Adaptive Data-Driven Estimation for Simultaneous Localization and Dynamic Signal Mapping in GNSS-Denied Vehicular Networks

Luigi D'Alfonso, *Senior Member, IEEE*, Giuseppe Fedele, *Senior Member, IEEE*,
Mauro Tropea, *Member, IEEE* and Floriano De Rango, *Senior Member, IEEE*

***Abstract*— The reliability of autonomous navigation in GNSS-denied indoor environments hinges on the ability to fuse heterogeneous sensor streams characterized by time-varying noise profiles and non-linear dynamics. Traditional model-based approaches, such as static multilateration or fixed-database fingerprinting, lack the flexibility to adapt to dynamic signal degradations caused by multipath, shadowing, or hardware limitations. This paper proposes a comprehensive Data-Driven Estimation Framework named Cooperative Multi-technology Simultaneous Localization and Signal Mapping (CM-SLASM). We advance the state-of-the-art by introducing an Adaptive Extended Kalman Filter (AEKF) that leverages the statistical properties of the innovation sequence (Innovation-based Adaptive Estimation - IAE) to estimate measurement noise covariance online, effectively ignoring corrupted data streams in real-time. Furthermore, we treat the Radio-Frequency (RF) environment not as a static prior, but as a latent variable learned recursively via Radial Basis Function (RBF) networks.**

NOMENCLATURE

x_k	State vector of the vehicle at time k
P_k	State estimation error covariance matrix
z_k	Measurement vector (UWB, LiDAR, WiFi)
ν_k	Innovation (residual) vector
R_k	Measurement noise covariance matrix
$\mathcal{S}(\cdot)$	Learned Signal Map function
$\hat{C}_k$	Estimated innovation covariance (Sample)
χ^2_α	Threshold for Chi-squared gating
τ_{rel}	Trace threshold for reliability gating

I. INTRODUCTION

The transition towards Level 4 and Level 5 autonomous driving requires vehicle positioning systems with sub-meter accuracy and high integrity [1]. This level of precision is a critical prerequisite not only for individual safe navigation but also for enabling advanced multi-vehicle coordination tasks, such as swarm formation and distributed perimeter surveillance [2]–[4]. While outdoor navigation benefits from redundant Global Navigation Satellite Systems (GNSS) and Real-Time Kinematic (RTK) corrections, indoor environments (e.g., tunnels, underground parking, automated warehouses) present a "capability gap" [5]. In these zones, vehicles must rely on local perception.

Modern Connected Vehicles (CVs) act as mobile sensing nodes, generating massive amounts of data: kinematic odometry, geometric ranges (LiDAR, UWB), and unstructured environmental signals (WiFi/5G RSSI) [6]. However, the naive fusion of these sources is perilous. Geometric sensors like UWB are precise but expensive and require Line-of-Sight (LoS) [7]. Conversely, WiFi signals are ubiquitous but suffer from non-Gaussian noise, shadowing, and hardware-dependent sensitivity variations [8].

Authors are with the Department of Informatics, Modeling, Electronics and Systems Engineering, University of Calabria, Rende 87036, Italy (e-mail: luigi.dalfonso@unical.it, giuseppe.fedele@unical.it, m.tropea@dimes.unical.it, derango@dimes.unical.it).

Traditional "Model-Based" approaches fall short in two key areas. First, they assume static noise statistics. Standard Kalman Filters utilize fixed measurement noise covariance matrices (R). If a sensor degrades (e.g., a "Class C3" low-sensitivity receiver entering a shadowing zone), the filter over-trusts the noisy data, leading to divergence. Second, they rely on static environmental maps. Fingerprinting methods [9] rely on offline surveys. If the environment changes (e.g., a truck blocks an Access Point), the pre-recorded map becomes a source of bias rather than information.

To bridge this gap, we propose a **Data-Driven Estimation Logic**. Unlike deterministic solvers that rely solely on geometric equations, our approach treats the estimation process as a learning problem. By analyzing the residuals (innovation) of the estimation process in real-time, the system "learns" the current quality of its sensors and weights them accordingly via adaptive covariance tuning. Furthermore, the environment itself, represented by the RSSI field [10], is treated not as a known prior, but as a latent variable to be regressed online from the data stream. This shift from "using a map" to "learning a map" fundamentally categorizes the CM-SLASM as a data-driven strategy.

