LIGA-Stereo: Learning LiDAR Geometry Aware Representations for Stereo-based 3D Detector

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Abstract

Stereo-based 3D detection aims at detecting 3D objects from stereo images, which provides a low-cost solution for 3D perception. However, its performance is still inferior compared with LiDAR-based detection algorithms. To detect and localize accurate 3D bounding boxes, LiDAR-based detectors encode high-level representations from LiDAR point clouds, such as accurate object boundaries and surface normal directions. In contrast, high-level features learned by stereo-based detectors are easily affected by the erroneous depth estimation due to the limitation of stereo matching. To solve the problem, we propose LIGA-Stereo (LiDAR Geometry Aware Stereo Detector) to learn stereo-based 3D detectors under the guidance of high-level geometry-aware representations of LiDAR-based detection models. In addition, we found existing voxel-based stereo detectors failed to learn semantic features effectively from indirect 3D supervisions. We attach an auxiliary 2D detection head to provide direct 2D semantic supervisions. Experiment results show that the above two strategies improved the geometric and semantic representation capabilities. Compared with the state-of-the-art stereo detector, our method has improved the 3D detection performance of cars, pedestrians, cyclists by 10.44%, 5.69%, 5.97% mAP respectively on the official KITTI benchmark. The gap between stereo-based and LiDAR-based 3D detectors is further narrowed. The code is available at [https://xy-guo.github.io/liga/](https://xy-guo.github.io/liga/).

1. Introduction

In recent years, LiDAR-based 3D detection [58, 28, 46, 45, 62, 61] has achieved increasing performance and stability in autonomous driving and robotics. However, the high cost of LiDAR sensors has limited its applications in low-cost products. Stereo matching [3, 18, 26, 35] is the most common depth sensing technique using only cameras. Compared with LiDAR sensors, stereo cameras are at a much lower cost and higher resolutions, which makes it a suitable alternative solution for 3D perception. 3D detection from stereo images aims at detecting objects using estimated depth maps [39, 52, 65] or implicit 3D geometry representations [30, 10, 53]. However, the performance of existing stereo-based 3D detection algorithms is still inferior compared with LiDAR-based algorithms.

LiDAR-based detection algorithms take raw point cloud as inputs and then encode the 3D geometry information into intermediate and high-level feature representations. To detect and localize accurate 3D bounding boxes, the model must learn robust local features about object boundaries and surface normal directions, which are essential for predicting accurate bounding box size and orientation. The features learned by LiDAR-based detectors provide robust high-level summarization of accurate 3D geometry structures. In comparison, due to the limitation of stereo matching, the inaccurately estimated depth or implicit 3D representation have difficulties in encoding accurate 3D geometry of objects, especially for distant ones. In addition, the target box supervisions only provide object-level supervisions (location, size, and orientation).

This inspires us to utilize superior LiDAR detection models to guide the training of stereo detection model via imitating the geometry-aware representations encoded by the LiDAR model. Comparing with traditional knowledge distillation [24] for recognition tasks, we did not take the final erroneous classification and regression predictions from...
the LiDAR model as “soft” targets, which we found benefits little for training stereo detection networks. The erroneous regression targets would constrain the upper-bound accuracy of bounding box regression. Instead, we force our model to align intermediate features with those of LiDAR models, which encode high-level geometry representations of the scene. The features from LiDAR models could provide powerful and discriminative high-level geometry-aware features, such as surface normal directions and boundary locations. On the other hand, the LiDAR features can provide extra regularization to alleviate the overfitting problem caused by erroneous stereo predictions.

Besides learning better geometry features, we further explore how to learn better semantic features for boosting the 3D detection performance. Instead of learning semantic features from indirect 3D supervisions, we propose to attach an auxiliary multi-scale 2D detection head on the 2D semantic features, which could directly guide the learning of 2D semantic features. Our baseline model, Deep Stereo Geometry Network (DSGN) [10], failed to benefit from extra semantic features effectively according to their ablation studies. We argue that the network provides erroneous semantic supervisions from indirect 3D supervisions because of depth estimation errors, while our proposed direct guidance could greatly benefit 3D detection performance from better learning of 2D semantic features. Experiment results show that the performance is further improved, especially for classes with few samples like cyclist.

The contributions can be summarized as follows. 1) We propose to utilize features from superior LiDAR-based detection models to guide the training of stereo-based 3D detection model. LiDAR features encode compact 3D geometry representations of the scene to guide and regularize the stereo features. 2) By attaching an auxiliary 2D detection head to provide direct 2D supervisions, our model significantly improves the learning efficiency for semantic features, which further improves the recall rate especially for rare categories. 4) On the official KITTI 3D detection benchmark, our proposed method surpasses state-of-the-art models by 10.44%, 5.69%, and 5.97% mAP on the car, pedestrian and cyclist classes respectively.

2. Related Work

Stereo Matching. Mayer et al. [55] proposed the first deep stereo algorithm DispNet, which regresses disparity map from feature-based correlation cost volume. DispNet is then extended using multi-stage refinement [37, 31] and auxiliary semantic features [48, 60]. State-of-the-art stereo models construct feature-based cost volume by concatenating left-right 2D features for all disparity candidates and then apply 3D aggregation network to predict the disparity probability distribution [26, 3, 18, 68]. State-of-the-art stereo detection networks [52, 65, 10, 53] also estimate depth by similar network structures. Zhang et al. [66] proposed novel cost volume aggregation strategies to improve the computational efficiency. Yin et al. [64] accelerated stereo matching by hierarchically estimating local disparity distributions at each scale and composing them together to form the final match density. Xu et al. [55] proposed a sparse points based intra-scale cost aggregation to alleviate the edge-fattening issue. Cheng et al. [11] employed neural architecture search (NAS) to automatically search the optimal network structure for stereo matching.

LiDAR-based 3D Detection. By leveraging the more accurate depth information captured by LiDAR sensors, 3D detection approaches [71, 40, 59, 46, 28, 47, 45] with LiDAR point clouds generally achieve better performance than image-based approaches. To learn effective features from irregular and sparse point clouds, most existing approaches adopt the voxelization operation to transfer point clouds to regular grids, where the 3D space is first divided into regular 3D voxels [71, 47] or bird-view 2D grids [59, 28] to be processed by convolutions for detection head. Yan et al. [58] proposed to utilize sparse convolutions [17] for efficient feature learning from sparse voxels. Da et al. [13] presented a feature imitation strategy to learn better perceptual features from synthesized conceptual scenes. Inspired by them, we propose to imitate the much informative feature maps from LiDAR models for better guidance beyond 3D box annotations.

Stereo-based 3D Detection. Stereo-based 3D detection algorithms can be roughly divided into three types:

1) 2D-based methods [7, 54, 30, 39, 57, 49, 38] first detect 2D bounding box proposals and then regress instance-wise 3D boxes. Stereo-RCNN [30] extended Faster R-CNN [43] for stereo-inputs to associate left and right images. Disp R-CNN [49] and ZoomNet [57] incorporated extra instance segmentation mask and part location map to improve detection quality. However, the final performance is limited by the recall of 2D detection algorithms, and 3D geometry information is not fully utilized.

