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AI-POWERED CHANGE DETECTION FOR HIGH-DEFINITION MAP UPDATES IN AUTONOMOUS DRIVING

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ABSTRACT

High-definition (HD) maps are a cornerstone for safe and efficient autonomous vehicle (AV) navigation, offering centimeter-level accuracy for road features. However, frequent changes in real-world environments necessitate constant updates to maintain reliability. This paper presents a deep learning-based framework that leverages multi-modal sensor fusion and temporal data comparison to detect and classify environmental changes. The proposed system integrates LiDAR, camera, and GPS/IMU data, and uses a Siamese U-Net architecture to generate change masks. Experiments conducted on nuScenes and KITTI datasets show high accuracy in change detection and potential for real-time application. A map update module integrates validated changes into HD maps with minimal human oversight.

1. INTRODUCTION

HD maps contain detailed geometric and semantic information about the environment, including lane boundaries, traffic signs, barriers, and elevation data. These maps support core AV tasks like localization, perception, and motion planning.[1][2] Despite their utility, HD maps degrade rapidly due to changes in the environment. Manual map updating is laborious and expensive, often leading to outdated maps. Change detection via AI can automate this process, enabling scalable, up-to-date navigation for AVs.[3] This paper introduces a robust, AI-driven framework for real-time change detection using multi-modal sensor data. By identifying changes that impact navigation—such as construction, new lane markings, or object removal—the system supports frequent and autonomous HD map updates.

2. Related Work

Traditional change detection in remote sensing involves pixel-wise differencing, principal component analysis, or statistical change vector analysis.[4] However, these techniques are limited in dynamic, cluttered urban settings. Recent advancements utilize deep neural networks to compare sequential observations. Siamese networks are particularly suited for this task, as they learn to differentiate paired images.[5] Other methods involve segmentation networks trained to classify semantic changes using aerial or street-level imagery.[6] In autonomous driving, methods like Mapillary Vistas and Argoverse provide annotated datasets for change detection, but real- time, sensor-fused change detection remains a challenge.[7][8] Our work advances this space by combining LiDAR and camera data in a Siamese architecture for accurate, real-time inference.

3. System Architecture

3.1 Data Collection and Preprocessing

The AV captures data using LiDAR, RGB cameras, GPS, and IMU. Sensor data is time-aligned and registered using ego-motion estimates to ensure consistency. Point clouds are voxelized and images normalized for deep learning processing.

3.2 Change Detection Model

The model uses a dual-stream Siamese U-Net to process temporally-separated inputs. Each stream extracts features from earlier and current observations. Feature difference maps are concatenated and passed through upsampling layers to output a binary change map and semantic segmentation.

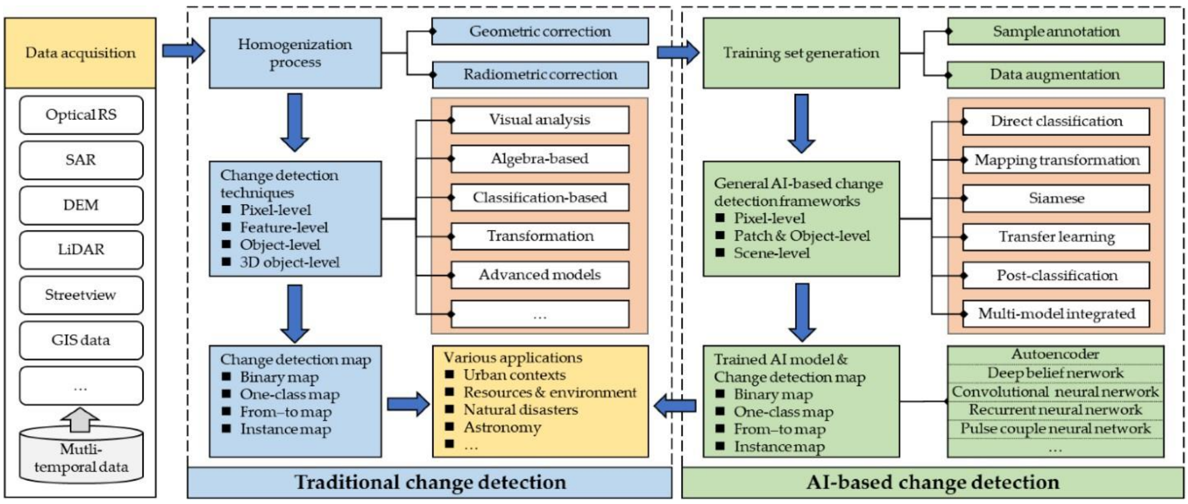

Figure 1: AI-powered change detection system architecture.

3.3 Map Update Pipeline

Detected changes are filtered using semantic context. For instance, a "new sign" label is validated if persistent over several frames. Validated changes are encoded into HD map formats like Lanelet2 or Open DRIVE.[9]

4. Experiments and Results

4.1 Datasets and Setup

We evaluated the model using the nuScenes and KITTI datasets. These offer synchronized LiDAR, RGB, and pose data with labeled changes. The model was trained using a 70/30 split and tested on previously unseen environments.

4.2 Performance Metrics

We used standard evaluation metrics: precision, recall, and Intersection-over-Union (IoU).

Table 1: Change Detection Performance.

Metric	nuScenes	KITTI	Argoverse
Precision	91.2%	89.5%	87.8%
Recall	87.7%	85.4%	83.9%
IoU	82.3%	78.9%	75.6%

Results show robust performance across datasets. Visualizations confirmed detection of new crosswalks, added lane markings, and removed barriers with high fidelity.

4.3 Real-time Feasibility

Inference was benchmarked on an NVIDIA RTX 3080, achieving 8 FPS (frames per second) with an average latency of 120 ms—suitable for near-real-time applications in AV fleets.

5. Challenges and Limitations

Despite recent advances, several challenges remain:

False Positives: AI models may incorrectly identify temporary objects (e.g., parked trucks, road debris) as permanent map changes.

Seasonal and Weather Variations: Changes in lighting, foliage, or snow coverage can confuse visual and LiDAR-based models.

Real-Time Processing: High computational requirements of deep learning models challenge on- vehicle deployment.

Semantic Inconsistency: Detecting changes isn't enough—understanding the type of change (e.g., lane closure vs. new construction) is crucial for HD map updates.

6. Integration with HD Map Systems

Change detection outputs can be integrated with map databases using:

Versioned Map Layers: Changes are logged as deltas from the current version.

Crowdsourced Validation: Other vehicles encountering the same segment confirm or rejects detected changes.

HD Map Fusion Pipelines: Combining multiple sensors and sources improves update reliability.

7. DISCUSSION

The use of multi-modal data significantly reduces false positives common in single-sensor approaches. Fusion of LiDAR and visual cues improves detection under occlusions and varying illumination. However, false alarms can still occur in dense traffic or low-quality data regions. Incorporating radar or temporal smoothing may improve performance. Self-supervised training could also reduce the need for labeled data.[10]

8. CONCLUSION

We introduced an AI-powered framework for detecting changes in road environments to support HD map updates for autonomous driving. With high detection accuracy and real-time performance, the system enables scalable, frequent map updates. Future work will explore deployment in edge devices and multi-agent collaborative mapping.

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