Related work. The foundations of our work lie in Probabilistic Robotics [11]. While Simultaneous Localization and Mapping (SLAM) typically focuses on geometric landmarks (walls, corners), our approach extends this to "Signal SLAM," where the landmarks are continuous scalar fields (RSSI maps). Yarovoi et al. [12] provide a comprehensive overview of SLAM algorithms, discussing their challenges, common approaches, and recent developments.

Cooperation enhances observability. Wang et al. [13] and Ren et al. [14] demonstrated that exchanging information via V2V links can mitigate individual sensor failures. Naturally, such effective V2V cooperation inherently relies on robust routing protocols capable of minimizing interference in dense vehicular scenarios [15]. Naturally, such effective V2V cooperation inherently relies on robust routing protocols capable of minimizing interference in dense vehicular scenarios [15]. Furthermore, ensuring that these mobile sensing nodes—often operating under resource constraints similar to IoT devices—exchange data securely requires lightweight and energy-efficient mechanisms [16]. We incorporate this by treating inter-vehicle ranges (from LiDAR/Radar) as dynamic coupling constraints in the state estimator [17].

The concept of adapting filter parameters online is crucial for robustness. Mehra's seminal work on Innovation-Based Adaptive Estimation (IAE) suggests using the windowed covariance of residuals to estimate the true noise statistics. While widely used in aerospace, its application to hybrid RF-Geometric vehicular fusion is under-explored. Recent works like [18] apply Extended Kalman Filters (EKF) but often stick to static tuning. Our work makes the covariance matrices R_k a function of the observed data stream $z_{1:k}$, transforming the filter into a reactive data-driven agent.

Starting from the seminal works [19], [20], the main contribution of this work is the integration of an **Innovation-Based Adaptive Estimation (IAE)** logic to dynamically tune sensor trust based on data statistics.

The remainder of this paper is organized as follows. Section II establishes the mathematical models for vehicle kinematics and heterogeneous sensors. Section III details the Adaptive CM-SLASM framework. Section IV presents the numerical results. Finally, Section V concludes the work and outlines future research directions.

II. System Modeling

We consider a system of ν cooperative vehicles. The goal is to estimate the joint state $\mathcal{X}_k = [x_1(k)^T, \ldots, x_\nu(k)^T]^T$ and the map parameters $\mathcal{S}$ using only local measurements.

Non-linear kinematics. We adopt the **Bicycle Model** (Ackermann steering) for the vehicle dynamics. The state vector for vehicle i is $x_i = [x, y, \theta, v]^T$, where $x_{i,1:2} = (x, y)$ is the position, θ is the heading, and v is the longitudinal velocity. The continuous-time evolution is:

$$\dot{x}_i(t) = \begin{bmatrix} v\cos\theta \\ v\sin\theta \\ \frac{v}{L}\tan\delta \\ a \end{bmatrix} + w(t) \tag{1}$$

where L is the wheelbase, δ is the steering angle, and a is the acceleration input.

Discretizing with a time step Δt, we obtain the transition function $x_{k+1} = \phi(x_k, u_k) + w_k$, where $u_k = [a_k, \delta_k]^T$.

Heterogeneous observation space. The measurement vector $z_i(k)$ is composed of three distinct subsets:

$$z_i(k) = \begin{bmatrix} z_i^U(k) \\ z_i^L(k) \\ z_i^R(k) \end{bmatrix} \tag{2}$$

Geometric data (UWB and LiDAR). These provide structural constraints:

$$z_{i,m}^U = \|p_i(k) - P_{U,m}\| + v_U \tag{3}$$
$$z_{i,j}^L = \|p_i(k) - p_j(k)\| + v_L \tag{4}$$

Here, v_U and v_L are typically low-variance Gaussian noises.

Environmental data (WiFi RSSI). This is the most complex term. The Received Signal Strength (RSS) follows a path-loss model with shadowing:

$$z_{i,r}^R(k) = \underbrace{\mathcal{S}_r(p_i(k))}_{\text{Signal Map}} + \underbrace{\eta_{shadow}}_{\text{Log-Normal}} + \underbrace{v_R}_{\text{Thermal}} \tag{5}$$

In our data-driven approach, we do not assume a path-loss exponent. Instead, $\mathcal{S}_r(p)$ is an unknown non-linear function to be learned. The measurement noise $v_{total} \sim \mathcal{N}(0, \sigma_R^2)$ is highly dependent on the receiver quality.