2) Pseudo-LiDAR [52, 65, 41, 29, 13] based 3D detection first estimate depth maps and then detect 3D bounding boxes using existing LiDAR-based algorithms. Pseudo-LiDAR++ [65] adapted stereo cost volume to depth cost volume for direct depth estimation. Qian et al. [41] made Pseudo-LiDAR pipeline end-to-end trainable. However, these models only take geometry information into consideration, which is lack of complementary semantic features.

3) Volume-based methods construct 3D anchor space [42] or detect from 3D stereo volume [10, 53]. DSGN [10] directly constructs differentiable volumetric representation, which encodes implicit 3D geometry structure of the scene, for one-stage stereo-based 3D detection. PLUME [53] directly constructs geometry volume in 3D space for acceleration. Our work takes DSGN [10] as the baseline model.
We solve several key problems existed in [10] and surpass state-of-the-art models by a large margin.

**Knowledge Distillation.** Distillation is first proposed by Hinton et al. [24] for model compression by supervising student networks with “softened labels” from predictions of large teacher networks. Going further from “softened labels”, knowledge from intermediate layers provide richer information from the teacher [44, 23, 63, 25, 27]. Recently, knowledge distillation has been successfully applied to detection [4, 51, 5, 56, 14] and semantic segmentation [56, 33, 22, 9]. The knowledge can also be transferred across modalities [19, 1, 2, 69]. However, the feature imitation from LiDAR-based to stereo-based 3D detectors is first explored in this paper.

### 3. Our Approach

In this work, to improve the performance of our model, we developed two strategies to learn better geometric and semantic features respectively. Due to the limitation of stereo matching, stereo-based detectors are fragile to the erroneous depth estimation, especially for low-texture surfaces, blurry boundaries and occlusion areas. In comparison, the features learned by LiDAR-based detectors provide robust high-level geometry-aware representations (accurate boundaries and surface normal directions). To minimize the gap between LiDAR-based and stereo-based detectors, we propose to utilize LiDAR models to guide the training of stereo-based detectors for better geometric supervision. In addition, we employ auxiliary 2D semantic supervisions to improve the learning efficiency for semantic features.

In the following section, we will first revisit the baseline model, Deep Stereo Geometry Network (DSGN) [10], in Sec. 3.1 to make the paper self-contained. In Sec. 3.2 we describe the proposed LiDAR imitation strategy for encoding better geometry representations. In Sec. 3.3 we discuss why the baseline model is of low efficiency for learning semantic features and propose the corresponding solution. The training losses are specified in Sec. 3.4.

#### 3.1. Revisit of Deep Stereo Geometry Network

In this paper, we utilize Deep Stereo Geometry Network (DSGN) [10] as our baseline model, which directly detects objects using implicit volumetric representations.

**Volume in Stereo Space.** Given a left-right image pair \( (I_L, I_R) \) and their features \( (F_L, F_R) \), a plane-sweep volume \( V_{st} \) is constructed by concatenating left features and corresponding right features for every candidate depth level,

\[
V_{st}(u, v, w) = \text{concat} \left[ F_L(u, v), F_R\left( u - \frac{fL}{d(w)|s_F|}, v \right) \right],
\]

in which \((u, v)\) is the current pixel coordinate, \( w=0, 1, \cdots \) is the candidate depth index, and \( d(w) = w \cdot v_d + z_{min} \) is the function to calculate its corresponding depth, where \( v_d \) is the depth interval, and \( z_{min} \) is the minimum depth of the detection area. \( f, L, \) and \( s_F \) are the camera focal length, the baseline of the stereo camera pair, and the stride of the feature map, respectively. After filtering \( V_{st} \) with a 3D cost volume aggregation network, we obtain an aggregated stereo volume \( V_{st} \) and a depth distribution volume \( P_{st} \). \( P_{st}(u, v, :) \) represents the depth probability distribution of pixel \((u, v)\) over all discrete depth levels \( d(w) \).

**Volume in 3D Space.** In order to convert the feature volume from stereo space to normal 3D space, the 3D detection area is divided into small voxels of the same size. For each voxel, we project its center \((x, y, z)\) back into the stereo space using the feature intrinsics \( K_F \) to obtain its reprojected pixel coordinate \((u, v)\) and depth index \( d^{-1}(z) = (z - z_{min})/v_d \). The volume in the 3D space is then
defined as the concatenation of resampled stereo volume and semantic features masked by depth probability,

\[
V_{3d}(x, y, z) = \text{concat}\left[ V_{st}(u, v, d^{-1}(z)) \right],
\]

\[
\mathcal{F}_{sem}(u, v) \cdot P_{st}(u, v, d^{-1}(z)),
\]

in which \(V_{st}\) and \(\mathcal{F}_{sem}\) provide geometric and semantic features respectively. Note that we ignore the trilinear and bilinear resampling operators for simplicity. **Feature in BEV Space and Detection Head.** The 3D volume \(V_{3d}\) is then rearranged into 2D bird’s eye view (BEV) feature \(\mathcal{F}_{BEV}\) by merging the channel dimension and the height dimension as \([10]\). A 2D aggregation network and detection heads are attached to \(\mathcal{F}_{BEV}\) to generate the aggregated BEV feature \(\tilde{\mathcal{F}}_{BEV}\) and predict the final 3D bounding boxes, respectively. The training loss is divided into two parts, depth regression loss and 3D detection loss,

\[
\mathcal{L}_{losl} = \mathcal{L}_{depth} + \mathcal{L}_{det}.
\]

We have made several modifications to the above baseline to improve both performance and efficiency. Please see details in Sec. 3 and Sec. 1 of the supplementary materials.

**3.2. Learning LiDAR Geometry-aware Representations**

LiDAR-based detection models \([71, 40, 59, 46, 28, 47, 45]\) take raw point clouds as inputs, which are then encoded into high-level features (such as accurate boundaries and surface normal directions) for accurate bounding box localization. For stereo-based models, pure depth loss and detection loss could not well make the model learn such features for occlusion areas, non-textured areas and distant objects due to erroneous depth representations. Experiment results show that the detection performance benefit little from imitating whole feature maps, thus \(M_{fg}\) is essential to make the imitation loss focus on foreground objects. We found that \(\mathcal{F}_{BEV}\) and \(V_{3d}\) provide the most effective supervisions for training our stereo detection network. Please check the ablation studies in Sec. 4.3.1.

