

A Semi-Decentralized Collaborative Framework for Lightweight Map Updates in Urban Navigation Systems

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Abstract

Autonomous vehicles currently rely on High-Definition (HD) maps for precise localization and path planning. However, traditional HD mapping approaches suffer from high costs, inherent rigidity, and slow update cycles, making them inadequate for dynamic urban environments. This paper presents a novel lightweight collaborative mapping architecture that enables real-time map updates through multi-agent cooperation. Our approach combines Joint Compatibility Branch and Bound (JCBB) for data association, Dempster-Shafer Theory (DST) for uncertainty quantification and landmark classification, and Extended Kalman Filter (EKF) for landmark pose estimation. Experimental validation using the CARLA simulator demonstrates accurate landmark classification and localization. Furthermore, collaborative data fusion reduces false positives and improves overall system reliability.

Keywords: Lightweight map, Collaborative mapping, Autonomous vehicles, Collaborative perception, map updating, HD map, Multi-agent perception, data fusion.

Introduction

Autonomous navigation represents one of the most ambitious technological challenges of the 21st century. Current autonomous vehicles rely heavily on HD maps, which provide centimeter-level accuracy for localization, static object detection, and path planning [1], well beyond the capabilities of standard GNSS (Global Navigation Satellite System). These maps incorporate rich geometric and semantic information, including road networks, lanes, 3D objects, traffic rules, and signage. However, despite their effectiveness in controlled environments, HD maps face significant structural challenges that limit their large-scale adoption in dynamic urban contexts. The production of HD maps relies on specialized mapping vehicles equipped with high-precision sensors, resulting in a rigid offline process that requires planning, data collection, and manual processing phases [1]. Any modification to the road network requires a return to the site and a partial reconstruction of the map, making HD mapping unsuitable to constantly evolving urban environments.

The economic barrier also poses significant challenges. The high equipment costs, coupled with the massive volumes of data to process (often tens of gigabytes per kilometer), make the process difficult to scale for all roads or every city. Furthermore, HD maps generate substantial data volumes due to their precision and density, creating challenges for storage, bandwidth, and integration into embedded systems. Moreover, leading HD map providers use proprietary formats due to a lack of standardiza-

tion, limiting interoperability and creating dependencies on closed commercial solutions.

Most critically, current update cycles can take several weeks or months, creating a critical time lag between the map and reality that compromises the reliability of autonomous navigation. Urban infrastructure frequently evolves due to construction, the addition of street furniture, changes in signage, and seasonal vegetation, but the slow update cycle cannot keep pace with these changes.

In response to these limitations, this paper proposes a paradigm shift towards lightweight collaborative mapping. Instead of relying on expensive, specialized vehicles, our approach leverages both standard vehicles equipped with commercial sensors, including cameras, low-cost LiDAR (Light Detection and Ranging), and GPS (Global Positioning System), as well as RSUs (Roadside Units) in the infrastructure, to collectively build and maintain simplified environmental maps. This collaborative approach enables continuous observation and economically viable updates while maintaining the precision required for autonomous navigation.

The fundamental innovation lies in transforming every connected vehicle into a mobile sensor capable of detecting environmental changes and contributing to the collective maintenance of the map. Rather than creating exhaustive static maps, the objective is to maintain a dynamic, relevant, and operational representation for navigation functions, cooperative perception, and local decision-making. This work presents several key contributions:

- A new distributed architecture for collaborative map updates combining multiple heterogeneous agents
- The integration of DST for robust uncertainty management in multi-agent environments
- A real-time framework for landmark classification and pose estimation
- Experimental validation demonstrating high accuracy in landmark classification, association and localization

This paper is organized as follows: Section II reviews related work in collaborative mapping and the limitations of HD maps. Section III presents our proposed architecture, including the data association, uncertainty management, and pose estimation components. Section IV details the experimental validation in the CARLA simulator with a performance analysis. Section V concludes and discusses future research directions.

Related Work

Updating HD maps is a major challenge for autonomous navigation, which must cope with the variability of urban envi-

ronments and scalability constraints. An initial generation of research relied on crowdsourced data to reduce costs and accelerate updates.

In [2], the authors use urban buses as mobile sensors to identify changes (signage, road markings). This approach, centered on Mahalanobis distance association and simple classification, demonstrated limitations in the presence of sensor uncertainties.

