Homogeneous Multi-modal Feature Fusion and Interaction for 3D Object Detection

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Abstract. Multi-modal 3D object detection has been an active research topic in autonomous driving. Nevertheless, it is non-trivial to explore the cross-modal feature fusion between sparse 3D points and dense 2D pixels. Recent approaches either fuse the image features with the point cloud features that are projected onto the 2D image plane or combine the sparse point cloud with dense image pixels. These fusion approaches often suffer from severe information loss, thus causing sub-optimal performance. To address these problems, we construct the homogeneous structure between the point cloud and images to avoid projective information loss by transforming the camera features into the LiDAR 3D space. In this paper, we propose a homogeneous multi-modal feature fusion and interaction method (HMFI) for 3D object detection. Specifically, we first design an image voxel lifter module (IVLM) to lift 2D image features into the 3D space and generate homogeneous image voxel features. Then, we fuse the voxelized point cloud features with the image features from different regions by introducing the self-attention based query fusion mechanism (QFM). Next, we propose a voxel feature interaction module (VFIM) to enforce the consistency of semantic information from identical objects in the homogeneous point cloud and image voxel representations, which can provide object-level alignment guidance for cross-modal feature fusion and strengthen the discriminative ability in complex backgrounds. We conduct extensive experiments on the KITTI and Waymo Open Dataset, and the proposed HMFI achieves better performance compared with the state-of-the-art multi-modal methods. Particularly, for the 3D detection of cyclist on the KITTI benchmark, HMFI surpasses all the published algorithms by a large margin.

Keywords: 3D object detection, multi-modal, feature-level fusion, self-attention

1 Introduction

3D object detection is an important task that aims to precisely localize and classify each object in the 3D space, thus allowing vehicles to perceive and under-
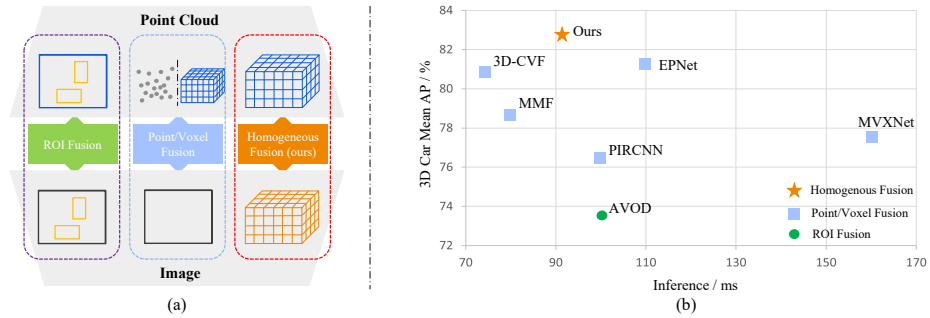
Fig. 1: (a) Schematic comparison between different feature-level fusion based methods. (b) Quantitative comparison with competitive multi-modal feature-level fusion methods. Our method achieves good performance-efficiency trade-off for the car category (Mean AP of all difficulty levels) on the KITTI [7] benchmark.

stand their surrounding environment comprehensively. So far, various LiDAR-based and image-based 3D detection approaches [33,34,36,24,40,18,41,39,9,6,26] have been proposed.

LiDAR-based methods can achieve superior performance over image-based approaches as point cloud contains precise spatial information. However, LiDAR points are usually sparse and do not have enough color and texture information. As to image-based approaches, they perform better in capturing semantic information while suffering from the lack of depth signal. Therefore, multi-modal 3D object detection is a promising direction that can fully utilize the complementary information of images and point cloud.

Recent multi-modal approaches can be generally categorized into two types: decision-level fusion and feature-level fusion. Decision-level fusion methods ensemble the detected objects in respective modalities and their performance is bounded by each stage [29]. Feature level fusion is more prevalent as they fuse the rich informative features of two modalities. Three representative feature-level fusion methods are depicted in Fig. 1(a). The first one is fusing multi-modal features at the regions of interest (RoI). However, these methods have severe spatial information loss when projecting 3D points onto the bird's eye view (BEV) or front view (FV) in 2D plane, while 3D information plays a key role in accurate 3D object localization. Another line of work conducts fusion on the point/voxel-level [43,49,55,21,22,50,14,59], which can achieve complementary fusion at a much finer granularity and involve the combination of low-level multi-modal features at 3D points or 2D pixels. However, they can only approximately establish a relatively coarse correspondence between the point/voxel features and image features. Moreover, these two schemes of feature fusion usually suffer from severe information loss due to the mismatched projection between 2D dense image pixels and 3D sparse LiDAR points.

To address the aforementioned problems, we propose a homogeneous fusion scheme that lifts image features from 2D plane to 3D dense voxel structure. In our homogeneous fusion scheme, we propose the Homogeneous Multi-modal Feature Fusion and Interaction method (HMFI), which exploits the complementary information in multi-modal features and alleviates severe information loss caused by the dimensional reduction mapping. Furthermore, we build the cross-modal feature interaction between the point cloud features and image features at object-level based on the homogeneous 3D structure to strengthen the model's ability to fuse image semantic information with the point cloud.