Sensor sensitivity classes. We model the receiver quality explicitly via the noise variance σ_R^2, derived from the sensitivity equation [21]. We define three classes:

- **Class C1 (Good):** low σ_R.
- **Class C2 (Medium):** medium σ_R.
- **Class C3 (Bad):** high σ_R.

III. The Adaptive CM-SLASM Framework

We propose a logic that fuses data not blindly, but based on its statistical consistency, as shown in Fig. 1.

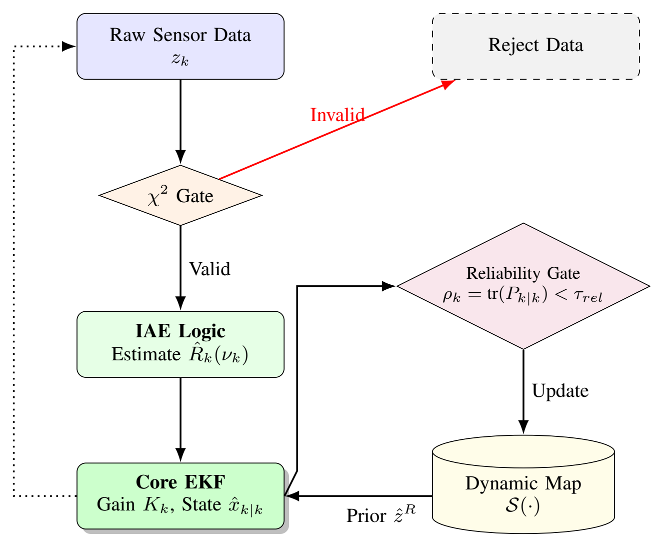

Fig. 1. Proposed data-driven logic flow. Hierarchical decision making: Statistical gating → adaptive tuning → estimation → reliability check → learning.

Innovation-Based Adaptive Estimation (IAE). In standard EKFs, R_k is constant. Here, we estimate it online. Let $\nu_k = z_k - h(\hat{x}_{k|k-1})$ be the innovation. Under the optimal filter assumption, ν_k is a white Gaussian sequence with covariance $S_k = H_k P_{k|k-1} H_k^T + R_k$.

If the measurement noise changes (e.g., multipath enters), the observed sample covariance $\hat{C}_k$ will diverge from the theoretical S_k. We compute $\hat{C}_k$ using a sliding window of size N and assuming zero-mean innovation:

$$\hat{C}_k = \frac{1}{N} \sum_{j=k-N+1}^{k} \nu_j \nu_j^T \tag{6}$$

From this, we infer the *true* measurement noise covariance $\hat{R}_k$ at the current step:

$$\hat{R}_k = \begin{cases} \hat{C}_k - H_k P_{k|k-1} H_k^T, \; if \; \det(\hat{C}_k - H_k P_{k|k-1} H_k^T) \neq 0 \\ R_{min} \; otherwise \end{cases} \tag{7}$$

where R_{min} prevents singularity and $max(\cdot,\cdot)$ has to be intended in the PSD.

Logic mechanism. If a sensor becomes noisy (Class C3 behavior), $\hat{C}_k$ spikes. Consequently, $\hat{R}_k$ increases. Since the Kalman Gain decreases as R increasesis. The filter automatically "disconnects" the noisy sensor and relies on the motion model or other sensors.

Chi-squared outlier rejection. Before fusion, we apply a statistical gate. A measurement z_k is rejected if its Mahalanobis distance exceeds a threshold $\chi^2_{d,\alpha}$ (where d is the degrees of freedom):

$$\nu_k^T S_k^{-1} \nu_k > \chi^2_{d,\alpha} \tag{8}$$

This effectively filters out transient non-line-of-sight (NLoS) outliers common in indoor WiFi.

Reliability-gated map learning. The map update is conditional. We define a reliability index $\rho_k = \text{trace}(P_{k|k})$. The Signal Map $\mathcal{S}_j$ is updated via Radial Basis Function (RBF) regression only if $\rho_k < \tau_{threshold}$. The update rule for a kernel centered at μ is:

$$\mathcal{S}_j(\mu)^{new} = \mathcal{S}_j(\mu)^{old} + \alpha \cdot \Psi(\|\hat{p}_i - \mu\|) \cdot (z^R_{i,j} - \mathcal{S}_j(\hat{p}_i)) \tag{9}$$

where $\Psi(d) = e^{-d^2/2\sigma^2_{kernel}}$ is the Gaussian kernel and α is a learning rate.

