Not All Points Are Equal: Learning Highly Efficient Point-based Detectors for 3D LiDAR Point Clouds

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Abstract

We study the problem of efficient object detection of 3D LiDAR point clouds. To reduce the memory and computational cost, existing point-based pipelines usually adopt task-agnostic random sampling or farthest point sampling to progressively downsample input point clouds, despite the fact that not all points are equally important to the task of object detection. In particular, the foreground points are inherently more important than background points for object detectors. Motivated by this, we propose a highly-efficient single-stage point-based 3D detector in this paper, termed IA-SSD. The key of our approach is to exploit two learnable, task-oriented, instance-aware downsampling strategies to hierarchically select the foreground points belonging to objects of interest. Additionally, we also introduce a contextual centroid perception module to further estimate precise instance centers. Finally, we build our IA-SSD following the encoder-only architecture for efficiency. Extensive experiments conducted on several large-scale detection benchmarks demonstrate the competitive performance of our IA-SSD. Thanks to the low memory footprint and a high degree of parallelism, it achieves a superior speed of 80+ frames-per-second on the KITTI dataset with a single RTX2080Ti GPU. The code is available at https://github.com/yifanzhang713/IA-SSD.

1. Introduction

Accurate recognition and localization of specific 3D objects is a fundamental research problem in 3D computer vision [10]. As a commonly-used 3D representation, point cloud has attracted increasing attention for its flexibility and compactness. However, the task of 3D object detection in LiDAR point clouds (i.e., predicting 3D bounding boxes with 7 degrees-of-freedom including 3D-location, 3D-size, orientation, and class labels) remains highly challenging due to the complex geometrical structure and non-uniform density.

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Figure 1. Comparison of the detection performance (accuracy) and efficiency (computational and memory) of different methods in KITTI benchmark. All experiments are conducted on a single RTX2080Ti GPU. Note that, we evaluate the memory efficiency by calculating the maximum number of parallel frames during inference when fully utilizing the GPU memory. Additionally, the FPS is calculated with the full utilization of GPU memory, more detailed analysis could be found in Table 6.

Due to the unstructured and orderless nature of 3D point clouds, early works usually first convert the raw point clouds into intermediate regular representation, including projecting the 3D point clouds into 2D images from birds-eye-view or frontal view [1, 17, 18, 41, 42, 50, 60], or transformed into dense 3D voxels [49, 61]. Then, several well-developed 2D detection paradigms can be deployed into the task of 3D object detection. Although remarkable progress has been achieved recently [2, 3, 7, 11, 24, 39, 53, 54], these
methods introduce the quantization error due to the 3D-2D projection or voxelization, which inevitably limits their performance of existing methods. Another stream of techniques following the point-based pipeline to directly operate on raw point clouds \[12,13,15,38,40,48,52\]. They usually learn point-wise features and then aggregate through specific symmetric functions such as max-pooling \[31,32\]. Although promising and without any explicit information loss, these methods still suffer from expensive computational/memory costs and limited detection performance.

In this paper, we first dive deep into the existing point-based frameworks and experimentally find that the heuristic sampling strategies used are far from satisfactory, since a number of the important foreground points have been dropped before the final bounding box regression step. As such, the detection performance, especially for small objects such as pedestrians, has been fundamentally limited. In this paper, we argue that *not all points are equally important to the task of object detection*. In particular, only the foreground points, are the things we really care about.

Motivated by this, we aim to propose a task-oriented, instance-aware downsampling framework, to explicitly preserve foreground points while reducing the memory/computational cost. Specifically, two variants, namely class-aware and centroid-aware sampling strategies are proposed. In addition, we also present a contextual instance centroid perception, to fully exploit the meaningful context information around bounding boxes for instance center regression. Finally, we build our IA-SSD based on the bottom-up single-stage framework. As shown in Figure 1, the proposed IA-SSD demonstrated to be highly efficient (up to inference 100 frames in parallel in a single pass, with a speed of 83 FPS on a single RTX 2080Ti GPU) and accurate on the KITTI benchmark \[8\]. In particular, thanks to the high instance recall ratio of the proposed sampling strategy, the proposed IA-SSD can be directly trained with multiple object categories, rather than the common practice, i.e., train separate models for different categories. Extensive experiments on Section 4 justify the compelling performance and superior efficiency of our method.

To summarize, the contributions are listed as follows:

- We identify the sampling issue in existing point-based detectors, and proposed an efficient point-based 3D detector by introducing two learning-based instance-aware downsampling strategies.
- The proposed IA-SSD is highly efficient and capable of detecting multi-class objects on LiDAR point clouds in a single pass. We also provided a detailed memory footprint vs. inference-speed analysis to further validate the superiority of the proposed method.
- Extensive experiments on several large-scale datasets demonstrate the superior efficiency and accurate detection performance of the proposed method.

2. Related Work

Here, we give a brief overview of existing voxel-based detectors, point-based detectors, and point-voxel detectors.

2.1. Voxel-based Detectors

To process unstructured 3D point clouds, voxel-based detectors usually first convert the irregular point clouds into regular voxel grids. This further allows leveraging the mature convolution neural architectures. Early works such as \[46\] densely voxelized the input point clouds and then utilized convolutional neural networks to learn specific geometrical patterns. However, efficiency is one of the main limitations of these methods, since the computational and memory cost grow cubically with the input resolution. To this end, Yan et al. \[49\] present an efficient architecture called SECOND by leveraging the 3D submanifold sparse convolution \[9\]. By reducing the calculation on empty voxels, the computational and memory efficiency have been significantly improved. Further, PointPillars \[18\] is proposed to further simplify the voxels to pillars (i.e., only voxelization in the plane).