Specifically, we design an image voxel lifter module (IVLM) to lift the 2D image features to the 3D space first and construct a homogeneous voxel structure of 2D images for multi-modal feature fusion, which is guided by the point cloud as depth hint. It will not cause information loss for fusing these two multi-modal data. We also notice that the homogeneous voxel structure of cross-modal data can help in feature fusion and interaction. Thus, we introduce the query fusion mechanism (QFM) that introduces a self-attention based operation that can adaptively combine point cloud and image features. Each point cloud voxel will query all image voxels to achieve homogeneous feature fusion and combine with the original point cloud voxel features to form the joint camera-LiDAR features. QFM enables each point cloud voxel to perceive image features in the common 3D space adaptively and fuse these two homogeneous representations effectively.

Besides, we explore building a feature interaction between the homogeneous point cloud and image voxel features instead of refining in regions of interest (RoI) based pooling which is applied to fuse low-level LiDAR and camera features with the joint camera-LiDAR features. We consider that, although point cloud and image representations are in different modalities, the object-level semantic properties should be similar in the homogeneous structure. Therefore, to strengthen the abstract representation of point cloud and images in a shared 3D space and exploit the similarity of identical objects' properties in two modalities, we propose a voxel feature interaction module (VFIM) at the object-level to improve the consistency of point cloud and image homogeneous representations in the 3D RoI. To be specific, we use the voxel RoI pooling [6] to extract features in these two homogeneous features according to the predicted proposals and produce the paired RoI feature set. Then we adopt the cosine similarity loss [5] between each pair of RoI features and enforce the consistency of object-level properties in point cloud and images. In VFIM, building the feature interaction in these homogeneous paired RoI features improves the object-level semantic consistency between two homogeneous representations and enhances the model's ability to achieve cross-modal feature fusion. Extensive experiments conducted on KITTI and Waymo Open Dataset demonstrate that the proposed method can achieve better performance compared to the state-of-the-art multi-modal methods. Our **contributions** are summarized as below:

1. We propose an image voxel lifter module (IVLM) to lift 2D image features into the 3D space and construct two homogeneous features for multi-modal fusion, which retains original information of image and point cloud.

2. We introduce the query fusion mechanism (QFM) to fuse two homogeneous representations of the point cloud voxel features and image voxel features effectively, which enables the fused voxels to perceive objects in a unified 3D space for each frame adaptively.
3. We propose a voxel feature interaction module (VFIM) to improve the consistency of identical objects' semantic information in the homogeneous point cloud and image voxel features which can guide the cross-modal feature fusion and greatly improve the detection performance.
4. Extensive experiments demonstrate the effectiveness of the proposed HMFI and achieve competitive performance on KITTI and Waymo Open Dataset. Notably, on the KITTI benchmark, HMFI surpasses all the published competitive methods by a large margin on detecting cyclist.

2   Related Works

2.1   LiDAR-based 3D Object Detection

Point-based methods: These methods [33,34,42,40] take the raw point cloud as input and employ stacked MLP layers to extract point features. PointR-CNN [40] uses the PointNets [33,34] as point cloud encoder, then generates proposals based on the extracted semantic and geometric features, and refines these coarse proposals via 3D ROI pooling operation. Point-GNN [42] designs a graph neural network to detect 3D objects and encodes the point clouds in a fixed radius near the neighbors' graph. Since the point clouds are unordered and large in number, point-based methods typically suffer from high computational costs.

Voxel-based methods: These voxel-based approaches [57,63,6,41,20,39,27] tend to convert the point cloud into voxels and utilize voxel encoding layers to extract voxel features. SECOND [57] proposes a novel sparse convolution layer to replace the original computation-intensive 3D convolution. PointPillars [18] converts the point cloud to a pseudo-image and applies 2D CNN to produce the final detection results. Some other works [6,39,20,41,26] follow [57] to utilize the 3D sparse convolutional operations to encode the voxel features and obtain more accurate detection results in the coarse-to-refine two-stage manner. The more recent CT3D [38] designs a channel-wise transformer architecture to constitute 3D object detection framework with minimal hand-crafted design.

2.2   Image-based 3D Object Detection

Many researchers are also very concerned about how to use camera images to perform 3D detection [24,60,25,9,36]. Specifically, CaDDN [36] designs a Frustum Feature Network to project image information into 3D space. We directly introduce depth bins through point cloud projection and use a non-parametrical module to lift image features into 3D space. LIGA-Stereo [9] utilizes the LiDAR-based model to guide the training of stereo-based 3D detection model and achieves the

state-of-the-art stereo detection performance. Although cameras are the most common sensors and inexpensive, the performance of image-based methods is still inferior to the LiDAR-based approaches due to the lack of accurate depth information.