The computational cost is critical for V2X onboard units. We analyze the complexity in Table I. Here, n is state dimension, m measurement dimension, L number of map kernels. Since n, m are small for vehicles, the algorithm supports real-time execution.

TABLE I

COMPLEXITY ANALYSIS PER TIME STEP

Algorithm Stage	Operation	Complexity
Prediction	FPF^T	$O(n^3)$
IAE Adaptation	Window Sum	$O(N \cdot m^2)$
EKF Update	Matrix Inversion	$O(m^3)$
Map Update (RBF)	k-NN Search	$O(\log L)$
Total		$\mathbf{O(n^3 + m^3)}$

The complete procedure for the i-th vehicle is detailed in Algorithm 1.

Algorithm 1 Adaptive CM-SLASM (per vehicle i, step k)

Require: State $\hat{x}_{k-1}$, Cov P_{k-1}, Window W_{innov}
Ensure: State $\hat{x}_k$, Map $\hat{\mathcal{S}}_k$

1. Prediction Step
$\hat{x}_{k|k-1} = \phi(\hat{x}_{k-1}, u_k)$
$P_{k|k-1} = F_k P_{k-1} F_k^T + Q_k$
2. Data Association and Pre-processing
Collect measurements $z_k = [z^U, z^L, z^R]^T$
Calculate Innovation $\nu_k = z_k - h(\hat{x}_{k|k-1}, \hat{\mathcal{S}}_{k-1})$
if $\nu_k^T S^{-1} \nu_k > \chi^2_{thresh}$ **then**
  Reject z_k (Outlier)
  return
end if
3. Adaptive Tuning (Data-Driven Logic)
Update window W_{innov}. Compute sample cov $\hat{C}_k$.
Estimate $\hat{R}_k$ via Eq. (7).
4. EKF Correction
$K_k = P_{k|k-1} H^T (H P_{k|k-1} H^T + \hat{R}_k)^{-1}$
$\hat{x}_{k|k} = \hat{x}_{k|k-1} + K_k \nu_k$
$P_{k|k} = (I - K_k H) P_{k|k-1}$
5. Map Learning
if trace$(P_{k|k}) < \tau_{rel}$ **then**
  for each WiFi AP j **do**
    Update $\hat{\mathcal{S}}_j$ using RBF Kernels at $\hat{p}_i$
  end for
end if

IV. RESULTS

This section reports simulation results that validate the proposed data-driven estimation logic, with particular emphasis on robustness against measurement quality and on the ability to build signal maps online. The results are obtained exploiting the three key mechanisms introduced in Sec. III: (i) innovation-based adaptation of $\hat{R}_k$ via $\hat{C}_k$ (Eq. (7)), (ii) χ^2 statistical gating based on the Mahalanobis distance, and (iii) reliability-gated map learning based on $\rho_k = \text{tr}(P_{k|k})$.

Scenario and evaluation protocol. We consider a GNSS-denied indoor environment of $200\,\text{m} \times 200\,\text{m}$ with walls/obstacles, N vehicles and heterogeneous infrastructure including UWB anchors and WiFi emitters (Fig. 2). The setup is designed to stress the estimator under different sensing conditions by varying the receiver sensitivity class, which directly affects the uncertainty of RSSI-derived measurements and considering different numbers of vehicles and different percentages of vehicles equipped with LiDAR.

The following metrics have been used to characterize the performance of the proposed approach.

$$e_p = \frac{1}{N} \sum_{i=1}^{N} \left(\frac{1}{K} \sum_{k=0}^{K} \|x_{i,1:2}(k) - \hat{x}_{i,1:2}(k|k)\| \right) \tag{10}$$

for the position error and

$$e_{\mathcal{M}} = \frac{1}{N_R} \sum_{i=1}^{N_R} \left(\frac{1}{\mathcal{M}(\mathcal{A})} \int_{\mathcal{A}} e^r_{i,\mathcal{S}}(p, K)\, dp \right) \tag{11}$$

for the mapping error, where the relative error

$$e^r_{i,\mathcal{S}}(p,k) = \frac{\left| \mathcal{S}_i\big|_p - \hat{\mathcal{S}}_i(k)\Big|_p \right|}{\left| \mathcal{S}_i\big|_p \right|} \tag{12}$$

has been exploited and, in particular, K is the total number of simulated steps, i.e., the time instant k is in the range

