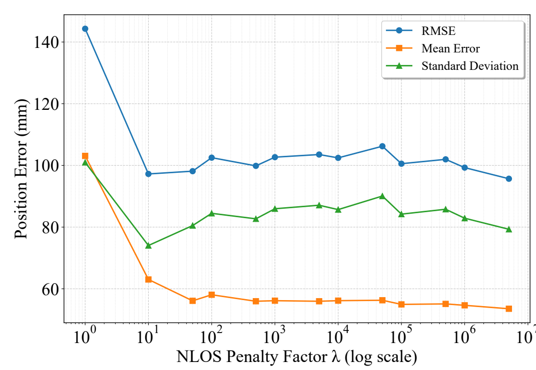

Fig. 7. Impact of NLOS Penalty Factor λ on NA-AEKF Performance Metrics (NA-AEKF with 20% calssification error)

Influence of NLOS Penalty Factor λ: The NLOS penalty factor, λ, significantly affects the NA-AEKF algorithm. The greater λ, the lower the RMSE, average error, and standard deviation, with increasingly better mitigation of NLOS bias measurements up to around $\lambda \approx 100$, where these metrics level off. While larger λ enhances resilience to NLOS errors, excessively large values over-penalize all NLOS measurements, potentially removing beneficial measurements and degrading filter performance.

Finally, the sensitivity of the NA-AEKF algorithm to λ

demonstrates its flexibility. Optimum performance is achieved when λ is sufficiently large (usually ≥ 100) to ensure stable statistics and dynamic response to measurement quality. Further increases in λ to much larger values (e.g. 10^5 or greater) would degrade over-penalty of NLOS measurements at the expense of accuracy and even filter instability in certain instances. This impact is added by LOS/NLOS classification errors, if an LOS signal is classified incorrectly as NLOS, a large λ greatly penalizes this useful data, further reducing positioning accuracy.

V. Conclusion and Perspectives

This article proposes the NA-AEKF, a technique that improves UWB-based indoor localization systems under NLOS conditions with a machine learning-based NLOS classifier within the AEKF adaptation process. Simulation outcomes demonstrated that NA-AEKF outperforms conventional approaches and provides better localization accuracy and lower variance even under weak NLOS classification.

Future work includes the incorporation of IMUs to enhance performance in dynamic conditions and transitioning to deployment on real world hardware. This entails addressing challenges such as real-time computation on embedded systems and classifier generalization across varying environments. Large scale experimental validation will be carried out to test the performance of NA-AEKF in real-world conditions.

Acknowledgements

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