2.3   Multi-modal 3D Object Detection

Multi-modal 3D object detection has received more and more attention [52] as it can utilize the complementary information of each single modality to the maximum extent. There are two levels of fusion: decision-level fusion [17,4,32,53,29]and feature-level fusion [56,59,49,55,14,43,21,22]. The former fusion methods [29] ensemble the detection results of each modality directly. Their performance is limited by each stage.

As for feature-level fusion methods which fuse multi-modal data in a much finer granularity, AVOD [17] utilizes point clouds BEV as well as images features and feeds the features into region proposal network (RPN) for improving detection performance. F-ConvNet [53] follows [32] to utilize frustum point clouds and front view images for 3D object detection. PointFusion [56] and PointPainting [49] enhance raw point cloud with the corresponding class prediction scores through a well pre-trained image semantic segmentation network [10]. EPNet [14] projects the point cloud into image plane to retrieve semantic information at multi-level resolutions in a point-wise manner. MVXNet [43] utilizes pre-trained 2D detectors [37] to produce semantic image features to strengthen the voxel feature representations in the early stage. These methods only exploit part of the rich information contained in an image and suffer from severe information loss [51]. 3D-CVF [59] lifts image features to the dense 3D voxel space but fuses the multi-modal feature in BEV via a cross-view spatial feature fusion strategy and it causes feature overlap in 3D space when constructing image voxel features.

Although many multi-modal networks have been proposed, they do not easily outperform state-of-the-art LiDAR-only based detectors. These fusion methods establish a coarse relationship between the point cloud features and semantic image features. Besides, they suffer from severe information loss by perspective projection. Moreover, existing fusion methods do not exploit the similarity of object-level semantic information in the cross-modal fusion. Our approach is designed to overcome these challenges and achieve better 3D detection performance.

2.4   Methodology

2.5   Framework Overview

The overall architecture of the proposed homogeneous multi-modal fusion and interaction (HMFI) method is illustrated in Fig. 2. We first leverage a point encoding network to extract the features of the point cloud and then pool them to obtain the voxel features $P \in \mathbb{R}^{X_P \times Y_P \times Z_P \times C_F}$ [63] where the C_F is the number of channels of the voxel feature and the (X_P, Y_P, Z_P) is the grid size.
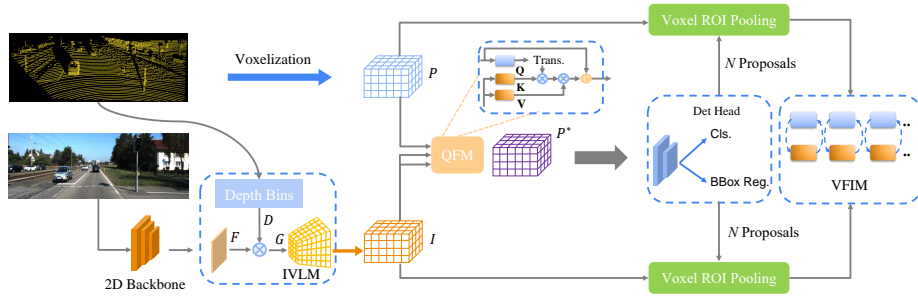
Fig. 2: The architecture of HMFI. Each image is processed by a 2D backbone network and fed into an image voxel lifter module (IVLM) to produce a homogeneous structure based on the depth bins transformed by the point cloud. Then, the processed homogeneous image and point cloud features are fused by the query fusion mechanism (QFM). Next, a voxel-based object detector is employed on fused features to produce 3D detection results. Finally, the voxel feature interaction module (VFIM) conducts feature interaction at object-level based on the detection results to improve semantic consistency in these two homogeneous cross-modal features.

The image $\tilde{I} \in \mathbb{R}^{W_{\tilde{I}} \times H_{\tilde{I}} \times 3}$ is fed into a ResNet-50 [12] backbone to extract image features $F \in \mathbb{R}^{W_F \times H_F \times C_F}$, where $W_{\tilde{I}}$ and $H_{\tilde{I}}$ are the width and height of the image and W_F, H_F and C_F are the width, height and number of channels of the image features.

In order to fuse point cloud features and image features in 3D space, we propose an image voxel lifter module (IVLM) to project the image feature F into 3D homogeneous image voxel space as the $I \in \mathbb{R}^{X_I \times Y_I \times Z_I \times C_F}$. Then we use the query fusion mechanism (QFM) to fuse the homogeneous point voxel P and image voxel I to generate the fused representation $P^* \in \mathbb{R}^{X_P \times Y_P \times Z_P \times C_F}$. Afterward, we use the detection module to generate the classification and 3D bounding box of each object based on P^*. Meanwhile, a voxel feature interaction module (VFIM) is proposed to conduct the feature interaction at object-level based on the detection results to improve semantic consistency in these two homogeneous cross-modal features. We introduce the details in the following sections.

2.6 Image Voxel Lifter Module

To encode perceptual depth information in the image effectively and construct a homogeneous structure for multi-modal feature fusion and interaction, we propose the image voxel lifter module (IVLM) to lift 2D image features into 3D space by associating image features and discretized depth maps. The procedure is shown in Fig. 3.