The existing approaches can be roughly divided into single-stage \[7,11,54,55,57,58\] and two-stage detectors \[4,36–39,53\]. Albeit simple and efficient, they usually failed to achieve satisfactory detection performance due to the downscaled spatial resolution and insufficient structural information, especially for small objects with sparse points. To this end, He et al. \[11\] present SA-SSD to leverage the structure information by introducing an auxiliary network. Ye et al. \[54\] introduce a Hybrid Voxel network (HVNet) to attentively aggregate and project the multi-scale feature maps to achieve better performance. Zheng et al. \[58\] present the Confident IoU-Aware (CIA-SSD) network to extract spatial-semantic features for object detection. In comparison, two-stage detectors can achieve better performance, but with high computational/memory cost. Shi et al. \[39\] propose a two-stage detector namely Part-A$^2$, which is composed of the part-aware and aggregation module to exploit the intra-object part locations. Deng et al. \[5\] extend the PV-RCNN \[36\] by introducing a fully convolutional network to further exploit volumetric representation for raw point cloud and refinement simultaneously.

Overall, voxel-based methods can achieve good detection performance with promising efficiency. However, voxelization inevitably introduces quantization loss. In order to compensate for the structural distortion in the pre-processing phase, complex module design needs to be introduced in \([20,25,27,28,35]\), which in turn greatly deteriorate the final detection efficiency. Additionally, it is not easy to determine the optimal resolution in practice, considering the complex geometry and various different objects.
2.2. Point-based Detectors

Different from voxel-based methods, point-based methods \cite{30,38,52} directly learning geometry from unstructured point clouds, further generate specific proposals for objects of interest. Considering the orderless nature of 3D point clouds, these methods typically adopt PointNet \cite{31} and its variants \cite{22,32,33,45,47} to aggregate independent point-wise features using symmetric functions. Shi et al. \cite{38} propose PointRCNN, a two-stage 3D region proposal framework for 3D object detection. This method first generates object proposals from segmented foreground points, and high-quality 3D bounding boxes are then regressed by exploiting the semantic feature and local spatial cues. Qi et al. \cite{30} introduce VoteNet, a one-stage point-based 3D detector based on deep Hough voting to predict the instance centroid. Inspired by single-stage detectors \cite{21} in 2D images, Yang et al. \cite{52} presents a 3D Single-Stage Detection (3DSSD) framework, while the key is a fusion sampling strategy comprising the Farthest Point Sampling on feature and Euclidean space. PointGNN \cite{40} is a framework by generalizing graph neural network to 3D object detection.

Point-based methods directly operate on the raw point clouds, without any extra preprocessing steps such as voxelization, hence usually intuitive and straightforward. However, the main bottleneck of point-based methods is insufficient learning capacity and limited efficiency.

2.3. Point-Voxel Methods

To overcome the drawbacks of both point-based methods (i.e., irregular and sparse data access, poor memory locality \cite{23}) and voxel-based methods (i.e., quantization loss), several methods \cite{3,16,36,37,53} have started to learning from 3D point clouds using point-voxel joint representations. Specifically, PV-RCNN \cite{36} and its follow-up work \cite{37} extract point-wise features from voxel abstraction networks to refine the proposals generated from 3D voxel backbone. Further, HVPR \cite{29}, a single-stage 3D detector, introduces an efficient memory module to augment point-based features, thereby providing a better compromise between accuracy and efficiency. Qian et al. \cite{34} propose a lightweight region aggregation refine network (BANet) via local neighborhood graph construction, which produces more accurate box boundary prediction.

Overall, different detection pipelines have their own merits. In this paper, we propose IA-SSD, a single-stage point-based detector, to simultaneously improve the detection accuracy and runtime efficiency. In particular, the key differences between our IA-SSD and existing point-based techniques lie in the instance-aware sampling strategies and the contextual instance centroid perception module, as illustrated in the following sections.

3. The Proposed IA-SSD

3.1. Overview

Different from dense prediction tasks such as 3D semantic segmentation, where point-wise prediction is required, 3D object detection naturally focus on the small yet important foreground objects (i.e., instances of interest including car, pedestrian, etc.). However, existing point-based detectors usually adopt task-agnostic downsampling approaches such as random sampling \cite{14} or farthest point sampling \cite{32,52} in their framework. Albeit effective for memory/computational cost reduction, the most important foreground points are also diminished in progressive downsampling. Additionally, due to the large difference in size and geometrical shape of different objects, existing detectors usually train separate models with various carefully tuned hyperparameters for different types of objects. However, this inevitably affects the deployment of these models in practice. Therefore, the objective of this paper is: Can we train a single point-based model, which is efficient and capable of detecting multi-class objects in a single pass?

Motivated by this, we propose an efficient, single-stage detector by introducing the instance-aware downsampling and contextual centroid perception module. As shown in Figure 2, our IA-SSD follows the lightweight encoder-only architecture used in \cite{52} for efficiency. The input LiDAR point clouds are first fed into the network to extract point-wise features, followed by the proposed instance-aware downsampling to progressively reduce the computational cost, while preserving the informative foreground points simultaneously. The learned latent features are further input to the contextual centroid perception module to generate instance proposals and regress the final bounding boxes.

3.2. Instance-aware Downsampling Strategy

For efficient 3D object detection, it is essential to reduce the memory and computational cost through progressive downsampling, especially for large-scale 3D point clouds. However, aggressive downsampling may lose most of the information of the foreground objects. Overall, it remains unclear how to achieve a desirable trade-off between computational efficiency and the preservation of foreground points. To this end, we first conduct an empirical study to quantitatively evaluate different sampling approaches. In particular, we follow the commonly-used encoding architecture (i.e., PointNet++ \cite{32} with 4 encoding layers), and report the Instance Recall (i.e., the ratio of instance retained after sampling) at each layer in Table 1. In particular, random point sampling \cite{14}, FPS based on Euclidean distance (D-FPS) \cite{32} and feature distance (Feat-FPS) \cite{52} are reported.