**3.3. Improving Semantic Features by Direct 2D Supervisions**

From Eq. \(2\) we can see before resampling semantic feature into 3D space, it is first multiplied by the depth probability from \(P_{st}\) (which can be seen as the estimation of 3D occupancy mask. Please see how we supervise \(P_{st}\) in Eq. \(6\)). In this way, semantic features are only resampled near the estimated surface (orange dashed lines in Fig. \(3\)). However, when there exist large errors in the estimated depth values, the semantic features will be resampled to the wrong positions as illustrated in Fig. \(3\). As a result, the resampled semantic features deviate from the ground-truth positions and are then assigned with negative anchors (red squares in Fig. \(3\)), and there is no resampled semantic feature around the positive anchors (green squares in Fig. \(3\)). Therefore, the supervision signals for the semantic features are incorrect in this case, which causes the low learning efficiency of semantic features.

To solve the problem, we add an auxiliary 2D detection head to provide direct supervisions for learning semantic
Table 1. Car detection results on the KITTI validation set. The results are evaluated using the original KITTI metric with 11 recall values for fair comparison. If not specified, all results in other tables are evaluated using 40 recall positions. * utilizes 4-beam LiDAR to refine stereo depth estimation.

| Sensor | Method | Car AP | Car APBEV | Car AP3D | Car APBEV
|--------|--------|--------|-----------|----------|----------|
| LiDAR  | MV3D [6] | 74.97 | 63.63 | 54.50 | 86.62 | 78.93 | 69.80 | Easy | Moderate | Hard | Easy | Moderate | Hard | Easy | Moderate | Hard |
|        | SECOND [53] | 84.34 | 72.55 | 65.82 | 89.39 | 83.77 | 78.59 | – | – | – | – | – | – | – | – | – |
|        | PointPillars [28] | 82.58 | 74.31 | 68.99 | 90.07 | 86.56 | 82.81 | 94.00 | 91.19 | 88.17 | 95.92 | 91.90 | 87.11 | 97.04 | 88.58 | 80.34 |
|        | POINT-RCNN [40] | 86.96 | 74.71 | 70.70 | 92.13 | 87.39 | 82.72 | 95.92 | 91.90 | 87.11 | 97.04 | 88.58 | 80.34 | 95.92 | 91.90 | 87.11 |
|        | SECOND (our teacher) | 90.25 | 81.43 | 76.82 | 94.98 | 90.67 | 82.81 | 97.04 | 91.90 | 87.11 | 97.04 | 88.58 | 80.34 | 95.92 | 91.90 | 87.11 |
| Stereo | PL++: P-RCNN [SDN+GDC]* [65] | 84.38 | 74.88 | 49.16 | 84.61 | 73.80 | 65.59 | 94.95 | 85.15 | 77.78 | – | – | – | – | – | – |

Table 2. Car detection results on the KITTI test set (official KITTI leaderboard). * utilizes 4-beam LiDAR to refine stereo depth estimation.

| Sensor | Method | Car APD (IoU=0.7) | Car APBEV (IoU=0.7) | Car AP3D (IoU=0.5) | Car APBEV (IoU=0.5) |
|--------|--------|------------------|---------------------|---------------------|---------------------|
| LiDAR  | MV3D (LiDAR) [8] | 71.29 | 62.68 | 56.56 | 86.35 | 78.10 | 76.67 | – | – | – | – | – | – | – | – |
|        | PL++: P-RCNN + SL* [65] | 75.1 | 63.8 | 57.4 | 88.2 | 76.9 | 73.4 | – | – | – | – | – | – | – | – |
|        | SECOND [53] | 87.43 | 76.48 | 69.10 | 89.96 | 87.07 | 79.66 | – | – | – | – | – | – | – | – |
|        | Point-RCNN [40] | 88.88 | 78.63 | 73.78 | – | – | – | – | – | – | – | – | – | – | – |
| Stereo | SECOND (our teacher) | 88.82 | 78.57 | 77.40 | 89.93 | 87.75 | 86.67 | 98.12 | 90.17 | 89.64 | 98.16 | 90.20 | 89.71 | – | – | – |

Note that we made several important modifications to DSGN to obtain a faster and more robust baseline model. 1) Decrease the number of channels and layers to reduce memory consumption and computation cost. 2) Utilize SECOND [53] detection head for 3D detection. 3) Replace the smooth-L1 depth regression loss with the uni-modal depth loss around re-projected 3D object centers. We made a small modification to the positive sample assignment algorithm of ATSS [67]. For each ground-truth bounding box \( g \), we select \( k \) candidate anchors from each scale if their centers are closest to the re-projected 3D object centers, instead of 2D bounding box centers as in [67]. The candidate anchors are then filtered by the dynamic IoU threshold as in ATSS [67] to assign the final positive samples.

3.4. Modifications to Baseline and Training Losses

To ensure the semantic alignment between 2D and 3D features, the 2D detection head should predict high scores for the closest candidate anchors (cf. Fig. 2(e)), which forms an information “bottleneck” to enforce all the semantic features to be encoded into multi-level features like [32, 67], we take only a single feature map \( F_{sem} \) to construct feature pyramids as shown in Fig. 2(e), which forms an information “bottleneck” to enforce all the semantic features to be encoded into \( F_{sem} \). Five consecutive convolution layers with a stride of 2 are attached to \( F_{sem} \) to construct a multi-level feature pyramid, which are then connected to an ATSS [67] head for 2D detection. Since we find that the dilated convolutions and spatial pyramid pooling (SPP) [20] have already produced highly semantic features with large receptive fields, we ignore the top-down path of FPN for simplicity. Please see detailed network structures in Sec. 1 of the supplementary materials.
loss [64] in Eq. (6) based on Kullback-Leibler divergence. 4) Use a combination of L1 loss and auxiliary rotated 3D IoU loss [70] for better bounding box regression. 5) Attach a small U-Net to the 2D backbone to encode full-resolution feature maps for stereo volume construction. Please check Sec. 1 & 2.1 of the supplementary material for detailed network structure and performance analysis for these modifications.

The new overall loss of our model is formulated as

$$\mathcal{L} = \mathcal{L}_{\text{depth}} + \mathcal{L}_{\text{det}} + \lambda_{\text{im}} \mathcal{L}_{\text{im}} + \lambda_{2d} \mathcal{L}_{2d},$$

$$\mathcal{L}_{\text{det}} = \mathcal{L}_{\text{cls}} + \mathcal{L}_{\text{det}} + \lambda_{\text{reg}} \mathcal{L}_{\text{reg}} + \lambda_{\text{dir}} \mathcal{L}_{\text{dir}},$$

where \(\mathcal{L}_{\text{cls}}, \mathcal{L}_{\text{det}}\) and \(\mathcal{L}_{\text{dir}}\) are the same classification loss, box regression loss, and direction classification loss as in SECOND [58]. \(\mathcal{L}_{\text{reg}}\) is the average rotated IoU loss [70] between 3D box predictions and ground-truth bounding boxes. The uni-modal depth loss \(\mathcal{L}_{\text{depth}}\) is formulated as

$$\mathcal{L}_{\text{depth}} = \frac{1}{N_{\text{gt}}} \sum_{u,v} \sum_{w} \left[ -\log \frac{\mathcal{P}(u,v,w)}{d^*} + \frac{d^*-d(w)}{d^*} \right],$$

in which \(d^*\) is the ground-truth depth. Note that the loss is only applied to the pixels \((u, v)\) with valid LiDAR depths, and \(N_{\text{gt}}\) denotes the number of valid pixels. Compared with the original L1 loss, the loss in Eq. (6) provides more concentrated supervisions to the target distribution.