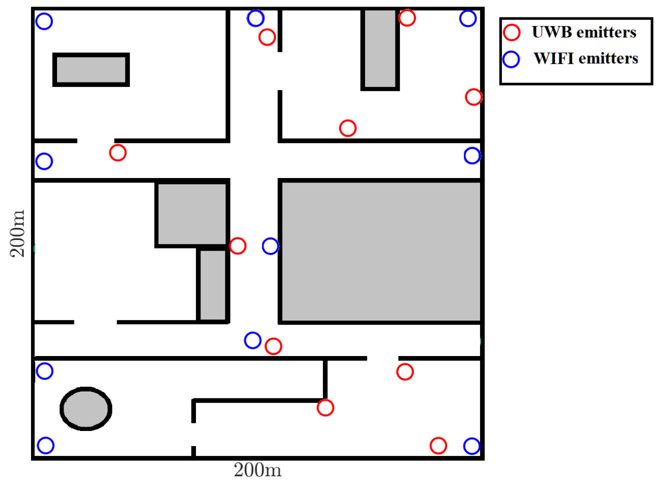

Fig. 2. Environment considered in the numerical simulations (indoor layout, obstacles, and anchor/emitter placement).

$[0, K)$, in each simulation; $\mathcal{S}_i|_p$ and $\hat{\mathcal{S}}_i(k)\Big|_p$ are the real value provided by the i-th WiFi emitter in the position p and the estimated one using the value of the estimated map $\hat{\mathcal{S}}_i(k)$; $\mathcal{A}$ defines the environment of interest and its area is denoted as $\mathcal{M}(\mathcal{A})$. To further highlight the improvements of the proposed CM-SLASM algorithm w.r.t. a multilateration-based positioning system, the error

$$e_t = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{1}{K}\sum_{k=0}^{K}\left\|x_{i,1:2}(k) - \hat{x}^t_{i,1:2}(k)\right\|\right) \tag{13}$$

has been considered to evaluate the performance obtained by a multilateration-based positioning providing $\hat{x}^t_{i,1:2}$ as shown in [22].

Positioning error vs. sensor quality and infrastructure density. Figs. 3 and 4 report positioning errors across multiple scenarios obtained by varying (i) the number of WiFi emitters and (ii) the receiver sensitivity class. Increasing the number of emitters improves performance because the RF field becomes more informative, whereas poorer receiver sensitivity increases RSSI uncertainty; however, the deterioration is mitigated by the data-driven fusion, which adapts $\hat{R}_k$ online and rejects inconsistent measurements.

Mapping error and on-the-fly convergence. Figures 3 (bottom part) and 5 report mapping performance across scenarios and over time. The key point is that the map is learned online (no offline fingerprinting survey is assumed), and its convergence is protected by reliability gating: updates are enabled only when the localization covariance indicates sufficient confidence.

Interpretation: data-driven localization–mapping loop. Overall, the reported positioning and mapping results are consistent with the intended CM-SLASM loop: innovation statistics drive adaptation of $\hat{R}_k$, gating prevents inconsistent measurements from entering the update, and reliability gating ensures that only high-confidence poses contribute to online map learning. These mechanisms are essential to maintain stable performance under poor receiver sensitivity (C3) and under sparse WiFi infrastructure, where static-tuned approaches typically over-trust corrupted RF data.

V. Conclusions and Future Research

This paper presented a robust **Data-Driven Estimation Framework** for vehicular environments. By moving beyond static models and treating sensor data as probabilistic evidence, the **Adaptive CM-SLASM** strategy achieves stable performance even with low-quality hardware. The integration of Innovation-Based Adaptive Estimation (IAE) allows the system to auto-tune its trust levels in real-time.

Future research directions. The CM-SLASM framework relies on a hybrid approach: a physical model for the state transition and a data-driven estimator for the noise statistics. Future developments will focus on deeper learning-based components in the estimation loop (e.g., residual whitening and deep kernels, richer graph-based cooperation, and active perception/control strategies.