Analysis. It can be seen that: 1) The instance recall rate dropped significantly after several random downsampling
operations, indicating massive foreground points have been dropped. 2) Both D-FPS and Feat-FPS achieve a relatively better instance recall rate at the early stage, but also fail to preserve enough foreground points at the last encoding layer. As such, it remains challenging to precisely detect the objects of interest, especially for small objects such as pedestrians and cyclists, where only extremely limited foreground points are left.

**Solutions.** To preserve foreground points as much as possible, we turn to leverage the latent semantics of each point, since the learned point features may incorporate richer semantic information as the hierarchical aggregation operates in each layer. Following this idea, we propose the following two task-oriented sampling approaches by incorporating the foreground semantic priors into the network training pipelines.

**Class-aware Sampling.** This sampling strategy aims to learn semantics for each point, so as to achieve selective downsampling. To achieve this, we introduce extra branches to exploit the rich semantics in latent features. In particular, two MLP layers were appended to the encoding layers to further estimate the semantic categories of each point. The point-wise one-hot semantic labels generated from the original bounding box annotations are used for supervision. Here we use the vanilla cross-entropy loss:

$$\mathcal{L}_{\text{cls-aware}} = - \sum_{c=1}^{C} (s_{c} \log(\hat{s}_{c}) + (1 - s_{c}) \log(1 - \hat{s}_{c}))$$ (1)

where \(C\) denotes the number of categories, \(s_{c}\) is the one-hot labels and \(\hat{s}_{c}\) denotes the predicted logits. During inference, the points with the top \(k\) foreground scores are retained and regarded as the representative points that feed into the next encoding layers. As shown in Table 1, this strategy tends to preserve more foreground points, hence achieving a high ratio of instance recall.

**Centroid-aware Sampling.** Considering instance center estimation is the key for final object detection, we further propose a centroid-aware downsampling strategy to give higher weight to points closer to instance centroid. Specifically, we define the soft point mask of instance \(i\) as follows:

$$\text{Mask}_i = \sqrt{\frac{\min(f^*, b^*)}{\max(f^*, b^*)}} \times \frac{\min(l^*, r^*)}{\max(l^*, r^*)} \times \frac{\min(u^*, d^*)}{\max(u^*, d^*)}$$ (2)

where \(f^*, b^*, l^*, r^*, u^*, d^*\) represent the distance of a point to the 6 surfaces (front, back, left, right, up and down) of the bounding box, respectively. In this case, the point closer to the centroid of the box is likely to have a higher mask score (max value is 1), while the point that lies on the surface will have a mask score of 0. During training, the soft point mask will be used to assign different weights for points within a bounding box based on the spatial locations, hence implicitly incorporates the geometry priors into the network training. In particular, the weighted cross-entropy loss is calculated as follows:

$$\mathcal{L}_{\text{ctr-aware}} = - \sum_{c=1}^{C} (\text{Mask}_i \cdot s_{c} \log(\hat{s}_{c}) + (1 - s_{c}) \log(1 - \hat{s}_{c}))$$ (3)

The soft point mask is multiplied with the loss term of foreground points, so as to assign a higher probability to the points near the center. Note that, the bounding boxes are no longer required during inference, we simply preserve the top \(k\) points with the highest scores after downsampling, if the model is well-trained.
3.3. Contextual Instance Centroid Perception

**Contextual Centroid Prediction.** Inspired by the success of context prediction in 2D images [6, 51], we attempt to leverage the contextual cues around the bounding box for instance centroid prediction. Specifically, we follow [30] to explicitly predict an offset $\Delta c_{ij}$ to the instance center. Additionally, a regularization term is added to minimize the uncertainty of the centroid prediction. Specifically, all votes per instance are aggregated in light of the surrounding interference, where the $\pi_i$ is the mean destination of $i$-th instance. Therefore, the centroid prediction loss is formulated as follows:

$$L_{cent} = \frac{1}{|p_i|} \frac{1}{|\mathcal{S}_i|} \sum_{i} \sum_{j} \left( |\Delta c_{ij} - \Delta c_{ij}| + |c_{ij} - \pi_i| \right) \cdot I_S(p_{ij})$$

where $\pi_i = \frac{1}{|\mathcal{S}_i|} \sum_{j} c_{ij}$, $I_S : \mathcal{P} \rightarrow \{0, 1\}$

(4)

where $\Delta c_{ij}$ denotes the ground-truth offset from point $p_{ij}$ to the center point. $I_S$ is an indicator function to determine whether this point is used to estimate the instance center or not. $|\mathcal{S}_i|$ is the number of points used to predict the instance center. Note that, instead of only using the points or the shifted points within the bounding box for instance center prediction [30, 52], we also exploit the surrounding representative points from a large context for centroid prediction in this paper. Specifically, we empirically investigate the impact of simple contextual cues on final detection performance. In particular, we manually expand the ground-truth bounding boxes or proportional enlarge the box to cover more related context near the objects. The sampled points that fall in the expanded bounding box are utilized to estimate offset and then shifted.

**Centroid-based Instance Aggregation.** For shifted representative (centroid) points, we further utilize a PointNet++ module to learn a latent representation for each instance. Specifically, we transform the neighboring points to a local canonical coordinate system, then aggregate the point feature through shared MLPs and symmetric functions.