To construct an image feature voxel, we follow [30,36] and convert the image plane features into frustum features G which can encode depth information in
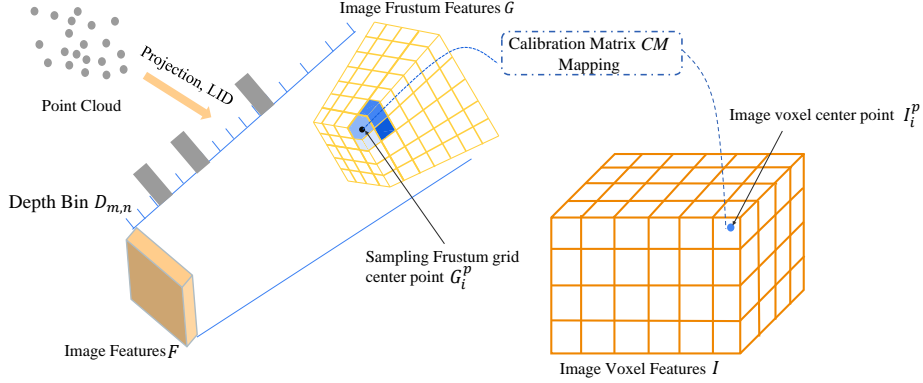
Fig. 3: The image voxel lifter module. Each feature pixel $F_{m,n}$ along the ray is determined by the discrete depth bins D to generate frustum features $G_{m,n}$. Then sampling grid center points in image voxel are projected into the frustum grid based on the calibration matrix CM. The neighboring sampled voxel grids (shown as blue in the image frustum features G) are combined using trilinear interpolation and assigned to the corresponding voxel in I.

image features. Thus, we scatter the vector $F_{m,n} \in \mathbb{R}^{C_F}$ of each pixel (m,n) in the image feature map F into the 3D space determined by the depth bin $D_{m,n}$ along the ray of image frustum perspective projection.

The depth bins D are produced by discretizing the depth map with a linear-increasing depth discretization (LID) method [46,36]. The $D \in \mathbb{R}^{W_F \times H_F \times R}$ consists of $W_F \times H_F$ one-hot discretized depth bins in $\mathbb{R}^R$. In order to associate image features with discretized depth information, we utilize the outer product to process the image features F and depth bins D to generate a frustum feature $G \in \mathbb{R}^{W_F \times H_F \times R \times C_F}$. Each $G_{m,n} \in \mathbb{R}^{R \times C_F}$ on pixel (m,n) can be calculated by:

$$G_{m,n} = F_{m,n} \otimes D_{m,n} \tag{1}$$

where $\otimes$ represents the outer product, (m,n) is the index of the each feature pixel.

Next, we transform the features from the frustum space $G \in \mathbb{R}^{W_F \times H_F \times R \times C_F}$ into the 3D space $I \in \mathbb{R}^{X_I \times Y_I \times Z_I \times C_F}$ by the trilinear interpolation.

Specifically, to acquire the i-th image voxel feature $I_i \in \mathbb{R}^{C_F}$, we sample the corresponding centroid in image frustum features G by a transformation based on calibration matrix CM as $G_i^p = CM \cdot I_i^p$, where the $G_i^p, I_i^p \in \mathbb{R}^3$ indicates the 3D position of the i-th grid in G, I. After that, we conduct the trilinear interpolation around the neighborhood of G_i^p to form the I_i^p. Finally, the image voxel features I is constructed by this process on each spatial index i.

2.7   Query Fusion Mechanism

To exploit the complementary information from point cloud and images, we introduce the query fusion mechanism (QFM) that enables each point cloud voxel feature to perceive the whole image and selectively combines image voxel features. Instead of simply fusing the cross-modal voxel pairs, we consider that the LiDAR voxel can perceive the whole image voxel feature. In order to aggregate these complementary information of two modalities effectively, we propose to use a self-attention [48] module which regards each voxel feature vector of image and point cloud as a homogeneous token.

To be more specific, we use the point cloud voxel features F_P as the queries, the image voxel features F_I as the keys as well as values to conduct the fusion and form the fused voxel features P^*. The construction of F_P and F_I is described as follows.

Considering that most of LiDAR voxels are empty, we produce $F_P \in \mathbb{R}^{M \times C_F}$ by selecting all M non-empty voxels within the homogeneous point cloud voxel features P. However, the image voxel features I is much denser than point cloud voxels. In order to reduce the computational cost, we adopt the 3D max-pooling on I with a scale factor λ to obtain the most informative features $I^* \in \mathbb{R}^{\frac{X_I}{\lambda} \times \frac{Y_I}{\lambda} \times \frac{Z_I}{\lambda} \times C_F}$. Then, we flatten I^* along the first three dimensions to make $F_I \in \mathbb{R}^{L \times C_F}$ where $L = \frac{X_I}{\lambda} * \frac{Y_I}{\lambda} * \frac{Z_I}{\lambda}$.