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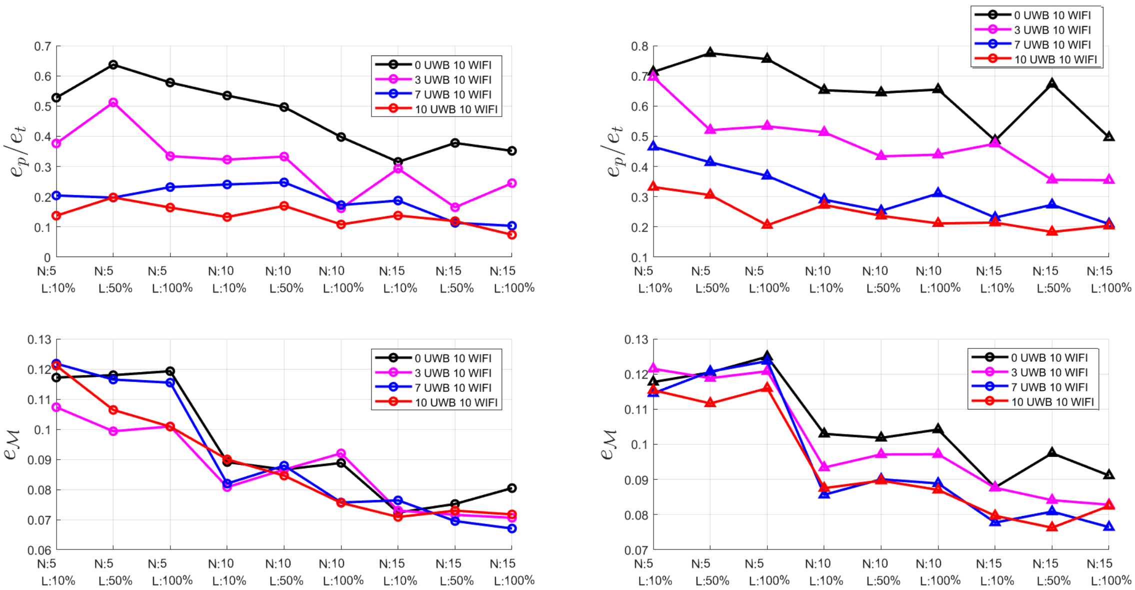


(a) (b)

Fig. 3. Positioning and mapping error across sensitivity classes. Detailed comparison for the case of 10 WiFi emitters under C1 (a) and C3 (b). L represents the percentage of vehicles equipped with LiDAR in the scenario of interest.

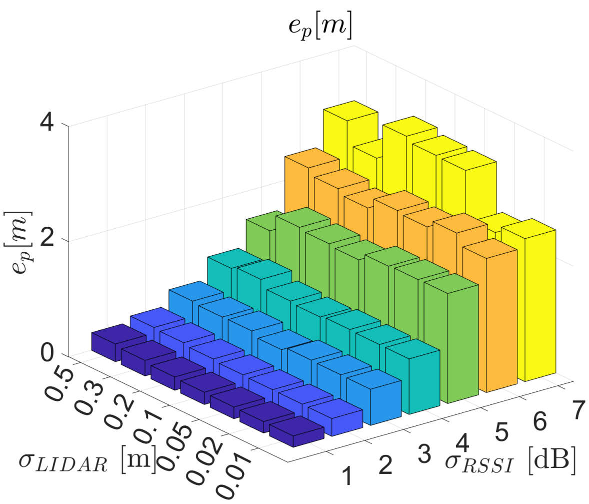
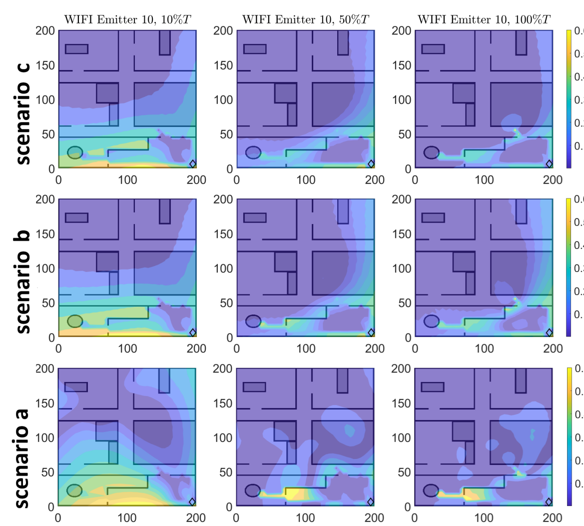


Fig. 4. Positioning error obtained considering scenarios with different sensitivity classes for (standard deviation σ_{RSSI} and for LiDAR (standard deviation σ_{LiDAR}).



(a)

Fig. 5. Mapping error across sensitivity classes, scenario a is with class C1, b is with class C2 and c with class C3, respectively.

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