**Proposal Generation Head.** The aggregated centroid point features are then fed into proposal generation head to predict bounding boxes with classes. We encode the proposal as a multidimensional representation with location, scale, and orientation. Finally, all proposals are filtered by 3D-NMS post-processing with a specific IoU threshold.

3.4. End-to-End Learning

Our IA-SSD can be trained in an end-to-end fashion. Multi-task loss is used in our framework for joint optimization. The total loss $L_{total}$ is composed of downsampling strategy loss $L_{sample}$, centroid prediction loss $L_{cent}$, classification loss $L_{cls}$ and box generation loss $L_{box}$:

$$L_{total} = L_{sample} + L_{cent} + L_{cls} + L_{box}$$

(5)

In particular, the box generation loss can be further decomposed into location, size, angle-bin, angle-res, and corner parts:

$$L_{box} = L_{loc} + L_{size} + L_{angle-bin} + L_{angle-res} + L_{corner}$$

(6)

4. Experiments

4.1. Implementation Details

We build our IA-SSD based on single-stage, encoder-only architecture for efficiency. Specifically, a number of SA layers [32] are used to extract point-wise features. Multi-scale grouping with increasing radius groups is used ([0.2, 0.8], [0.8, 1.6], [1.6, 4.8]) to steady extract local geometrical features. Considering limited semantics incorporated in early layers, we adopt D-FPS in the first two encoding layers, followed by the proposed instance-aware downsampling. Next, 256 representative point features are fed into the contextual centroid prediction module, followed by three MLP layers (256→256→3) to predict the instance centroid. Finally, the classification and regression layers (three MLP layers) are appended to output the semantic labels and the corresponding bounding boxes. More implementation details are reported in the Appendix.

| Sampling strategies | 4096 points | 1024 points | 512 points | 256 points |
|--------------------|-------------|-------------|-------------|-------------|
|                    | Car | Ped. | Cyc. | Car | Ped. | Cyc. | Car | Ped. | Cyc. | Car | Ped. | Cyc. |
| Random [4]         | 96.6% | 99.1% | 97.4% | 87.5% | 92.7% | 84.1% | 78.8% | 84.9% | 73.3% | 67.4% | 72.1% | 57.3% |
| D-FPS [32]         | 98.3% | 100% | 97.2% | 97.9% | 99.3% | 97.2% | 96.8% | 90.6% | 90.8% | 91.4% | 69.1% | 71.6% |
| Feat-FPS [52]      | 98.3% | 100% | 97.2% | 97.7% | 98.0% | 97.2% | 96.3% | 87.6% | 94.5% | 95.3% | 80.1% | 91.7% |
| Cls-aware (Ours)   | 98.3% | 100% | 97.2% | 97.9% | 99.3% | 97.2% | 97.9% | 99.0% | 95.4% | 97.9% | 97.4% | 92.7% |
| Ctr-aware (Ours)   | 98.3% | 100% | 97.2% | 97.9% | 99.3% | 97.2% | 97.9% | 99.0% | 97.2% | 97.9% | 98.4% | 97.2% |

Table 1. The instance recall rate for foreground points (i.e., car, pedestrian, and cyclist) after several downsampling on the entire validation set (3769 frames) of the KITTI benchmark. Note that, the input point clouds with 16384 points are progressively downsampled to 256 points through four downsampling layers. D-FPS are used in the first two layers for the proposed instance aware downsampling strategies.
| Method             | Reference    | Type       | 3D Car (IoU=0.7) | 3D Ped. (IoU=0.5) | 3D Cyc. (IoU=0.5) | Speed |
|--------------------|--------------|------------|------------------|-------------------|------------------|-------|
| VoxelNet [41]      | CVPR 2018    | 1-stage    | 77.47            | 65.11             | 57.73            | 61.22 |
| SECOND [49]        | Sensors 2018 | 1-stage    | 84.65            | 75.96             | 68.71            | 75.83 |
| PointPillars [18]  | CVPR 2019    | 1-stage    | 82.58            | 74.31             | 68.99            | 77.10 |
| 3D IoU Loss [59]   | 3DV 2019     | 1-stage    | 86.16            | 76.50             | 71.39            | 79.17 |
| Associate-3Ddet [7]| CVPR 2020    | 1-stage    | 85.99            | 77.40             | 70.53            | 78.69 |
| SA-SSD [11]        | CVPR 2020    | 1-stage    | 88.71            | 79.79             | 74.16            | 80.61 |
| CAA-SSD [38]       | AAI 2021     | 2-stage    | 89.59            | 80.28             | 72.87            | 81.43 |
| TANet [28]         | AAI 2020     | 2-stage    | 84.39            | 75.94             | 68.82            | 82.47 |
| Part-4’ [19]       | TPMI 2020    | 2-stage    | 87.81            | 78.49             | 73.51            | 85.81 |

Table 2. Quantitative detection performance achieved by different methods on the KITTI test set. All results are evaluated by mean Average Precision with 40 recall positions via the KITTI evaluation server. The results of our IA-SSD are shown in bold, and the best results are underlined.

| Method          | Reference    | Type       | 3D Car (IoU=0.7) | 3D Ped. (IoU=0.5) | 3D Cyc. (IoU=0.5) | Speed |
|-----------------|--------------|------------|------------------|-------------------|------------------|-------|
| Fast Point R-CNN [3] | ICCV 2019   | 2-stage    | 85.29            | 77.40             | 70.24            | 79.96 |
| STD [53]        | ICCV 2019    | 2-stage    | 87.95            | 79.71             | 75.09            | 81.29 |
| PV-RCNN [36]    | CVPR 2020    | 2-stage    | 90.25            | 81.43             | 76.82            | 82.60 |
| VIC-Net [16]    | ICRA 2021    | 1-stage    | 88.25            | 80.61             | 75.83            | 82.89 |
| HVPR [29]       | CVPR 2021    | 1-stage    | 86.38            | 77.92             | 73.04            | 83.68 |
| IA-SSD (single-class) | -            | 1-stage    | 88.87            | 80.32             | 75.10            | 84.65 |
| IA-SSD (multi-class) | -            | 1-stage    | 88.34            | 80.13             | 75.04            | 84.22 |

Table 3. Quantitative comparison of different approaches on the validation split of the KITTI dataset. The average precision is measured with 11 recall positions (vs. 40 recall positions in the KITTI test set) [8]. The results achieved by our IA-SSD are shown in bold, while the top-performed results are shown in underline.