After constructing the point voxel F_P and the image voxel F_I, we utilize a multi-head self-attention[48] layer as the query fusion mechanism (QFM). We adopt three learnable linear transformation for each head i on the query F_P, key F_I and value F_I, denoted as $Q_i \in \mathbb{R}^{M \times d_k}$, $K_i \in \mathbb{R}^{L \times d_k}$ and $V_i \in \mathbb{R}^{L \times d_v}$ respectively:

$$Q_i = F_P \cdot W_i^Q, \quad K_i = F_I \cdot W_i^K, \quad V_i = F_I \cdot W_i^V \tag{2}$$

where $W_i^Q \in \mathbb{R}^{C_F \times d_k}$, $W_i^K \in \mathbb{R}^{C_F \times d_k}$ and $W_i^V \in \mathbb{R}^{C_F \times d_v}$.

Then we perform the multi-head self-attention with r heads:

$$A_M = \text{Concat}(\text{head}_1, \text{head}_2, \cdots, \text{head}_r)W^O$$
$$\text{head}_i = \text{softmax}\left(\frac{Q_i K_i^T}{\sqrt{d_k}}\right) V_i \tag{3}$$

where $A_M \in \mathbb{R}^{M \times C_F}$ is the output of multi-head attention module, $W_O \in \mathbb{R}^{r*d_v \times C_F}$ is a linear transformation matrix to project the concatenation of r attention heads into the homogeneous point voxel space. Then we concatenate the A_M and the non-empty point voxel features F_P to acquire the fused voxel features $F_P^* \in \mathbb{R}^{M \times (2*C_F)}$. Finally, we restore F_P^* into the homogeneous voxel space as $P^* \in \mathbb{R}^{X_P \times Y_P \times Z_P \times (2*C_F)}$ as the input of the downstream 3D object detection module.

2.8   Voxel Feature Interaction Module

LiDARs and cameras have different representations of identical objects in the scene. Though the modalities are different from each other, the object-level representations should be similar. Motivated by this observation, we design a voxel
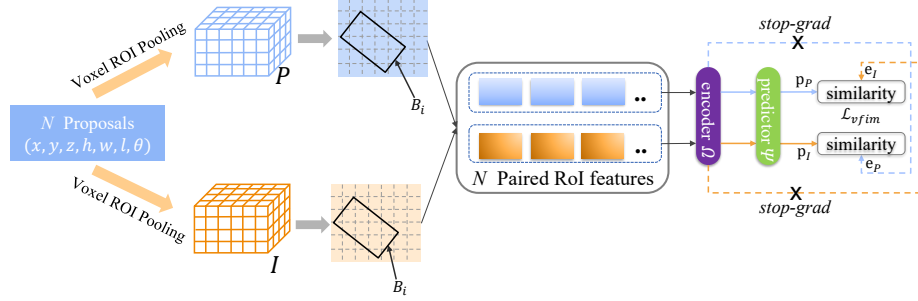
Fig. 4: The voxel feature interaction module. We use the voxel RoI pooling to extract features in these two homogeneous features according to the predicted proposals and form the paired RoI feature set. Then we adopt feature interaction between each pair of RoI features based on the symmetry similarity constraint loss to improve the object-level semantic consistency between two homogeneous representations

feature interaction module (VFIM) to build the feature interaction in these two cross-modal features based on the consistency of object-level properties in point cloud and images. And we can fully utilize the similarity constraint between homogeneous features P and I with the object-level guidance to achieve better cross-modal feature fusion.

As shown in Fig. 4, we sample the N 3D detection proposals from 3D detection head as $B = \{B_1, B_2, , ..., B_N\}$. Then, we introduce the voxel RoI pooling [6] on homogeneous point voxel features P and image voxel features I to obtain the respective RoI features including $P_B = \{P_{B_1}, P_{B_2}, \ldots, P_{B_N}\}$ and $I_B = \{I_{B_1}, I_{B_2}, \ldots, I_{B_N}\}$.

Finally, inspired by [5], to improve the similarity between the output vectors from the paired RoI features P_{B_i} and I_{B_i}, we feed both of them into an encoder Ω and use a MLP-based predictor Ψ to transform the output of these encoded RoI features into the metric space: $p_P = \Psi(\Omega(P_{B_i}))$, $e_I = \Omega(I_{B_i})$, $p_I = \Psi(\Omega(I_{B_i}))$, $e_P = \Omega(P_{B_i})$.

We minimize the paired feature distance by using cosine similarity:

$$CosSim(p, e) = -\frac{p}{\|p\|_2} * \frac{e}{\|e\|_2} \tag{4}$$

where $\|\cdot\|_2$ means l_2 normalization.