An evolution proposed in [3] introduces a hierarchical structuring of road observation data and recursive Bayesian classification of landmarks (Normal, Removed, New, Anomaly), offering improved robustness. However, the Gaussian assumption and lack of dynamic adaptation reduce its effectiveness in heterogeneous urban contexts.

Other approaches aim to improve the reliability of crowdsourced contributions. For instance, [4] introduces a blockchain-based reputation mechanism that ensures traceability and trust, but it is computationally expensive.

Meanwhile, [5] combines particle filters and boosting to detect changes, with good performance but without fine-grained categorization (new/removed).

A significant milestone is presented by [6], which combines SLAM logic with existence inference based on DST of belief functions. In this framework, each observation is no longer limited to a classical probability of existence but generates a mass function distributed across several hypotheses: existence, non-existence, ignorance, and conflict. These mass functions are updated over time, enabling robust decision-making on the true state of landmarks, even in the presence of uncertainties, sensor noise, or contradictory observations. This approach surpasses the limitations of purely Bayesian methods by explicitly modeling ignorance and conflict. However, its implementation relies on a Rao-Blackwellized Particle Filter, which remains computationally expensive and poorly suited for massively distributed, real-time applications. In line with this, several studies such as [7, 8] have moved towards collaborative and distributed strategies. The core idea is to distribute the update load across multiple connected vehicles or local units (RSUs) to reduce bottlenecks associated with strict centralization and to leverage the redundancy of observations. These approaches demonstrate that multi-agent fusion enhances system reliability and resilience, particularly on a large metropolitan scale. However, they leave a central question open: how to optimally fuse beliefs from multiple agents while preserving the system's coherence and scalability? This question forms the anchor point for our contribution.

Finally, it is important to mention research that may appear peripheral but provide essential methodological building blocks for a global solution. This is the case for works [9, 10, 11], which propose advanced techniques for structuring and indexing spatial data (via geographic tiling, hierarchical trees, or partitioning schemes). These solutions become crucial in the face of the growing data volumes generated by vehicle fleets, as they enable efficient management of scalability and ensure fast, localized map updates, an essential condition for reliable autonomous navigation.

Proposed Method

Autonomous navigation requires HD maps that are not only precise but also perpetually updated to reflect the dynamics of the road environment. As revealed by the state-of-the-art analy-

sis, existing approaches, while varied and innovative, often struggle to reconcile informational richness, computational efficiency, robustness to uncertainties, and scalability within a distributed framework. Our proposed architecture aims to address these challenges. This section details our technical and algorithmic choices designed to balance performance, precision, and low computational cost in a dynamic multi-agent environment.

A. Architectural Overview

Several research efforts have challenged the centralized approach for updating HD maps. For instance, [12] proposes that each vehicle updates its map locally using detected buildings as landmarks; this reduces reliance on a central server but limits generalizability. Meanwhile, [8] presents a decentralized and coordinated update scheme where each vehicle manages a portion of the map. This approach leverages the density of connected vehicles but at the cost of high aggregation complexity and significant bandwidth consumption. To overcome these limitations, we propose a semi-decentralized architecture (Figure 1) based on Local Map Servers (LMSs), each responsible for a distinct geographical sub-map. These local servers are interconnected with a Global Map Server (GMS).

The architecture operates through a hierarchical workflow: the Global Map Server distributes geographical sub-maps to Local Servers based on their operational zones, which then share these sub-maps with agents (RSUs and vehicles) via RSUs acting as communication intermediaries. Each agent independently performs the complete processing pipeline—from perception-based data acquisition to landmark extraction of sub-map landmarks within their Field of View using R-tree algorithms, followed by landmark association via JCBB algorithm, existence inference through DST, and pose estimation using EKF. This architecture is modular and generic; it can be applied to multiple types of landmarks, such as traffic lights, traffic signs, road markings, buildings, and other urban elements.

Upon exiting their operational zone, agents transmit their processed data (pose estimations, covariance matrices, and existence inferences) back to RSUs, which aggregate and forward this information to Local Servers. The Local Servers then perform global association and classification (normal, deleted, added) of landmarks, followed by fusion of covariance matrices and global pose estimation.

Finally, using R-tree data structures, each Local Server updates its sub-map through landmark insertion, deletion, or addition operations before synchronizing with the Global Map Server to maintain overall map consistency. This organizational structure combines the responsiveness of local updates with global consistency, while ensuring scalability and controlled communication resource usage.