4.2. Comparison with State-of-the-Art Methods

Evaluation on KITTI Dataset. In the KITTI benchmark, objects belong to car, pedestrian and cyclist are classified into three subsets (“Easy”, “Moderate” and “Hard”) based on the levels of difficulty. The results on “Moderate” are usually adopted as the main indicator for final ranking. We report the results achieved by different methods (voxel, point, and point-voxel-based methods) on the test set of the KITTI dataset in Table 2. Note that, since [52] does not provide reproducible implementation or pre-trained models for pedestrian and cyclist, we have no choice but to provide both the results reported in their paper, the best-reproduced results, and the results achieved by OpenPCDet\(^1\) implementation for a fair comparison.

Analysis. It can be seen that: 1) the proposed IA-SSD achieves the best cyclist detection performance, even outperforming several strong point-voxel and voxel detectors [36, 39]. This is mainly because the proposed instance-aware sampling can effectively preserve foreground points, enabling accurate detection of small objects. 2) Our IA-SSD also achieves best car detection performance compared with other point-based detectors, outperforming PointRCNN [38] by (1.91\%, 4.68\%, 4.4\%), and the SoTA method 3DSSD [52] by (0.51\%, 0.75\%, 0.55\%) mAP. 3) Despite the competitive detection performance, the proposed IA-SSD also shows superior efficiency. It can detect with a speed of 85 FPS on a single NVIDIA RTX 2080Ti with Intel I9-10900X CPU@3.7GHz. 4) Thanks to the instance-aware sampling strategy and the contextual centroid perception module, our framework can be trained with multi-class together (i.e., training a single model for detecting multi-class objects), rather than training separate models for different objects [52]. In particular, the performance is still comparable with other state-of-the-art approaches. This allows our model much more efficient and flexible during inference. Finally, we also show the qualitative results achieved by our IA-SSD in Figure 3. We can clearly see

\(^1\)https://github.com/open-mmlab/OpenPCDet
that the proposed IA-SSD is capable of detecting small and far-away instances such as pedestrian and cyclist.

Apart from the detection results on the test split, we also report the performance comparison on the validation set of the KITTI dataset in Table 3. We can see our IA-SSD achieved the best performance for all three classes among all point-based detectors. In particular, our IA-SSD is single-stage, lightweight, and efficient, requiring only a single model for detecting multi-class objects.

**Evaluation on Waymo Dataset.** We further evaluate the performance of our IA-SSD on Waymo [44] dataset. This dataset is composed of nearly 160k 360-degree LiDAR samples in the training set and 40k in the validation set with panoramic annotated objects. For a fair comparison, we adapt our framework on the Waymo Dataset by only changing the number of input points from 16384 to 65536, and increasing the sampling scale up to fourfold in each sampling layer, while remaining the rest unchanged. Additionally, all baselines are implemented based on the OpenPCDet codebase for a rigorous comparison. As shown in Table 4, our IA-SSD achieves significantly better detection performance among all point-based detectors. This again verifies the superiority of the proposed component and the efficiency of our method applied on the large-scale complicated LiDAR scenarios.

**Efficiency of IA-SSD.** Next, we evaluate the computational and memory efficiency of the proposed IA-SSD. In light of the performance variations on different hardware configurations, we re-implemented several representative approaches and report the memory and speed on the same platform for a fair comparison. Note that, we report the memory consumption by feeding the same input point cloud of batches that can be parallelized on one RTX2080Ti (11GB). "Speed" is inference speed when processing one frame or full-loaded GPU memory, " Speed" is the ratio of speed between IA-SSD and baseline methods, and " Input Scale" means dividing the scene into four parallel parts to speed up the first sampling layer. For a fair comparison, we also report each input scale of voxels/points according to their official setting.

shown in Table 5, our method yields the competitive performance among all baselines. This again verifies the superiority of the proposed component and the efficiency of our method applied on the large-scale complicated LiDAR scenarios.

Table 4. Quantitative detection performance achieved by different methods on the Waymo [44] validation set. The results of our IA-SSD are shown in bold, and the best results are underlined.

| Method       | Type      | Vehicle (LEVEL 1) mAP  | Ped. (LEVEL 1) mAP  | Cyclic. (LEVEL 1) mAP  |
|--------------|-----------|------------------------|---------------------|------------------------|
|              |           | mAPH                   | mAPH                | mAPH                   |
| PointPillars [18] | Voxel-based | 60.67                  | 59.79                | 52.78                  |
| SECOND [49]     | Voxel-based | 68.03                  | 67.44                | 59.57                  |
| Part-â‡’ [39]   | Voxel-based | 71.82                  | 71.29                | 64.33                  |
| PV-RCNN [36]    | Point-Voxel | 74.06                  | 73.38                | 64.99                  |
| IA-SSD (Ours)   | Point-based | 70.53                  | 69.67                | 61.55                  |

Table 5. Quantitative detection performance on the ONCE [26] validation set. The results of our IA-SSD are shown in bold, and the best results are underlined.