Meanwhile, the stop-gradient operation is also adopted for better modeling the similarity constraint, then we utilize the symmetry similarity constraint loss $\mathcal{L}_{vfim}$ as:

$$\mathcal{L}_{vfim} = \frac{1}{2}CosSim(p_P, stop\_grad(e_I)) + \frac{1}{2}CosSim(p_I, stop\_grad(e_P)) \tag{5}$$

2.9   Loss Function

In previous methods, the image backbone is directly initialized with the fixed pre-trained weights from other external datasets such as ImageNet. On the contrary, our HMFI is trained via two-stage training process in an end-to-end manner. We utilize a multi-task loss function for jointly optimizing the whole network. The total loss $\mathcal{L}_{total}$ can be formulated as:

$$\mathcal{L}_{\text{total}} = \mathcal{L}_{\text{rpn}} + \mathcal{L}_{rcnn} + \gamma \mathcal{L}_{vfim} \tag{6}$$

where γ is set to 0.1. $\mathcal{L}_{rpn}$ and $\mathcal{L}_{rcnn}$ denote the training objectives for the region proposal network (RPN) and the refinement network, We follow [6,57] to devise the loss of the RPN as:

$$\mathcal{L}_{\text{rpn}} = \omega_1 \mathcal{L}_{\text{cls}} + \omega_2 \mathcal{L}_{reg} \tag{7}$$

where ω_1 and ω_2 are set to 1 and 2, respectively. We adopt the focal loss [23] to balance the positive and negative samples in classification loss with default hyperparameters and the $smooth_{L1}$ loss is utilized for the box regression. The proposal refinement loss $\mathcal{L}_{rcnn}$ includes the IoU-guided confidence prediction loss $\mathcal{L}_{iou}$ and the box refinement loss $\mathcal{L}_{refine}$ as

$$\mathcal{L}_{\text{rcnn}} = \mathcal{L}_{\text{iou}} + \mathcal{L}_{refine} \tag{8}$$

3   Experiments

In this section, we evaluate the performance of the proposed HMFI on the KITTI [7] and Waymo Open Dataset [45].

3.1   Datasets

KITTI is a widely used dataset. It consists of 7,481 training frames and 7,518 testing frames, with 2D and 3D annotations of cars, pedestrians and cyclists on the streets. Objects are divided into three difficulty levels: easy, moderate and hard, according to their size, occlusion level and truncation level. For validation, training samples are commonly divided into a train set with 3,712 samples and a val set with 3,769 samples.

Waymo Open Dataset (WOD) is a large-scale dataset for autonomous driving. There are totally 798 scenes for training and 202 scenes for validation. Each scene is a sequential segment that has around 20 seconds of sensor data. Note that cameras in WOD only cover around 250° field of view (FOV), which is different from LiDAR points and 3D labels in full 360°. To follow the same setting of KITTI, we only select LiDAR points and ground-truth in the FOV of front camera for training and evaluating. We sample every 5th frames from all the training samples to form the new training set ($\sim$32k frames) due to the large dataset size and high frame rate.

3.2   Implementation Details

Experimental Settings. On the KITTI benchmark, we set the range of point cloud to [0, 70.4], [-40, 40], [-3, 1]m in the (x, y, z) axis. The LiDAR voxel structure is divided by a voxel size (0.05, 0.05, 0.1)m, while each image voxel size is set to (0.2, 0.2, 0.4)m to fit with the feature size of the point cloud branch. As for Waymo, we use [0, 75.2], [-75.2, 75.2], [-2, 4]m for the point cloud range, (0.1, 0.1, 0.15)m for the voxel size. And each image voxel size is set to (0.4, 0.4, 0.6)m to fit the point cloud feature size. In the QFM, the scale factor λ is set as 4, the count r and hidden units of attention heads are set to 4 and 64, respectively. In the VFIM, the settings of the voxel RoI pooling operation are the same as Voxel-RCNN [6] and we sample $N = 128$ proposals, half of them are positive samples that have $IoU > 0.55$ with the corresponding ground truth boxes. The number of hidden units of the encoder Ω and predictor Ψ are both set to 256.

Table 1: Quantitative comparison with the state-of-the-art 3D object detection methods on KITTI *test* set.