B. Spatial Structuring of Local Maps

- Rapid spatial search to extract landmarks within an agent's FoV (Field of View)
- Dynamic insertion and deletion of landmarks without frequent global reconstruction
- Independence from the density of mapped objects

Unlike the KD-tree [11], which is rigid in the face of modifications and limited to point landmarks, the R-tree is based

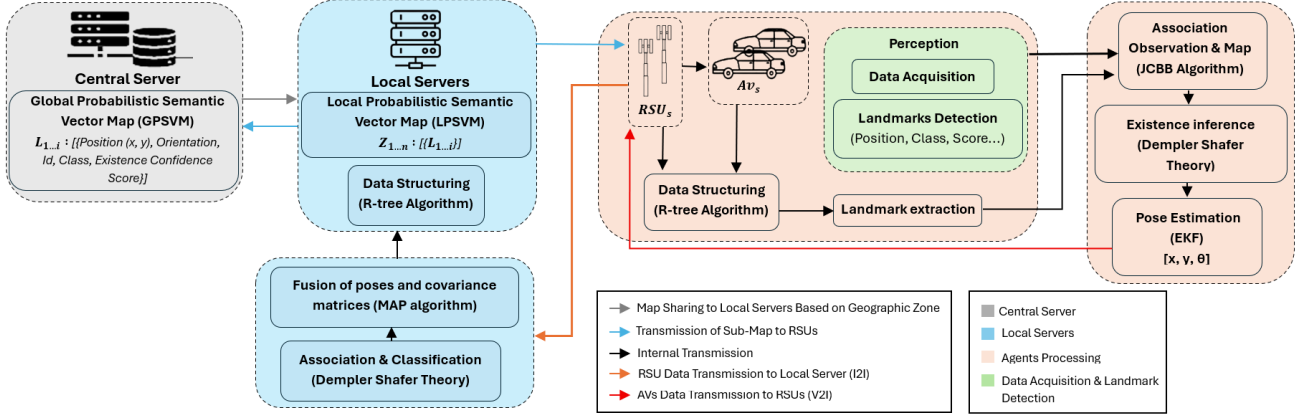


Figure 1: Architecture of the Semi-Decentralized Collaborative Framework for Lightweight Map Updates

on hierarchical bounding boxes. This structure facilitates a future extension to continuous landmarks (e.g., lines, curbs). This flexibility makes the R-tree a particularly suitable choice for a scalable architecture.

C. Observation-to-Map Association

Change detection relies on a reliable association between observations from onboard sensors and elements in the local map. We selected the JCBB algorithm due to its ability to evaluate not only individual compatibilities but also the joint compatibility between sets of potential matches, as emphasized in [13]. In that work, the authors compares JCBB to the Individual Compatibility Nearest Neighbor (ICNN) method and proposes an improvement (DOJCBB) by dynamically adapting the threshold G used to manage multiple associations with joint compatibility. This is crucial when a large number of landmarks are observed simultaneously.

Unlike methods using Mahalanobis distance alone or ICNN, JCBB drastically reduces false positives in dense environments. This mechanism ensures robust data association, which is essential for reliable collaborative map updating.

D. Uncertainty Management and Landmark Classification

Uncertainty management constitutes a central challenge in collaborative environments, where multiple agents may provide noisy or contradictory observations. While some works, such as [3], rely on probabilistic modeling via the belief function $bel(x)$, these approaches do not clearly distinguish between ignorance and conflict and struggle to aggregate heterogeneous data. To overcome these limitations, our architecture integrates DST [6], applied at both the intra-agent and multi-agent levels.

Mass Functions from Perception

Each observation (z_t) is extracted from the perception module as a bounding box, which provides a set of attributes: the detected landmark's class, its pose in the sensor frame, orientation, and an existence score. This score forms the basis of the initial mass function (1):

$$\begin{cases} m(\exists) = \lambda, & m(\bar{\exists}) = 0, & m(\Omega) = 1 - \lambda, & m(\emptyset) = 0 \\ m(\exists) = 0, & m(\bar{\exists}) = \lambda, & m(\Omega) = 1 - \lambda, & m(\emptyset) = 0 \end{cases} \quad (1)$$

where the first line applies if the landmark is detected, and the second line applies if the expected landmark is not detected.