### 4. Experiments

#### 4.1. Implementation Details

**Dataset.** We evaluate our method on the challenging KITTI 3D object detection benchmark [16]. There are 7,481 training and 7,518 testing stereo image pairs with synchronized LiDAR point clouds in the dataset. Following previous papers [46, 10], the training images are split into training set with 3,712 images and validation set with 3,769 images. There are three object classes in KITTI dataset, car, pedestrian, and cyclist, and each class is divided into three difficulty levels, easy, moderate, and hard.

**Evaluation Metric.** We performed detailed evaluation and analysis for 2D, BEV (bird-view) and 3D detection performance. All the performance results are measured using IoU-based criteria to compute mean averaged precision (mAP) over 40 recall values, except for the results in Table 1 which are evaluated using the old metric with 11 recall values for fair comparison with previous methods.

**Network Structure.** The main structure of our stereo detector follows that of DSGN [10], which consists of 2D feature extraction network (left side of Fig. 2(a)), stereo aggregation network (right side of Fig. 2(a)), and BEV feature aggregation network (Fig. 2(b)). As described in Sec. 3.4, we made several important modifications to [10] to reduce computation cost and memory consumption. Compared with [10], we reduced the numbers of blocks of \(\text{conv} 2\) to \(\text{conv} 5\) from \(\{3, 6, 12, 4\}\) to \(\{3, 4, 6, 3\}\), which is the same as ResNet-34 [21]. In addition, we append a small U-Net on the top of the 2D backbone to upsample the SPP feature back into full resolution to provide high-resolution features for stereo matching. The number of channels of the stereo aggregation network is halved from 64 to 32, and the 3D hourglass module for the 3D geometry volume \(\mathcal{V}_{3d}\) in [10] is removed. For the 3D detection head, we follow the open source implementation of SECOND [58] in OpenPCDet [50] to replace the original FCOS head in [10], which we found having inferior performance.

For the LiDAR “teacher”, we employ SECOND [58] because of its simplicity and similarity with our stereo detector. To make the teacher model and the student model as consistent as possible, we modify the stride of the last sparse convolution layer from 2 to 1, to obtain 1/4 downsampled features to match the feature map size of our stereo detector. Please refer to Sec. 1 of the supplementary materials for detailed network structures of our stereo detector and the LiDAR “teacher”.

**Training Details.** Our stereo detector is trained using AdamW [54] optimizer, with \(\beta_1 = 0.9, \beta_2 = 0.999\). The batch size is fixed to 8. We train the networks with 8 NVIDIA TITAN Xp GPUs, with 1 training sample on each GPU. The model is first trained for 50 epochs using a base learning rate of 0.001, and then for 10 more epochs with a reduced learning rate of 0.0001. The weight decay is set to 0.0001. We apply only horizontal flipping as augmentations. Instead of training individual networks for different classes as [10], we employ only a single model to train on all three classes of the KITTI dataset. To improve training stability, the weight normalizers for all the loss terms are averaged across all GPUs to avoid unstable gradients. For the

| Method          | Pedestrian AP_{3D} | Pedestrian AP_{BEV} | Cyclist AP_{3D} | Cyclist AP_{BEV} |
|-----------------|---------------------|---------------------|-----------------|------------------|
|                 | Easy    Moderate  Hard | Easy    Moderate  Hard | Easy    Moderate  Hard | Easy    Moderate  Hard |
| OC-Stereo [29]  | 24.48    17.58    15.60 | 29.79    20.80    18.62 | 29.40    16.63    14.72 | 32.87    19.23    17.11 |
| DSGN [10]       | 20.53    15.55    14.15 | 26.61    20.75    18.86 | 27.76    18.17    16.21 | 31.23    21.04    18.93 |
| Disp-RCNN [69]  | 37.12    25.80    22.04 | 40.21    28.34    24.46 | 40.05    24.40    21.12 | 44.19    27.04    23.58 |
| CG-Stereo [29]  | 33.22    24.31    20.95 | 39.24    29.56    25.87 | 47.40    30.89    27.73 | 55.33    36.25    32.17 |
| LIGA-Stereo (Ours) | 40.46    30.00    27.07 | 44.71    34.13    30.42 | 54.44    36.86    32.06 | 58.95    40.60    35.27 |

Table 3. Pedestrian and cyclist detection results on KITTI test set (official KITTI leaderboard).
Table 4. Ablation studies on the KITTI validation set. The tricks include full-resolution features for stereo volume construction, auxiliary 3D IoU loss, and the uni-modal depth loss as described in Sec. 3.4. IM denotes imitating geometry-aware representations of LiDAR models in Sec. 3.2. 2D denotes auxiliary direct 2D supervision in Sec. 3.3. pt means ImageNet pre-trained weights, which help learn better semantic features. (We only load pre-trained weights for layer conv1-3 due to structure differences). * The results for DSGN [10] are obtained by evaluating the officially released checkpoints using the new evaluation metrics with 40 recall values for fair comparison.

| # trick | IM | 2D | pt | Car AP_{3D-IoU0.7} | Car AP_{3D-IoU0.5} | Ped AP_{3D-IoU0.7} | Ped AP_{3D-IoU0.5} | Cyclist AP_{3D-IoU0.7} | Cyclist AP_{3D-IoU0.5} |
|--------|----|----|----|-------------------|-------------------|-------------------|-------------------|-------------------|-------------------|
|        |     |    |    | Easy Mod Hard     | Easy Mod Hard     | Easy Mod Hard     | Easy Mod Hard     | Easy Mod Hard     | Easy Mod Hard     |
| SECONDb [15] (teacher) | IM | 2D | pt | Car AP_{3D-IoU0.7} | Car AP_{3D-IoU0.5} | Ped AP_{3D-IoU0.7} | Ped AP_{3D-IoU0.5} | Cyclist AP_{3D-IoU0.7} | Cyclist AP_{3D-IoU0.5} |
| a. X   | ✓  | ✓  | ✓  | 91.89 81.08 78.58 | 99.36 94.55 93.65 | 72.30 64.79 57.82 | 86.83 82.03 76.02 | 83.17 65.81 62.00 | 89.31 69.41 66.07 |
| b. ✓   | ✓  | ✓  | ✓  | 82.51 72.74 57.34 | 98.85 90.21 84.81 | 41.18 33.72 29.19 | 76.19 66.04 57.98 | 45.63 26.77 24.97 | 29.12 16.27 15.14 |
| c. ✓   | ✓  | ✓  | ✓  | 84.89 66.57 60.16 | 98.84 92.47 87.32 | 47.82 38.89 33.66 | 57.54 33.70 31.23 | 74.39 48.44 44.93 | 51.50 32.39 30.48 |
| d. ✓   | ✓  | ✓  | ✓  | 84.45 63.32 57.65 | 96.23 89.94 84.55 | 40.72 34.23 29.12 | 76.13 66.36 58.99 | 52.65 30.26 28.14 | 58.59 37.96 35.42 |
| e. ✓   | ✓  | ✓  | ✓  | 85.26 65.64 60.12 | 98.98 92.50 87.33 | 43.97 36.95 31.82 | 77.57 69.14 62.13 | 54.59 34.07 31.42 | 65.19 42.96 40.28 |
| f. ✓   | ✓  | ✓  | ✓  | 81.03 63.07 56.50 | 98.91 92.22 87.04 | 40.29 34.13 29.31 | 77.60 68.54 61.42 | 42.77 26.13 24.26 | 52.11 34.63 32.78 |
| g. ✓   | ✓  | ✓  | ✓  | 86.84 67.71 62.02 | 98.87 93.21 87.97 | 45.54 37.80 32.09 | 81.87 72.18 64.10 | 60.00 37.31 34.25 | 79.89 52.17 48.09 |