| Method       | Type      | Vehicle overall | Pedestrian overall | Cyclist overall |
|--------------|-----------|-----------------|--------------------|-----------------|
|              |           | 0-30m 30-50m >50m| 0-30m 30-50m >50m | 0-30m 30-50m >50m|
| PointPillars [18] | Voxel-based | 68.57 80.86 62.07 | 47.04             | 47.45 32.75 18.99 |
| SECOND [49]     | Voxel-based | 71.19 84.04 63.02 | 47.25             | 47.45 32.75 18.99 |
| CenterPoints [56] | Voxel-based | 66.99 80.10 59.55 | 43.39             | 47.45 32.75 18.99 |
| PV-RCNN [36]    | Point-Voxel | 77.77 89.39 72.55 | 58.64             | 47.45 32.75 18.99 |
| IA-SSD (Ours)   | Point-based | 70.30 83.01 62.84 | 47.01             | 47.45 32.75 18.99 |

Table 6. Efficiency comparison of different methods on the KITTI validation set. Here, “Mem.” and “Paral.” denote the GPU memory footprint per frame during inference and the maximum number of batches that can be parallelized on one RTX2080Ti (11GB). “Speed” is inference speed when processing one frame or full-loaded GPU memory, " Input Scale" means dividing the scene into four parallel parts to speed up the first sampling layer. For a fair comparison, we also report each input scale of voxels/points according to their official setting.

| Method       | Mem. | Paral. | Speed | Speed | Input Scale |
|--------------|------|-------|-------|-------|-------------|
| PointPillars [18] | 354 MB | 28 | 48 | 58 | 2~9k |
| SECOND [49] | 710 MB | 14 | 30 | 40 | 11~17k |
| TA-Net [24] | 3000 MB | 3 | 20 | 28 | <12k |
| 3DSSD [52] | 502 MB | 19 | 11 | 28 | 16384 |
| PointRCNN [36] | 560 MB | 18 | 10 | 14 | 16384 |
| Part-â‡’ [39] | 702 MB | 13 | 12 | 19 | 11~17k |
| PV-RCNN [36] | 1223 MB | 8 | 8 | 10 | 11~17k |
| IA-SSD (Ours) | 102 MB | 100 | 23/48 | 83 | 16384 |


Figure 3. Qualitative results achieved on the KITTI test set. Red point for centroid perception, while gold points denote the 256 representative points. Green boxes for car, cyan for pedestrian and yellow for cyclist. Best viewed in color.

| Centroid Perception Type | Car Mod (IoU=0.7) | Ped. Mod (IoU=0.5) | Cyc. Mod (IoU=0.5) |
|-------------------------|-----------------|-----------------|-----------------|
| (1) Centers-assign      | 79.27           | 24.90           | 37.12           |
| (2) Origin-assign       | 79.18           | 55.62           | 69.37           |
| (3) Extend-factor assign| 79.37           | 58.36           | 68.16           |
| (4) Extend-length assign| 79.57           | 58.91           | 71.24           |

Table 8. Ablation study of IA-SSD framework with different centroid perception strategies.

For small objects, since the representative points lie in the ground-truth bounding boxes are actually quite limited. We are also noticed that both the extend-factor (2 × size for each bounding box) and extend-length (+1.0m for each bounding box) have their own advantage in specific categories, showing that different contextual information may have a varying impact on different objects.

5. Conclusion

In this paper, we propose an efficient solution termed IA-SSD for point-based 3D object detection in LiDAR point clouds. Considering the task of object detection inherently focuses on the foreground information, we propose an instance-aware learning-based downsampling way to automatically select the sparse yet important instance points. Additionally, a dedicated contextual centroid perception module is proposed to fully exploit the geometrical structure around the bounding boxes. Extensive experiments conducted on three detection benchmarks demonstrated the superior efficiency and accuracy of the proposed IA-SSD.

Limitations. Although the proposed IA-SSD can achieve remarkable efficiency in object detection of large-scale LiDAR points clouds, it also has limitations. e.g., the instance-aware sampling relies on the semantic prediction of each point, which is susceptible to class imbalances distribution. For future work, we will further explore advanced techniques to alleviate the imbalanced issue.

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Appendix

A. Details of The Proposed IA-SSD

(1) Detailed Network Architecture. Here, we provide the detailed architecture of our IA-SSD. The proposed IA-SSD has a lightweight backbone, which consists of three SA (Set Abstraction) layers [32] with only two radii for the spherical neighbor query. The detailed architecture deployed on KITTI Dataset is as follows:

Syntax: \( SA(npoint, \text{radii}, \text{nquery}, \text{dimension}) \)

\[
SA(4096, [0.2, 0.8], [16, 32], [[16, 16, 32], [32, 32, 64]]) \rightarrow MLP(96 \rightarrow 64) \\
SA(1024, [0.8, 1.6], [16, 32], [[64, 64, 128], [64, 96, 128]]) \rightarrow MLP(256 \rightarrow 128) \\
SA(512, [1.6, 4.8], [16, 32], [[128, 128, 256], [128, 256, 256]]) \rightarrow MLP(512 \rightarrow 256)
\]

where \( npoint \) denotes the number of sampled points, \( \text{radii} \) denote the grouping radii, \( \text{nquery} \) denotes the number of grouping points, \( \text{dimension} \) denotes the feature dimensions.