Initially, landmarks present in the HD map are assigned a mass function based on their existence confidence λ approximately equal to 1, while newly observed objects are initialized with a vacuous mass function (2), representing the absence of prior information.

$$\begin{cases} mass_{new\{j\}}(\emptyset) = 0, & mass_{new\{j\}}(\bar{\exists}) = 0, \\ mass_{new\{j\}}(\bar{\exists}) = 0, & mass_{new\{j\}}(\Omega) = 1 \end{cases} \quad (2)$$

Intra-Agent and Multi-Agent Inference

Inspired by [6], each agent locally performs a temporal inference of masses between time $t - 1$ and t . This improves the stability and robustness of the pose estimation performed by the EKF. This temporal fusion reduces the impact of outlier observations and progressively consolidates the confidence assigned to each landmark. Our key contribution lies in extending this mechanism to a collaborative multi-agent framework. The results from each vehicle are transmitted to the local server, where the masses are fused globally using DST rule (3):

$$m_{1 \oplus 2}(A) = \frac{\sum_{B \cap C = A} m_1(B) \cdot m_2(C)}{1 - \sum_{B \cap C = \emptyset} m_1(B) \cdot m_2(C)}, \quad \forall A \subseteq \Omega, A \neq \emptyset \quad (3)$$

This process enables a coherent and robust aggregation of beliefs from multiple agents operating in the same area.

Landmark Classification

Following the inference process, each landmark is classified according to the following rules:

- **Normal Landmark:** If initially present in the map and the mass $m(\exists)$ dominates (or $m(\Omega)$) remains the majority but without strong contradiction)
- **Removed Landmark:** If initially present in the map but the $m(\bar{\exists})$ comes to dominate
- **New Landmark:** If initially absent from the map and after multi-agent inference the mass $m(\exists)$ dominates

This mechanism ensures intelligent arbitration between contradictory data. For example, a correctly identified removed landmark reported by an RSU will not be reintroduced by an isolated false detection from a single vehicle. Conversely, the appearance of a new landmark is only validated through the convergence of beliefs from multiple agents, thereby limiting false positives.

E. Landmark Pose Estimation

When a new landmark is detected, it is necessary to estimate its pose (position and orientation). Several filters have been studied: Kalman, UKF, particle filters, and GraphSLAM. The EKF was chosen for its compromise between accuracy, complexity, and real-time performance. Unlike GraphSLAM, which is too computationally expensive for online processing despite its high accuracy, the EKF enables incremental estimation suitable for embedded systems. This characteristic makes it well-suited for a potential future evolution of our architecture towards a hybrid distributed and semi-decentralized model. In such a scenario, in the absence of a local server, agents could mutually exchange a subset or the entirety of their estimations by leveraging their a priori knowledge of each other's poses. Furthermore, the robust data association provided by JCBB reduces the risks associated with detection noise. Consequently, the EKF represents a natural and coherent choice that aligns with the entire processing chain, while remaining lightweight, easily implementable within ROS framework, and scalable in a multi-landmark context.

F. Collaborative Fusion Strategy

The adopted fusion strategy is a late fusion approach: each vehicle performs preprocessing (data association, inference, and landmark pose estimation) before transmitting the information to the local server. This choice, already validated in [7], reduces bandwidth requirements, prevents premature conflicts, and preserves the computational autonomy of the agents. For the final fusion of pose estimates, we compared two paradigms:

Recursive Least Squares (RLS)

The RLS method [12] updates an estimate \hat{x}_t from successive observations by minimizing a weighted quadratic error (4), (5), (6):

$$\hat{x}_t = \hat{x}_{t-1} + K_t(y_t - H_t\hat{x}_{t-1}) \quad (4)$$

with the updated covariance given by:

$$P_t = (I - K_t H_t) P_{t-1} \quad (5)$$

where the gain K_t is:

$$K_t = P_{t-1} H_t^T (H_t P_{t-1} H_t^T + R_t)^{-1} \quad (6)$$

Maximum A Posteriori (MAP)

The MAP approach [7] estimates the optimal pose \hat{x}_{MAP} by maximizing the posterior probability (7) given the local estimates $\{x_i\}$ (8) and their covariances $\{P_i\}$:

$$\hat{x}_{MAP} = \arg \max_x p(x | \{x_i, P_i\}) \quad (7)$$

This reduces to the closed-form solution:

$$\hat{x}_{MAP} = \left(\sum_{i=1}^N P_i^{-1} \right)^{-1} \left(\sum_{i=1}^N P_i^{-1} x_i \right) \quad (8)$$

Based on our tests, both methods produce similar results in our use case. However, the MAP estimator provides a major computational advantage, with a computation time approximately ten times lower than RLS. This efficiency is crucial for enabling the frequent, real-time updates required by the mapping system.