4.2. Main Results

In this section, we provide detailed comparison with state-of-the-art 3D detectors on the KITTI dataset (see Table 2). Our model is only trained with the KITTI dataset, without any pre-training on Scene Flow datasets.

As shown in Table 1, our method surpasses the state-of-the-art method CG-Stereo by 8.75%, 9.24%, 9.17% in 3D mAP (IoU=0.7) for easy, moderate and hard difficulty levels of car class. Our model even achieves almost the same performance as our LiDAR teacher (see SECOND (teacher) item in Table 1) based on 0.5-IoU evaluation metrics. The gap between our model and the LiDAR teacher is only 0.2%. The input size is fixed to 320×1248, we crop the upper part of input images which does not contain any object to reduce memory consumption. The overall training time is about 12 hours.

For the KITTI dataset, the detection area is set to [2m, 59.6m] for the Z (depth) axis, [−30m, 30m] for the X axis, and [−1m, 3m] for the Y axis (in camera coordinate system). The voxel size of $V_{3d}$ in our stereo model is (0.2m, 0.2m, 0.2m). The input voxel size of the LiDAR detector is set to (0.05m, 0.1m, 0.05m). The spatial resolutions of BEV features of both models are 0.2m×0.2m.

4.3. Ablation Study

In this section, we conduct ablation experiments to validate the contribution of each component of our model on the KITTI validation set. The results are summarized in Table 4. The first row SECOND (teacher) is the performance of our LiDAR teacher. The model (a.) is our re-implementation of DSGN [10], but with less channels and using SECOND [58] detection head (due to memory limitation and simplicity), which achieves superior performance on cars compared with the original paper, but inferior results for pedestrians and cyclists because we train only a single model for all three classes instead of individual models. We applied a series of important tricks to model (a.) to obtain a stronger baseline model (b.), including full-resolution features for stereo volume construction, auxiliary 3D IoU loss for bounding box regression, and the uni-modal depth loss in Eq. (6). Please refer to Sec. 2 of the supplementary materials for details. By now, we have obtained a stronger baseline model with 61.35%, 34.11%, 24.04% 3D mAPs on the three classes of the KITTI validation set. In the following parts, we will prove the effectiveness of the proposed LiDAR feature imitation strategy in Sec. 4.3.1 and the auxiliary direct 2D supervisions in Sec. 4.3.2.
4.3.1 Ablation study of LiDAR feature imitation

Influence of LiDAR feature imitation. We first study whether imitating LiDAR features can benefit 3D detection and which layer is the optimal one. From Table 4, we can see that each of the three feature layers can provide meaningful geometry-aware guidance, among which \( V_{3d} \) and \( \tilde{F}_{BEV} \) produce the most effective guidance. We also tried different combinations of imitation layers but found no further gain. However, when combining \( V_{3d} \) and \( \tilde{F}_{BEV} \) as the imitation features, we found the model gives more stable results. As a result, we choose \( \mathcal{F}_\text{im} = \{ V_{3d}, \tilde{F}_{BEV} \} \) as our final choice.

Necessity of foreground mask. We then study the necessity of the foreground mask \( M_{fg} \). If \( M_{fg} \) is removed, the imitation loss would be applied for both foreground and background features with an extreme class imbalance ratio. As expected, after removing \( M_{fg} \), there is almost no improvement in our model (w/o \( M_{fg} \)) compared with the baseline model as shown in Table 6.

Imitation weight. As shown in the last section of Table 6, we tested different weights \( \lambda_{\text{im}} \) for the LiDAR imitation loss term and found 1.0 is the optimal choice.

Therefore, the optimal choice is to imitate foreground features of the 3D volume \( V_{3d} \) and the aggregated BEV features \( \tilde{F}_{BEV} \). In Table 4, by comparing model (b.) and (c.), the feature imitation strategy improves 3D detection performance by 2.9%, 5.2% and 6.9% on car, pedestrian and cyclist classes of the KITTI dataset. Similar conclusions can be drawn by comparing model (d.) and (e.).

4.3.2 The effectiveness of direct 2D supervisions

Due to the inefficiency of the 3D supervision for learning semantic features, we appended an auxiliary 2D detection head to provide direct 2D semantic supervisions for the semantic feature \( \mathcal{F}_{\text{sem}} \). By comparing the model (d.) and the baseline model (b.) in Table 4, the direct 2D supervision improves 3D AP of cars from 62.74% to 63.32%, pedestrians from 33.72% to 34.23%, and cyclists from 26.77% to 30.26%. The category with few data, cyclist, benefits more from this strategy.

We also evaluated our semantic features by training 2D detection only, but found poor performance on the KITTI dataset, the 2D APs are only 88%, 52% and 36% for cars, pedestrians and cyclists. We owe the poor results to the lack of data and pre-trained weights. With ImageNet pre-trained weights, the 2D APs are improved to 92%, 54% and 41%. To learn more discriminative 2D semantic features, we also performed experiments with ImageNet pre-trained weights to initialize the model. The two proposed strategies can consistently improve 3D detection performance with pre-trained weights (see model (f.) and (g.) in Table 4). Our final model (model (g.) is able to learn both high-quality geometric features and semantic features, which further reduces the gap between LiDAR-based and stereo-based 3D detection algorithms. Note that due to the structure differences between our backbone and ResNet-34, we only load pre-trained weights for the first three blocks from \( \text{conv1} \) to \( \text{conv3} \). For the detailed 2D detection results, please refer to Sec. 2 of the supplementary materials.

