# MapFusion: A General Framework for 3D Object Detection with HDMaps

## Abstract

3D object detection is a key perception component in autonomous driving. Most recent approaches are based on Lidar sensors only or fused with cameras. Maps (e.g., High Definition Maps), a basic infrastructure for intelligent vehicles, have not been well exploited for boosting object detection tasks. In this paper, we propose a simple but effective framework - MapFusion to integrate the map information into modern 3D object detector pipelines. In particular, we design a FeatureAgg module for HD Map feature extraction and fusion, and a MapSeg module as an auxiliary segmentation head for the detection backbone. Our proposed MapFusion is detector independent and can be easily integrated into different detectors. The experimental results of three different baselines on large public autonomous driving dataset demonstrate the superiority of the proposed framework. By fusing the map information, we can achieve 1.27 to 2.79 points improvements for mean Average Precision (mAP) on three strong 3d object detection baselines.

## Introduction

Autonomous driving (AD) has drawn significant attention over the past years. Despite recent progress, AD is still considered as one of the most challenging tasks. Developing autonomous driving systems needs to integrate many advanced robotics techniques such as perception, planning, and control. Perception module interprets the surrounding environment and provides inputs for downstream planning and control modules. For object detection tasks, cameras are the most commonly used sensors and many advanced camera-based 2D detectors have been developed. However, autonomous driving vehicles need to recover 3D locations of surrounding objects accurately and reliably, which are extremely hard for 2D image-based detectors, due to the loss of distance information in the perspective projection process from 3D space to 2D image. Therefore, active 3D sensors such as LiDAR devices, are prerequisites for most AD systems.

With the development of deep learning on the 3D point clouds, many LiDAR-based 3D object detectors have been proposed. Based on the different input representations, approaches can be generally categorized as point-based and voxel-based methods. Compared with point-based methods, the latter is much more efficient and its computation time is independent of the size of the point cloud. The performance for existing LiDAR-based 3D object detection approaches, however, can be further improved, especially on reducing the false positives and false negatives for detected objects. This problem comes from two main reasons. First, without enough texture information, it is difficult to distinguish between foreground and background objects. Second, the number of scanned points for small objects or objects far away is very sparse, which results in the failure of object detection and recognition. Fusing with other sensors e.g., camera, radar is a commonly used strategy to handle this kind of problem. However, as image quality is easily affected by the environment illumination and weather situation, solely relying on fusion with images can’t provide stable detection results. [[FIGURE: page1\_img1.jpg | Caption: "Detection results comparison" | Explanation: "Figure shows the comparison between detection results from PointPillars with and without the MapFusion framework applied. In the MapFusion case, false positives are notably reduced." | Ref: PDF p.1]]

## Proposed Approach

### Overview

The overview of our proposed MapFusion framework is divided into two parts: the standard 3D object detection block and the map feature extraction block. The standard LiDAR-based 3D object detection pipeline is described in the top red dotted box. The input LiDAR point cloud is sent to a 3D feature extractor and outputs the features for voxels. The map feature extraction block takes the HDMap as the input. After a 2D feature extractor, the map feature with the same size of voxel feature is extracted. Then the 3D point cloud features and the map information are aggregated with a concatenation operation for each voxel. A detection head including the region proposals, box regression, and categories classification follows the fused features. An auxiliary segmentation head, namely MapSeg, is added to further improve the feature extraction capability. Our MapFusion is an end-to-end framework that can be easily integrated into any standard 3D object detection pipeline with only slight modifications. [[FIGURE: page2\_img1.jpg | Caption: "Overview of MapFusion framework" | Explanation: "This diagram illustrates the components of our MapFusion framework, highlighting both the standard 3D object detection and the Map Feature Extraction workflows." | Ref: PDF p.2]]

### HDMap Representation

HDMaps contain rich information on road elements, such as drivable areas, walking areas, and lanes. We use a raster representation by rendering the semantic elements with an ego car at the center of the image. For the object detection tasks, only three kinds of elements are selected, which are “drivable area”, “walkway”, and “carpark area”. Instead of using the three raster images directly for fusion, we leverage a 2D Feature Extractor module to extract high-level features from satellite imagery. The structure of the 2D Feature Extractor includes layers of 2D convolution operations with kernels sized at 3 × 3, batch normalization, and a ReLU activation function. The consecutive layers have an increasing number of filters, aiming to gradually refine the features extracted from the HDMaps to be conducive for fusion with Lidar-derived features. [[FIGURE: page3\_img1.jpg | Caption: "Detailed architecture of 2D Feature Extractor" | Explanation: "The figure demonstrates the internal structure of the 2D Feature Extractor used in our MapFusion framework. It highlights the convolution layers and other components designed to process the HDMap inputs effectively." | Ref: PDF p.3]]

### FeatureAgg Module

The FeatureAgg module is designed to fuse the extracted map features and the voxel features by keeping both tensors of the same size and concatenating them along the feature channel. This simple operation provides satisfactory fusion results, although the performance can be further improved with a subsequent 1x1 convolutional operation applied to the concatenated features before being forwarded to the detection head. Such modifications enhance the feature integration, ensuring more coherent and context-aware outputs from the model. Further details and ablation studies on this module reveal its significant contributions to the overall efficacy of the framework in real-world scenarios.

## Experimental Results

Initially, MapFusion is integrated and tested with three baseline state-of-the-art detectors: SECOND, PointPillars, and CenterPoint. Consistent improvement across all metrics was observed under the integration of the MapFusion framework compared to the baselines. Comprehensive experiment configurations and resulting performance metrics display the enhanced accuracy and robustness of the fused approach, especially in complex urban driving scenarios with high variability in object types and density. [[FIGURE: page4\_img1.jpg | Caption: "Qualitative detection results of CenterPoint with MapFusion" | Explanation: "This figure displays the qualitative results showcasing the detection enhancements when MapFusion is applied within the CenterPoint architecture, emphasizing the precision in object detection." | Ref: PDF p.4]]

## Conclusion and Future Works

In this work, we presented MapFusion, an effectively designed fusion framework that integrates high precision HDMap data into standard 3D object detection pipelines to enhance detection accuracy and reliability. Further, we aim to expand the framework's capability to encompass additional sensory data like radar and camera feeds, along with exploring the potential integration of widely accessible regular maps when HDMaps are not available. The development and integration of a map prediction model could potentially offset the limitations posed by the dependency on high-precision HDMaps, thus broadening the applications and adaptability of the MapFusion framework in various operational environments.

### References

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