Experimental Setup and Results

A. Experimental Scenario

To validate our collaborative update architecture, we designed a realistic urban scenario within the CARLA simulator (central intersection of Town05). The environment features a four-way intersection, traffic lights, signage, and traffic cones. Two types of agents collaborate:

- **Mobile Vehicle** (RGB camera) exploring the entire area.
- **Fixed RSU** (RGB camera) limited to a restricted field of view.

Controlled modifications (addition of temporary signs, removal of cones) were introduced to test the detection, classification, and propagation of cartographic changes. In the absence of a full perception pipeline, observations were generated from ground-truth object positions, with added Gaussian noise ($\sigma_x = \sigma_y = 1.1$ m / $\sigma_\theta = 0.5$ rad for the vehicle, $\sigma_x = \sigma_y = 0.4$ m / $\sigma_\theta = 0.4$ rad for the RSU). These noisy observations were then transformed into the sensor frame. The experimental setup was limited to two agents (1 RSU, 1 vehicle), as illustrated in Figure 2.



Figure 2: Test scenario with vehicle-RSU infrastructure in CARLA (Town05) showing false detections (green bounding boxes) and true detections (blue bounding boxes)

B. Performance Analysis

The results are evaluated along three main axes: classification robustness, localization accuracy, and the efficiency of multi-agent fusion. Figure 3 illustrates the cartographic update performed by our system, comparing the initial state (9 landmarks) and the updated map. The results show that 5 landmarks were preserved (KEEP), 2 were added (ADD), 2 were deleted (DELETE), and 2 remained classified as NORMAL as they were excluded from the fusion process. Critical changes are accurately detected. For instance, WARNINGACCIDENT 001 is replaced by NEW Cone 001 (i.e., deleted and added), whereas WARNINGACCIDENT 005 is correctly identified as deleted.

Robust Classification (Multi-Agent DST)

In contrast to heuristic approaches [3] based on temporal rules, our method, grounded in DST, combines mass functions from multiple agents to effectively distinguish between normal, removed, and new landmarks. The results, shown in Figure 3, demonstrate the system's capacity to filter out false detections.

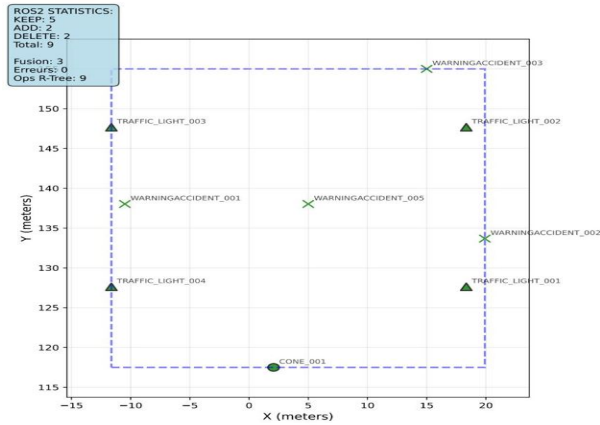
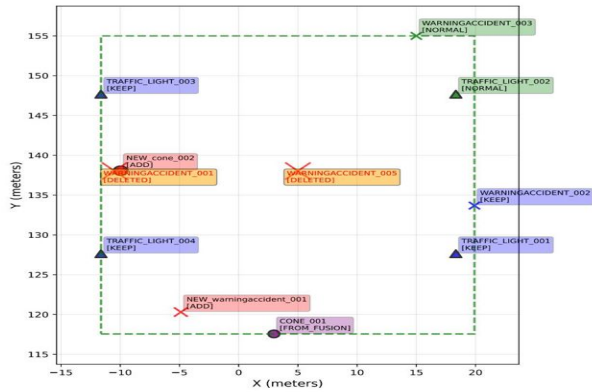


Figure 3: Landmark map before(left)/after(right) collaborative update



For instance, Figure 4 illustrates a conflict scenario where the mobile vehicle generated increasing mass functions for sign existence (false detection from degraded perception conditions) while the RSU concurrently produced increasing mass functions for non-existence (reliable observation of actual absence). Classification metrics—precision, recall, and F1-score—achieved perfect scores of 1.0 after fusion (Figure 5).