The class/centroid-aware prediction layer:

\[ MLP(256 \rightarrow 256 \rightarrow 3) \]

The architecture of the contextual instance centroid perception module is as follows:

\[ MLP(256 \rightarrow 128 \rightarrow 3) \]

The architecture of centroid-based instance aggregation is as follows:

\[ SA(256, [4.8, 6.4], [16, 32], [[356, 356, 512], [256, 512, 1024]]) \rightarrow MLP(1536 \rightarrow 512) \]

The final detection head is composed of two branches:

\[
\text{cls branch} : FC(512) \rightarrow FC(256) \rightarrow FC(256) \rightarrow FC(3) \\
\text{reg branch} : FC(512) \rightarrow FC(256) \rightarrow FC(256) \rightarrow FC(30)
\]

Considering the large-scale spatial ranges and increasing number of potential instances in the Waymo and ONCE datasets, the number of sampled points are improved to 16384, 4096, 2048, and 1024 in our framework, and the contextual centroid perception boundary is improved to 2.0m. The rest of the hyperparameters are kept consistent for a fair comparison.

B. Additional Implementation Details

(1) Data augmentation. During training, we also apply two data augmentation strategies including scene-level augmentation and object-level augmentation. The detailed settings and hyperparameters are as follows:

Scene-level augmentation:

- Random scene flip with a 50% probability.
- Random scene rotation around z-axis with a random value from \([−\frac{π}{2}, \frac{π}{2}]\).
- Random scene scaling with a random factor from [0.95, 1.05].

Object-level augmentation:

- Transform objects from other scenes. In particular, 20 cars, 15 pedestrians, and 15 cyclists are copied to the current scene. Note that, the minimum number of points for a sampled instance is 5.

(2) Training and inference. We train the proposed IA-SSD in an end-to-end fashion with a maximum of 80 epochs. Adam solver with onecycle learning strategy [43] is used for optimization. In our experiment, the batch size is set to 8, and the learning rate is set to 0.01. During inference, our IA-SSD is able to take raw point clouds and generate proposals for all objects in a single forward pass. Finally, all proposals are filtered by 3D-NMS post-processing with an IoU threshold of 0.01 on KITTI and 0.1 on Waymo/ONCE.

C. Additional Experimental Results

(1) Preserving more foreground points really benefits the final detection performance? As mentioned in section 3.2, two instance-aware strategies are proposed to keep high instance recall while hierarchically downsampling the points. However, it remains unclear that whether the more foreground points really benefit the final detection performance. To this end, we further justify the motivation of our IA-SSD here. Specifically, we conduct several groups of experiments based on our framework with different sampling strategies. Note that, the network architecture and parameter settings are kept consistent. The quantitative detection results, accompanied with the instance recall ratio after the last downsampling layers by using different possible combinations of the sampling approaches are shown in Table 9.

From the results in Table 9 we can see that: (1) the instance recall ratio is positively correlated with the final detection performance, especially for small objects with a limited number of points such as pedestrians and cyclists. (2) The detection performance of cars is relatively robust to the variations of sampling strategies, primarily because that car usually has a sufficient number of foreground points remaining after downsampling, hence relatively easy to be
detected. (3) Adopting the proposed instance-aware sampling strategies at the early encoding layers may negatively affect the final detection performance, primarily because of the insufficient semantic information in the early latent point features. (4) Deploying the proposed instance-aware downsampling strategies at the last two encoding layers can significantly improve the detection performance. Overall, this experiment further demonstrates that more foreground points are appealing for object detection task, especially for small but important objects.

(2) Efficiency of Sampling. We further explore the efficiency of different sampling strategies, to have an intuitive idea of the advantages of our instance-aware sampling. Table 10 compares the time and memory consumption of different sampling strategies with a varying number of points. We can clearly see that the proposed instance-aware sampling has superior efficiency compared with the Feat-FPS [52], hence leading to a higher frame rate of our method.

(3) Evaluation on KITTI validation set. We also report the detection results achieved by several representative approaches on the validation set of the KITTI Dataset in Table 9. Note that, all results achieved by baselines are reproducible based on the OpenPCDet library. Note that, all detectors are trained with multi-class objects together, and the results are achieved by using a single detection model.

(4) Efficiency of our IA-SSD on large-scale LiDAR scenarios. To further verify the efficiency of our IA-SSD on large-scale 3D datasets, we further report the efficiency of our IA-SSD on the validation set of Waymo and ONCE datasets. As shown in Table 12, the proposed IA-SSD can still achieve satisfactory real-time performance in such complex panoramic scenes.

(5) Qualitative visualization of our instance-aware downsampling. To intuitively compare the performance of different sampling approaches, we qualitatively show the visualization of the downsampled point clouds achieved by different approaches in Figure 4. Clearly, the proposed instance-aware sampling can effectively preserve more foreground points (shown in red), especially for foreground points belonging to small and sparse instances (e.g., pedestrian), as well instances far away from the sensors.

(6) Visualization of the Contextual Centroid Perception. We also visualize the results produced by our contextual

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Table 9. The correlation between the instance recall ratio and the final detection performance.

| Method       | Recall Car (IoU=0.7) | Recall Car (IoU=0.5) | Recall Ped. (IoU=0.7) | Recall Ped. (IoU=0.5) | Recall Cyc. (IoU=0.7) | Recall Cyc. (IoU=0.5) |
|--------------|----------------------|----------------------|-----------------------|-----------------------|-----------------------|-----------------------|
| Random       | 67.4%                | 72.1%                | 57.3%                 | 75.02                 | 51.16                 | 66.07                 |
| D-FPS        | 91.4%                | 69.1%                | 71.6%                 | 78.12                 | 50.46                 | 65.19                 |
| D-FPS        | 95.3%                | 80.1%                | 91.7%                 | 79.00                 | 54.31                 | 71.08                 |
| D-FPS        | 97.9%                | 94.7%                | 92.7%                 | 79.19                 | 58.81                 | 70.15                 |
| D-FPS        | 97.9%                | 97.7%                | 96.3%                 | 79.54                 | 58.49                 | 71.33                 |
| D-FPS        | 97.9%                | 98.4%                | 97.2%                 | 79.57                 | 58.91                 | 71.24                 |