5. Conclusion

In this paper, we propose to learn stereo-based 3D detectors under the guidance of high-level geometry-aware LiDAR features and direct semantic supervisions, which successfully improved the geometric and semantic capabilities. Our model surpasses the state-of-the-art algorithms over 10.44% mAP on the official KITTI 3D detection benchmark, which is closing the gap between stereo-based and LiDAR-based 3D detection algorithms. However, stereo-based 3D detectors still suffer from occlusions, non-textured area and distant objects. By utilizing more advanced “teachers” and more robust stereo algorithms, we expect this problem to be solved step by step in the future.

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1. More Implementation Details

1.1. The Structure of the Stereo Detector

The main structure of our stereo 3D detector follows that of DSGN [2] but with much less memory consumption and lower computation cost. The network structure is described in Table 1 in details.

2D Feature Extraction. For the 2D backbone network, we employ a modified version of ResNet-34 [3] with spatial pyramid pooling (SPP) module and feature upsampling. Compared with [2], the numbers of blocks in conv2-5 are reduced from \(\{3, 6, 12, 4\}\) to \(\{3, 4, 6, 3\}\). The channels of conv2-5 are set to \(\{64, 128, 128, 128\}\). The SPP module is the same as previous implementations [1, 2]. In addition, we append a small U-Net [5] on the top of the 2D backbone to upsample the SPP feature back into full resolution to provide high-resolution features for stereo matching.

Stereo Aggregation Network. Although the 2D stereo features \(F_1, F_r\) are at full image resolution, we still construct the plane sweep volume (the stereo cost volume) at 1/4 resolution to save memory. The number of base channels of the stereo aggregation network is set to 32, which is half of the number of channels in [2].

Space Conversion. The volumetric feature in stereo space \(V_{st}\) is converted into 3D space using Eq. (2) in the paper, which is then filtered by a 3D convolution layer and average pooling layer (along Y dimension) to output the volume in 3D space \(V_{3d}\). The BEV feature is constructed by merging the y dimension and the channel dimension of \(V_{3d}\) and then compressed into 64 channels.

BEV Aggregation Network. The structure for the BEV aggregation network follows [2], which is a shallow hourglass-like network.

3D Detection Head. For the 3D detection head, we follow the open source implementation of SECOND [7] in OpenPCDet [6]. For each class and each \((x, z)\) location in the BEV space, we create two anchors with fixed average size and rotations of 0 and 90 degrees. The default anchor sizes are \(l_a=3.9, w_a=1.6, h_a=1.56\) for cars, \(l_a=0.8, w_a=0.6, h_a=1.73\) for pedestrians, and \(l_a=1.76, w_a=0.6, h_a=1.73\) for cyclists, and their y coordinates are set to \(y_a=\{1.78m, 0.6m, 0.6m\}\), respectively. The training targets are assigned with IoU-based criteria. The matched and unmatched IoU thresholds for the three classes are set to 0.6, 0.5, 0.5 and 0.45, 0.35, 0.35. Anchors with IoU between matched and unmatched thresholds are ignored for training. For each anchor, we output 3-dimensional classification and 7-dimensional regression predictions. The 3D bounding box regression targets are given by the following box encoding functions,

\[
\begin{align*}
x_t &= \frac{x_a - x_i}{d_a}, \quad y_t = \frac{y_a - y_i}{h_a}, \quad z_t = \frac{z_a - z_i}{d_a}, \\
w_t &= \log \frac{w_a}{w_i}, \quad l_t = \log \frac{l_a}{l_i}, \quad h_t = \log \frac{h_a}{h_i},
\end{align*}
\]

where the subscripts \(t, a, g\) denote the encoded regression targets, the anchors, and the ground truth. \(\theta\) is the yaw direction around the y-axis.

The classification loss \(L_{cls}\), the direction classification loss \(L_{dir}\), and the L1 regression loss \(L_{reg}^{l1}\) are the same as SECOND [7], and the auxiliary IoU-based regression loss is defined by

\[
L_{IoU} = 1 - \text{IoU}_{3d}(\text{decode}(\delta_p, \xi_a), \xi_g)
\]

where \(\delta_p\) is the regression predictions, \(\xi_a\) is the anchor \(\{x_a, y_a, z_a, l_a, w_a, h_a, \theta_a\}\), and \(\xi_g\) is the assigned ground-truth bounding box \(\{x_g, y_g, z_g, w_g, l_g, h_g, \theta_g\}\). Similar to the L1 regression loss, the IoU regression loss is only applied to positive samples. Non-maximum suppression (NMS) is applied to the 3D box predictions for each class separately, with the IoU threshold set to 0.25.

2D Detection Head. From the 2D feature extraction part, we have obtained 5-level FPN features \(sppl-5\) from \(F_{src}\) with a sequence of stride-2 convolution layers. The strides of these features are \(\{4, 8, 16, 32, 64\}\). For each level of the features, we apply a 2D detection head with two branches, classification branch and regression branch, to predict 2D bounding boxes. Following ATSS [8], each position is only
Table 1. Detailed network structure of our stereo-based 3D detection network. By default, the convolution layers in the 2D feature extraction module and the 2D head module are followed by batch normalization layers, and the other convolution layers are attached with group normalization layers (the number of groups is set to 32).

| Module | Config | #Channel | Size |
|--------|--------|----------|------|
| **2D Feature Extraction** | | | |
| conv1 | \( L_{1/4} \) | Conv \((y \times x)\), \( s=2 \) | 64 | \( H \times 2x W \times 2 \) |
| conv2 | BasicBlock \( \times 3 \) | | 64 | \( H \times 2x W \times 2 \) |
| conv3 | BasicBlock \( \times 4 \), \( s=2 \) | | 128 | \( H \times 4x W \times 4 \) |
| conv4 | BasicBlock \( \times 6 \), \( d=2 \) | | 128 | \( H \times 4x W \times 4 \) |
| conv5 | BasicBlock \( \times 4 \), \( d=4 \) | | 128 | \( H \times 4x W \times 4 \) |
| spp1 | | AvgPool \((64 \times 64)\); Conv \((1 \times 1)\); Upsample \(64 \times 32 \) | 32 | \( H \times 4x W \times 4 \) |
| spp2 | | AvgPool \((32 \times 32)\); Conv \((1 \times 1)\); Upsample \(32 \times 16 \) | 32 | \( H \times 4x W \times 4 \) |
| spp3 | | AvgPool \((16 \times 16)\); Conv \((1 \times 1)\); Upsample \(16 \times 8 \) | 32 | \( H \times 4x W \times 4 \) |
| spp4 | | AvgPool \((8 \times 8)\); Conv \((1 \times 1)\); Upsample \(8 \times 4 \) | 32 | \( H \times 4x W \times 4 \) |
| spp | | | | |
| hrev1 | conv2 | Conv \((1 \times 1)\) | 64 | \( H \times 2x W \times 2 \) |
| hrev2 | \( L_{1/4} \) | Conv \((1 \times 1)\) | 32 | \( H \times W \) |
| spp | | Conv \((3 \times 3)\); Upsample \(2 \times 1\); Add \( hrev1\); ReLU | 64 | \( H \times 2x W \times 2 \) |
| up1 | spp | Conv \((3 \times 3)\); Upsample \(2 \times 1\); Add \( hrev2\); ReLU | 32 | \( H \times W \) |
| up2 | | Conv \((3 \times 3)\) \times 2 | 32, 32 | \( H \times W \) |
| \( F^{\text{conv}} \) | spp of \( L_{1} \) | Conv \((3 \times 3)\) \times 2 | 128, 32 | \( H \times 4x W \times 4 \) |
| spp | | Conv \((1 \times 1)\) | 64 | \( H \times 4x W \times 4 \) |
| spp0 | Conv \((3 \times 3)\) | 64 | \( H \times 4x W \times 4 \) |
| spp1 | Conv \((3 \times 3), s=2 \) | | 64 | \( H \times 8x W \times 8 \) |
| spp2 | Conv \((3 \times 3), s=2 \) | | 64 | \( H \times 16x W \times 16 \) |
| spp3 | Conv \((3 \times 3), s=2 \) | | 64 | \( H \times 32x W \times 32 \) |
| spp4 | Conv \((3 \times 3), s=2 \) | | 64 | \( H \times 64x W \times 64 \) |