Method	Modality	Car 3D AP			Pedestrian 3D AP			Cyclist 3D AP		
		Easy	Mod.	Hard	Easy	Mod.	Hard	Easy	Mod.	Hard
PointPillars [18]	LiDAR	82.58	74.31	68.99	51.45	41.92	38.89	77.10	58.65	51.92
SECOND [57]	LiDAR	87.44	79.46	73.97	-	-	-	-	-	-
PointRCNN [40]	LiDAR	86.96	75.64	70.70	47.98	39.37	36.01	74.96	58.82	52.53
PointGNN [42]	LiDAR	88.33	79.47	72.29	51.92	**43.77**	40.14	78.60	63.48	57.08
Part A^2 [41]	LiDAR	87.81	78.49	73.51	**53.10**	43.35	40.06	79.17	63.52	56.93
PV-RCNN [39]	LiDAR	90.25	81.43	76.82	52.17	43.29	**40.29**	78.60	63.71	57.65
Voxel-RCNN [6]	LiDAR	**90.90**	81.62	77.06	-	-	-	-	-	-
M3DETR [8]	LiDAR	90.28	81.73	76.96	-	-	-	**83.83**	**66.74**	**59.03**
CT3D [38]	LiDAR	87.83	81.77	77.16	-	-	-	-	-	-
Pyramid RCNN-V [26]	LiDAR	87.06	81.28	76.85	-	-	-	-	-	-
Pyramid RCNN-PV [26]	LiDAR	88.39	**82.08**	**77.49**	-	-	-	-	-	-
MV3D [4]	LiDAR+RGB	74.97	63.63	54.00	-	-	-	-	-	-
Confuse [6]	LiDAR+RGB	83.68	68.78	61.67	-	-	-	-	-	-
F-PointNet [32]	LiDAR+RGB	82.19	69.79	60.59	50.53	42.15	38.08	72.27	56.12	49.01
MVXNet [43]	LiDAR+RGB	83.20	72.70	65.20	-	-	-	-	-	-
PointPainting [49]	LiDAR+RGB	82.11	71.70	67.08	50.32	40.97	37.77	77.63	63.78	55.89
AVOD-FPN [17]	LiDAR+RGB	83.07	71.76	65.73	50.46	42.27	39.04	63.76	50.55	44.93
MAFF [62]	LiDAR+RGB	85.52	75.04	67.60	-	-	-	-	-	-
PI-RCNN [55]	LiDAR+RGB	84.37	74.82	70.03	-	-	-	-	-	-
F-Convnet [53]	LiDAR+RGB	87.36	76.39	66.69	**52.16**	**43.38**	38.80	81.98	65.07	56.54
MMF [21]	LiDAR+RGB	88.40	77.43	70.22	-	-	-	-	-	-
CLOCs_PVCas [29]	LiDAR+RGB	88.94	80.67	77.15	47.30	39.42	36.97	77.33	62.02	55.52
EPNet [14]	LiDAR+RGB	**89.81**	79.28	74.59	-	-	-	-	-	-
3D-CVF [59]	LiDAR+RGB	89.20	80.05	73.11	-	-	-	-	-	-
HMFI (ours)	LiDAR+RGB	88.90	**81.93**	**77.30**	50.88	42.65	**39.78**	**84.02**	**70.37**	**62.57**

Training. To validate the effectiveness of our HMFI, we select the Voxel-RCNN [6] as the baseline. Our HMFI is trained via the two-stage training process. We adopt OpenPCDet [47] as our codebase, and a pre-trained ResNet50[12] is adopted as the 2D backbone to produce image features F for the image voxel lifter module. We train the model with the Adam [15] optimizer, which uses the one-cycle

policy [44] with the initial learning rate being 0.0005. Batch size is set as 2. The total number of training epochs is set as 80 for KITTI [7] and 30 epochs for WOD [45].

3.3   Results on KITTI dataset

KITTI Test set. Experiments on the KITTI test split [7] are evaluated using average precision (AP) via 40 recall positions. We compare our HMFI with other state-of-the-art approaches by submitting the detection results to the KITTI server for evaluation. Table 1 presents the quantitative comparison with state-of-the-art 3D object detection methods on the KITTI test set. It is apparent that the HMFI achieves better or comparable performance over the state-of-the-art methods on car and cyclist for all difficulty levels, respectively. The HMFI achieves up to 1.88% gains (for moderate difficulty) over 3D-CVF [59] which is the best feature-level fusion based method. The HMFI outperforms most of the LiDAR-based 3D object detectors except for the Pyramid RCNN-PV [26] which introduces the raw point features to achieve a better result but with a worse efficiency. By contrast, our method outperforms the Pyramid RCNN-V [26] in the same settings. Especially, our HMFI surpasses all the published algorithms by a large margin for the 3D detection of cyclist. Note that none of the models in Table 1 can achieve superior performance to our model on car and cyclist simultaneously.
KITTI Val set. In addition, we also report the performance on the KITTI val set with AP calculated by 11 recall positions. As shown in Table 2, our HMFI achieves the state-of-the-art performance on moderate level on the val set, even better than the LiDAR-based method [26].

To sum up, the results on both val set and test set consistently demonstrate that our proposed HMFI achieves superior 3D detection performance. Specifically, we achieve satisfactory performance on pedestrian and cyclist which usually have very few points in LiDAR measurements. As shown in Fig. 1 (b), we also report the inference time per frame of some feature-level fusion methods, and our HMFI achieves the best balance between the accuracy and efficiency among all methods.

3.4   Results on Waymo Open Dataset

To further validate the effectiveness of the proposed HMFI, we also conduct experiments on the large-scale Waymo Open Dataset. Two difficulty levels are also introduced, where the LEVEL_1 mAP is calculated on objects that have more than 5 points and the LEVEL_2 mAP is measured on objects that have 1∼5 points. Table 3 summarizes the performance of our method and baselines. It is obvious that our HMFI performs superbly over all the object classes and two difficulty levels. In particular, we achieve remarkable gains on pedestrian and cyclist with +2.17% and +1.86% mAP on LEVEL 2, which demonstrates the outstanding performance of our method on detecting objects with fewer than 5

Table 2: Performance comparison on the moderate level of KITTI val split with AP calculated by 11 recall positions, † means the our re-implementation results. $Car_{Mod.}$, $Pedestrian_{Mod.}$ and $Cyclist_{Mod.}$ donate the performance of Car, Pedestrian and Cyclist on moderate level respectively.