Table 10. Time and memory consumption of different methods.

| Method       | D-FPS [30]          | Feat-FPS [52]       | Cls/Ctr-aware         |
|--------------|---------------------|---------------------|-----------------------|
| Method       | 256p                | 1024p               | 4096p                 | 16384p                |
| D-FPS        | <0.1 ms             | 0.5 ms              | 2.8 ms                | 23.7 ms               |
| Feat-FPS     | 0.3 ms              | 0.7 ms              | 4.2 ms                | 40.6 ms               |
| Cls/Ctr-aware| 0.2 ms              | 0.2 ms              | 0.3 ms                | 0.5 ms                |

Table 11. Performance comparison of different detectors based on the OpenPCDet library.

| Dataset      | Mem. | Paral. | Speed† | Speed‡ | Input Scale |
|--------------|------|--------|--------|--------|-------------|
| Waymo [44]   | 626 MB | 16     | 9°     | 14     | 81920       |
|              | 433 MB | 23     | 8°     | 20     | 65536       |
| ONCE [26]    | 401 MB | 25     | 11°    | 21     | 60k         |

Table 12. Efficiency of our IA-SSD on Waymo and ONCE Datasets. The number of input points to our framework is increased, considering the large-scale panoramic scenes compared with KITTI. Here “Mem.” and “Paral.” denote the GPU memory footprint per frame during inference and the maximum number of batches that can be parallelized on one RTX2080Ti (11GB).

† "Speed°": "Speedº" is inference speed when processing one frame or full-loaded GPU memory. ‡ We divide the whole scene into four parallel parts in the first sampling layer.

Footnotes:
1. https://github.com/open-mmlab/OpenPCDet
2. https://github.com/qiqihaer/3DSSD-pytorch-openPCDet
centroid perception module in Figure 5. It is clear that the
downsamled point clouds at this stage are quite sparse and
insufficient, which makes the centroid estimation and in-
stance regression considerably difficult. Therefore, it is nec-
essary to exploit the useful information around the instance,
even outside the ground-truth bounding boxes. Thanks to
the proposed contextual centroid perception module, our
IA-SSD can even precept the objects with extremely indis-
tinguishable geometry and limited points (shown in purple
dotted circles). This further demonstrated the effectiveness
of the proposed module.

(7) Additional qualitative detection results on the KITTI
Dataset. We also show extra qualitative detection results
achieved by our IA-SSD on the validation (Figure 6) and
test (Figure 7) split of the KITTI Dataset. It can be seen
that our IA-SSD can achieve satisfactory detection perfor-
mance on this dataset, even for some challenging cases. It
is also worth mentioning that the detection results of dif-
ferent objects are achieved by our IA-SSD in a single pass,
instead of the common practice to train separate models for
different objects.

(8) Additional qualitative detection results on the large-
scale datasets. Here, we present extra qualitative detection
results achieved by our IA-SSD on two large-scale datasets
with challenging panoramic scenarios. Figure 8 and Fig-
ure 9 illustrate the detection results on the validation set of
Waymo and ONCE Dataset respectively. It can be seen that
our IA-SSD can also achieve promising detection perfor-
mance in challenging and complex 3D scenes.

D. Potential Negative Societal Impact

In this paper, we proposed an efficient point-based solu-
tion capable of achieving promising low-cost objects detec-
tion in autonomous driving scenarios. Our model is trained
and evaluated totally based on open-sourced datasets, and
there is no known potential negative impact on society.

E. Video Illustration

We provide a video demo illustrating the detection per-
formance of our IA-SSD in 3D point clouds, which can be viewed at https://youtu.be/3jP2o9KXunA.
Figure 4. Qualitative visualization of the downsampled point clouds achieved by different sampling strategies (From left to right, D-FPS, F-FPS, and the proposed instance-aware sampling). Note that, the raw point clouds and representative points are colored in white and gold, respectively. Positive representative points are highlighted in red.

Figure 5. Visualization of the contextual centroid perception on the validation split of the KITTI dataset. All representative points and predicted centroid are colored in gold and red, respectively. In particular, we also show the offsets of representative points inside/around the objects in red/gold. Best viewed in color.
Figure 6. Extra qualitative results achieved by our IA-SSD on the validation set of the KITTI Dataset. We also show the corresponding projected 3D bounding boxes on images. Note that, the ground-truth bounding boxes are shown in red, and the predicted bounding boxes are shown in green for car, cyan for pedestrian, and yellow for cyclist. Best viewed in color.
Figure 7. Extra qualitative results achieved by our IA-SSD on the test set of the KITTI Dataset. We also show the corresponding projected 3D bounding boxes on images. Note that, there is no ground-truth bounding boxes available, hence we only show the predicted bounding boxes in green for car, cyan for pedestrian, and yellow for cyclist. The centroid predictions are marked in red, while the 256 representative points are shown in gold. Best viewed in color.
Figure 8. Extra qualitative results achieved by our IA-SSD on the val set of the Waymo Dataset. Here we demonstrate our detection results on some challenging scenes. Note that, the ground-truth bounding boxes are shown in red, and the predicted bounding boxes are shown in green for vehicle, cyan for pedestrian, and yellow for cyclist. Best viewed in color.

Figure 9. Extra qualitative results achieved by our IA-SSD on the val set of the ONCE Dataset. Here we demonstrate our detection results on some challenging scenes. Note that, the ground-truth bounding boxes are shown in red, and the predicted bounding boxes are shown in green for vehicle, cyan for pedestrian, and yellow for cyclist. Best viewed in color.