**Stereo Aggregation Network**

| \( V_{st} \) | \( F_{st} \) | Construct Plane Sweep Volume \((\text{Eq}(11))\) | 64 | \( D \times H \times 4x W \times 4 \) |
| \( st_{conv1} \) | Conv \((3 \times 3)\) \times 3 | 32 | \( D \times 4x H \times 4x W \times 4 \) |
| \( st_{conv2} \) | Conv \((3 \times 3)\); Add \( st_{conv1} \) | 32 | \( D \times 4x H \times 4x W \times 4 \) |
| \( st_{hg1} \) | Conv \((3 \times 3)\) \times 2, \( s=2 \) | 64 | \( D \times 8x H \times 8x W \times 8 \) |
| \( st_{hg2} \) | Conv \((3 \times 3)\) \times 2, \( s=2 \) | 64 | \( D \times 16x H \times 16x W \times 16 \) |
| \( st_{hg3} \) | Deconv \((3 \times 3)\); Add \( st_{hg1}\); ReLU | 64 | \( D \times 8x H \times 8x W \times 8 \) |
| \( st_{hg4} \) | Deconv \((3 \times 3)\); Add \( st_{conv2} \) | 32 | \( D \times 4x H \times 4x W \times 4 \) |
| \( st_{prob} \) | \((3 \times 3)\) \times 2 | 32, 1 | \( D \times 4x H \times 4x W \times 4 \) |
| \( F^{\text{BEV}} \) | Upsample \(4 \times 4\); Softmax | 1 | \( D \times H \times W \) |

**Stereo Space \( \rightarrow \) 3D Space \( \rightarrow \) BEV Space**

| \( V_{st} \) | \( F_{st}, V_{st} \) | Construct 3D Volume \((\text{Eq}(12))\) | 64 | \( N_{x} \times N_{y} \times N_{z} \) |
| \( V_{BEV} \) | Conv \((3 \times 3)\); AvgPool \((1 \times 4)\) | 32 | \( N_{x} \times N_{y} \times N_{z} \) |
| \( F^{\text{BEV}} \) | Reshape; Conv \((3 \times 3)\) | 32 \times N_{x} / 4, 64 | \( N_{x} \times N_{z} \) |

**BEV Aggregation Network**

| \( bcv_{hg1} \) | \( F_{BCV} \) | Conv \((3 \times 3)\) \times 2, \( s=2 \) | 128 | \( N_{x} \times N_{y} \times N_{z} \) |
| \( bcv_{hg2} \) | Conv \((3 \times 3)\) \times 2, \( s=2 \) | 128 | \( N_{x} \times N_{y} \times N_{z} \) |
| \( bcv_{hg3} \) | Deconv \((3 \times 3)\); Add \( bcv_{hg1}\); ReLU | 128 | \( N_{x} \times N_{y} \times N_{z} \) |
| \( F^{\text{BEV}} \) | Deconv \((3 \times 3)\) | 64 | \( N_{x} \times N_{y} \times N_{z} \) |

**3D Detection Head**

| \( bcv_{cls} \) | \( bcv_{cls} \) | Conv \((3 \times 3)\) \times 2 | 64 | \( N_{x} \times N_{y} \times N_{z} \) |
| \( bconv_{cls} \) | Conv \((3 \times 3)\) | 6 \times 3 | \( N_{x} \times N_{y} \times N_{z} \) |
| \( bcv_{dir} \) | Conv \((1 \times 1)\) | 6 \times 2 | \( N_{x} \times N_{y} \times N_{z} \) |
| \( bcv_{reg} \) | \( bcv_{reg} \) | Conv \((3 \times 3)\) \times 2 | 64 | \( N_{x} \times N_{y} \times N_{z} \) |
| \( F^{\text{BEV}} \) | Conv \((3 \times 3)\) | 6 \times 7 | \( N_{x} \times N_{y} \times N_{z} \) |

**2D Detection Head**

| \( bcv_{cls} \) | \( bcv_{cls} \) | Conv \((3 \times 3)\) \times 4 | 64 | \( H \times 4x W \times 4 \times 4 \) |
| \( bconv_{cls} \) | Conv \((3 \times 3)\) | 3 | \( H \times 4x W \times 4 \times 4 \) |
| \( bcv_{reg} \) | \( bcv_{reg} \) | Conv \((3 \times 3)\) \times 4 | 64 | \( H \times 4x W \times 4 \times 4 \) |
| \( bcv_{reg} \) | Conv \((3 \times 3)\) | 3 \times 4 | \( H \times 4x W \times 4 \times 4 \) |
| \( bconv_{centerness} \) | \( bconv_{centerness} \) | Conv \((3 \times 3)\) | 1 | \( H \times 4x W \times 4 \times 4 \) |

Table 2. Detailed network structure of the LiDAR detector.
Construct stereo volume with high-resolution features.

In PSNet [1] and DSGN [2], the stereo volume is constructed using left-right image features of 1/s size. However, for stereo detection, high-resolution features are essential to improve the depth estimation precision, especially for distant objects. Inspired by the observation, we append an extra small upsampling network (U-Net) to construct full-resolution features from SPP features. From Table 3, the U-Net improves the 3D detection performance of moderate samples by 0.6% mAP and hard samples by 2.0% mAP.