Method	Modality	$Car_{Mod.}$	$Pedestrian_{Mod.}$	$Cyclist_{Mod.}$
SECOND [57]	LiDAR	76.48	59.84	64.89
PointRCNN [40]	LiDAR	76.05	51.59	66.67
PV-RCNN [39]	LiDAR	83.69	57.90	70.47
Voxel-RCNN [6]	LiDAR	84.52	-	-
Voxel-RCNN† [6]	LiDAR	84.27	60.11	72.07
Pyramid RCNN-PV [26]	LiDAR	84.38	-	-
PointPainting [40]	LiDAR+RGB	77.74	61.67	71.62
CLOCs_SecCas [29]	LiDAR+RGB	79.31	56.20	67.92
3D-CVF [59]	LiDAR+RGB	79.88	-	-
HMFI (ours)	LiDAR+RGB	**85.14**	**62.41**	**74.11**

LiDAR points. The results on the Waymo Open Dataset further validate both the effectiveness and generalization of the HMFI.

Table 3: Performance comparison on the Waymo Open Dataset with 202 validation sequences (~40k samples)

Method	Vehicle L1/L2		Pedestrian L1/L2		Cyclist L1/L2	
	AP	APH	AP	APH	AP	APH
Baseline	66.46/64.21	64.81/62.40	64.35/62.74	58.11/55.43	62.34/59.85	59.64/57.67
Ours	68.34/65.66	66.84/64.57	66.62/64.91	59.76/57.24	64.25/61.71	61.23/59.21
Improvements	+1.88/+1.45	+2.03/+2.17	+2.27/+2.17	+1.65/+1.81	+1.91/+1.86	+1.59/+1.54

3.5   Ablation Study

In this section, we present an ablation study for validating the effect of each component in the HMFI method. The ablation study is conducted on the KITTI validation set. We adopt the mean average precision (mAP) on easy, moderate and hard difficulty levels via 11 recall positions for evaluation. As shown in Table 4, our HMFI can bring over 1.8% AP performance gain on all difficulty levels of three objects.

Effect of Query Fusion Mechanism. The query fusion mechanism (QFM) combines the image and point cloud features selectively depending on their relevance according to the attention map between the image features and point cloud features. In Table 4, we observe that QFM can generate the enhanced joint camera-LiDAR features and lead to 0.83%, 0.58%, and 0.62% performance gains in AP_{Easy}, $AP_{Mod.}$, AP_{Hard}, respectively.

Table 4: Effect of each component of our HMFI on KITTI val set. AP_{Easy}, $AP_{Mod.}$, and AP_{Hard} are the mAP performance of easy, moderate, and hard levels respectively.

Method	QFM	IVLM	VFIM	AP_{Easy}	$AP_{Mod.}$	AP_{Hard}
Baseline [6]	-	-	-	81.34	71.76	67.09
	✓	-	-	82.17	72.34	67.73
Ours	✓	✓	-	82.52	72.94	68.45
	✓	✓	✓	83.36	73.89	68.98
Improvements				+2.02	+2.13	+1.89

Effect of Multi-modal Feature Structure. In Table 4, We observe that the IVLM can bring 0.35%, 0.60%, and 0.72% performance gains in AP_{Easy}, $AP_{Mod.}$, AP_{Hard}. IVLM lifts image features to the homogeneous space with point cloud voxel features, which not only facilitates feature fusion, but also enables object-level semantic consistency modeling between two homogeneous features.

Effect of Voxel Feature Interaction. We observe that the voxel feature interaction module (VFIM) improves the baseline by 0.84%, 0.95%, and 0.53% in AP_{Easy}, $AP_{Mod.}$, AP_{Hard}, respectively. It indicates that our VFIM plays a pivotal role in our multi-modal detection framework. It can improve object-level semantic consistency between two homogeneous features and enables the detector to aggregate paired features across homogenous representations based on object-level semantic similarity.

4   Conclusions

In this paper, we propose the homogeneous multi-modal feature fusion and interaction (HMFI) method for 3D detection which fuses image and point cloud features in a homogeneous structure and enforces the consistency of object-level semantic information between two homogeneous features. We propose an image voxel lifter module (IVLM) to lift 2D image features to the 3D space and generate homogeneous image voxel features with point cloud voxel features. Then, image and point cloud features are selectively combined by the query fusion mechanism (QFM). Besides, we build the feature interaction in the homogeneous image and point cloud voxel features based on the similarity of object-level semantic information. Extensive experiments conducted on KITTI and Waymo Open Dataset show that significant performance gains can be obtained by our proposed HMFI. Particularly, for the detection of cyclist on the KITTI benchmark, HMFI surpasses all published algorithms by a large margin.

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