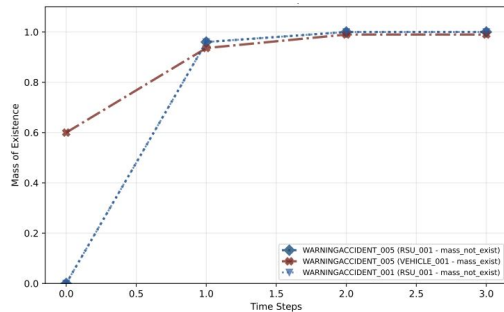


Figure 4: Temporal analysis of landmark states showing confidence scores for normal (maintained), removed (deleted), and conflicting detection scenarios

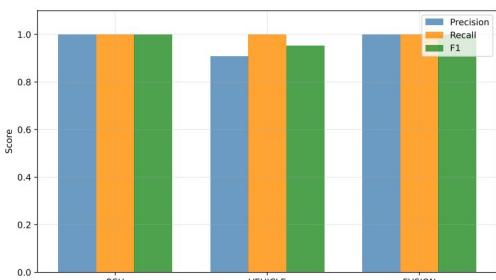


Figure 5: Performance metrics (Precision, Recall, F1-score) for RSU, Vehicle, and Fusion approaches

Localization Accuracy (RMSE)

Figure 6 compares the localization errors. The fixed RSU achieves remarkable accuracy (0.174 m, 0.02 rad), while the mobile vehicle exhibits higher errors (1.088 m, 0.79 rad) due to its mobility and the simulated sensor noise. Collaborative fusion significantly improves the overall localization, reducing the final error to 0.101 m.

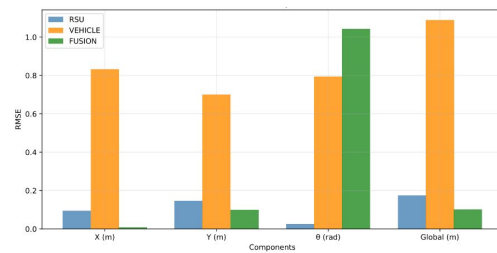


Figure 6: Comparison of localization errors (RMSE) between RSU, vehicle and fusion

Efficiency of Multi-Agent Fusion

The cross-validation rule (requiring at least two agents to confirm a change) reduces false positives and guarantees decision reliability. Out of the 9 initial landmarks, only 7 were jointly validated (78%); the remaining two were excluded during fusion and preserved in their initial state to prevent false detections, despite receiving input from the vehicle agent. This strategy enhances overall system reliability by filtering out isolated observations as shown in Figure 7.

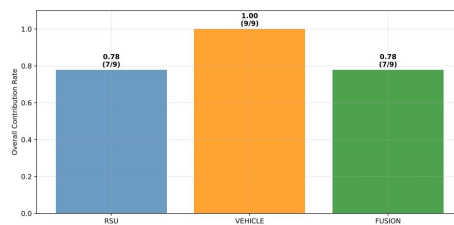


Figure 7: Multi-agent fusion effectiveness and cross-validation

Conclusion and perspectives

This paper presents an innovative architecture for lightweight collaborative mapping, designed to address the costly and rigid limitations of traditional HD maps. Our solution, leveraging a fleet of vehicles and RSUs equipped with commercial sensors, is inherently scalable: regardless of the number of participating agents, the computational processing remains constant while precision increases proportionally with agent density. This approach demonstrates that it is possible to maintain a dynamic, economical, and responsive map that adapts to environmental changes without sacrificing the precision

required for autonomous navigation. The core of our approach integrates a suite of robust algorithms: JCBB for reliable data association, Dempster-Shafer reasoning (DST) for Bayesian-like uncertainty management and classification, and EKF for the accurate pose estimation of new landmarks. Validation in a simulated environment with ROS2 and CARLA confirmed the efficacy of this distributed architecture. Despite the absence of a complete perception module, the system excelled at detecting, classifying, and locating changes (additions/removals of landmarks), achieving low RMSE values. Collaborative data fusion was crucial for eliminating false positives and consolidating decisions, as evidenced by the high performance metrics under dynamic conditions (Precision: 0.92, F1-score: 0.96).

Research Perspectives :

Future work will focus on the following priorities :

- **Develop and integrate a perception module** for automatic landmark extraction from camera data.
- **Complete the experimental deployment** by integrating additional vehicles and RSUs into the CARLA scenario.
- **Validate system robustness** under varied weather conditions (rain, fog, night).
- **Evaluate algorithm performance** under dynamic occlusion scenarios.
- **Extend functionality to continuous landmarks** (road markings, curbs) through R-tree adaptation and EKF observation models.
- **Conduct real-world validation** using instrumented vehicles and V2X infrastructure.

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