Depth Supervision Loss. According to [9], indirectly learning cost volume by soft-argmin and smooth-L1 loss is prone to overfitting since the cost volume is under constrained. In comparison, directly minimizing Kullback–Leibler divergence between the predicted distribution and the unimodal distribution centered at true disparities provides stronger constraints to the cost volume, which can learn more robust implicit depth features $\tilde{V}_d$. Since the ground-truth distribution is constant, the KL divergence can be simplified as cross entropy loss with soft targets,

$$L_{depth} = \frac{1}{N_{gt}} \sum_{u,v,w} \sum_{w} [-p_w\log P_{st}(u,v,w)], \quad (3)$$

where $p_w$ is the ground-truth distribution centered at true disparity $d^*$. Here we investigate several variants of ground-truth distributions, including the bilinearly interpolated distribution (Eq. (6) in the paper), hard-assigned distribution ($p_w=1$ if $d(w)$ is closest to $d^*$), Gaussian distribution ($p_w \propto \exp \left( -\frac{1}{2} \frac{(d(w)-d^*)^2}{\sigma} \right)$), and Laplacian distribution ($p_w \propto \exp \left( \frac{(d(w)-d^*)}{\lambda} \right)$). The results are shown in Table 4. To evaluate local depth embeddings, instead of using global soft-argmin [1] to parse depth values from depth distributions, we employ local soft-argmin to predict the final depth,

$$\tilde{d}_{u,v} = \sum_{w=k-2}^{k+2} d(w) \cdot \frac{P_{st}(u,v,w)}{\sum_{w'=k-2}^{k+2} P_{st}(u,v,w')}, \quad (4)$$

where $k=\arg\max(P_{st}(u,v,:))$ is the depth index with the

| Table 3. Ablation studies for the tricks. |
|----------------------------------------|
| Supervision | Err. Med. | < 0.2m | < 0.4m | AP3D (%) |
| Smooth-L1 | 0.61/0.10 | 55.2/32.9 | 35.7/20.5 | 76.44/56.73/49.52 |
| Hard-assigned | 0.63/0.094 | 50.9/29.9 | 32.8/18.7 | 78.31/59.17/52.07 |
| Gaussian $\sigma=0.2$ | 0.63/0.094 | 56.5/29.5 | 32.3/18.2 | 75.5/59.2/51.9 |
| Gaussian $\sigma=0.4$ | 0.66/0.11 | 55.1/32.6 | 35.4/19.7 | 58.9/36.9/35.4 |
| Gaussian $\sigma=0.8$ | 0.70/0.13 | 59.5/37.1 | 38.4/22.0 | 50.5/29.9/20.5 |
| Laplacian $\lambda=0.2$ | 0.64/0.10 | 52.9/31.3 | 33.8/19.3 | 88.3/61.3/54.2 |
| Laplacian $\lambda=0.4$ | 0.66/0.11 | 55.5/33.4 | 35.6/20.3 | 54.3/19.3/13.7 |
| Laplacian $\lambda=0.8$ | 0.68/0.13 | 58.9/36.9 | 38.2/22.2 | 50.5/29.9/13.7 |
| Bilinear (Eq. (6)) | 0.63/0.091 | 51.1/29.9 | 33.1/18.7 | 91.3/59.2/51.9 |

| Table 4. Comparison between different depth losses. Depth Err. Med. denotes the average median of depth errors. Foreground (Fg) in the Table metrics are evaluated by averaging object-level results, where boxes with less than 5 ground-truth LiDAR points are ignored. |
|----------------------------------------|
| Fg/All (mm) | 0.64/0.10 | 55.2/32.9 | 35.7/20.5 | 76.44/56.73/49.52 |
| Hard-assigned | 0.63/0.094 | 50.9/29.9 | 32.8/18.7 | 78.31/59.17/52.07 |
| Gaussian $\sigma=0.2$ | 0.63/0.094 | 56.5/29.5 | 32.3/18.2 | 75.5/59.2/51.9 |
| Gaussian $\sigma=0.4$ | 0.66/0.11 | 55.1/32.6 | 35.4/19.7 | 58.9/36.9/35.4 |
| Gaussian $\sigma=0.8$ | 0.70/0.13 | 59.5/37.1 | 38.4/22.0 | 50.5/29.9/20.5 |
| Laplacian $\lambda=0.2$ | 0.64/0.10 | 52.9/31.3 | 33.8/19.3 | 88.3/61.3/54.2 |
| Laplacian $\lambda=0.4$ | 0.66/0.11 | 55.5/33.4 | 35.6/20.3 | 54.3/19.3/13.7 |
| Laplacian $\lambda=0.8$ | 0.68/0.13 | 58.9/36.9 | 38.2/22.2 | 50.5/29.9/13.7 |
| Bilinear (Eq. (6)) | 0.63/0.091 | 51.1/29.9 | 33.1/18.7 | 91.3/59.2/51.9 |

| Table 5. Ablation studies for 2D detection head. * only loads pre-trained weights in conv1, conv2, and conv3. |
|----------------------------------------|
| 2D Detection Network | $pt$ | AP2D |
| ResNet-34 [3] | ✓ | 88.3/64.4/49.4 |
| ResNet-34 [3] w/o MaxPool | ✓ | 93.2/71.9/58.4 |
| Ours (2D only) | ✓ | 88.6/51.7/36.3 |
| Ours (2D only) | ✓ | 91.6/54.3/41.6 |
| Ours (2D only) | ✓ | 93.2/69.2/59.2 |
| Ours (Full model) | ✓ | 90.8/51.9/34.3 |
| Ours (Full model) | ✓ | 91.3/60.2/47.2 |

Table 2. Ablation studies for the tricks.
maximum probability. Local soft-argmin can avoid the influence of the probability values that are far from the peak probability, which can be utilized to evaluate the local geometric accuracy of the implicit stereo embeddings $\hat{\mathbf{v}}_{st}$. Results in Table 4 show that ground-truth distributions $p_w^*$ that are sharper and more concentrated around $d^*$ can give...
better results. The choice of distribution encoding methods is not essential, and hard-assigned distribution can even give better performance than L1 loss. The good choices include hard-assigned distribution, gaussian distribution with $\sigma=0.2$, laplacian distribution with $\lambda=0.2$, and bilinearly interpolated distribution.

### 2.2. 2D Detection Performance

We compare our 2D detection branch with ResNet-34 [3] to confirm that our semantic bottleneck $F_{sem}$ does not constrain the performance of 2D detection. Since our model does not employ max pooling after $conv1$, we give the results of ResNet-34 without max pooling in the second row of Table 5 for fair comparison. By comparing the results of ResNet-34 w/o Maxpool and Ours (2D only), both models achieve similar performance given ImageNet pretrained weights, which proves that the semantic bottleneck does not constrain the 2D detection performance and has the capability of learning good semantic features. By comparing the models without and with ImageNet pretrained weights, we can see pretrained weights are essential for 2D detection due to the limit of training data in the KITTI dataset.

### 3. Visualization Results

Please see the visualization results in Fig. 1. Most of the objects can be detected with high IoU successfully, even for distant objects. We also visualize several failure cases in Fig. 2. Most of the failure cases are caused by occlusions and depth estimation errors. Several predictions give large orientation errors, which we believe can be fixed by incorporating predictions of 2D key-points of bounding boxes in the future.

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