SEFormer: Structure Embedding Transformer for 3D Object Detection

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Abstract
Effectively preserving and encoding structure features from objects in irregular and sparse LiDAR points is a crucial challenge to 3D object detection on the point cloud. Recently, Transformer has demonstrated promising performance on many 2D and even 3D vision tasks. Compared with the fixed and rigid convolution kernels, the self-attention mechanism in Transformer can adaptively exclude the unrelated or noisy points and is thus suitable for preserving the local spatial structure in the irregular LiDAR point cloud. However, Transformer only performs a simple sum on the point features, based on the self-attention mechanism, and all the points share the same transformation for value. A such isotropic operation cannot capture the direction-distance-oriented local structure, which is essential for 3D object detection. In this work, we propose a Structure-Embedding transformer (SEFormer), which can not only preserve the local structure as a traditional Transformer but also have the ability to encode the local structure. Compared to the self-attention mechanism in traditional Transformer, SEFormer learns different feature transformations for value points based on the relative directions and distances to the query point. Then we propose a SEFormer-based network for high-performance 3D object detection. Extensive experiments show that the proposed architecture can achieve SOTA results on the Waymo Open Dataset, one of the most significant 3D detection benchmarks for autonomous driving. Specifically, SEFormer achieves 79.02\% mAP, which is 1.2\% higher than existing works. https://github.com/tdzdog/SEFormer.

Introduction
Point cloud-based 3D object detection has attracted more and more attention with the development of autonomous driving and robotics. Due to the lack of texture and color information in the point cloud, 3D object detection highly depends on the structure information of local areas. However, unlike the grid-arranged 2D images, the sparse and irregular nature of LiDAR point clouds makes the local structure often incomplete and noisy. Hence, how to effectively extract the essential structure feature still needs to be solved.

Inspired by the success of 2D object detection (Ren et al. 2015; Wu et al. 2021a,b; Shrivastava, Gupta, and Girshick 2016; Sun et al. 2021b; Chi, Wei, and Hu 2020; Dong et al. 2022), convolution rapidly becomes the mainstream operator in 3D object detection. Traditional convolution-based 3D object detection can be divided into two main trends: point (Qi et al. 2017a,b; Shi, Wang, and Li 2019; Qi et al. 2018; Yang et al. 2020; Chen et al. 2022; He et al. 2022b) and voxel-based solutions (Yan, Mao, and Li 2018; Shi et al. 2020; Deng et al. 2020; Zheng et al. 2021; Lang et al. 2019; Shi et al. 2022; Li et al. 2021b,a; Xu, Zhong, and Neumann 2022).

However, convolution is designed with fixed and rigid kernel sizes and treats all neighboring points equally. Therefore, it inevitably contains unrelated or noisy points from other objects or backgrounds. Recently, Transformer (Vaswani et al. 2017) has shown its effectiveness in 3D vision tasks such as classification, segmentation and object detection (Zheng et al. 2022; Zhao et al. 2021; Wang et al. 2022).
Our main contributions are threefold: first, final bounding boxes are generated based on such object-level structure description for 3D object detection. Precisely, we extract multi-scale SEFormer network to extract local structure description for 3D object detection. Secondly, we introduce the proposed SEFormer unit, including its motivation and corresponding architecture. Then, we present the proposed detection architecture in the following sections.

Method

3D Object Detection on Point Cloud. 3D object detection methods on point clouds have made a giant leap recently. According to different input representations, recent research can be categorized into two families: point- and voxel-based.

(1) Point-based Object Detection. Many works (Qi et al. 2019; Xie et al. 2021; Chen et al. 2022) propose to directly process raw point cloud data by adopting point-based backbones, such as PointNet (Qi et al. 2017a) and PointNet++ (Qi et al. 2017b). To process a mass of LiDAR points in outdoor environments, i.e., KITTI (Geiger et al. 2013) and Waymo (Sun et al. 2020), previous point-based approaches (Qi et al. 2018; Shi, Wang, and Li 2019; Yang et al. 2019) usually downsample the input point cloud and disturbed by the information loss. (2) Voxel-based Object Detection. Voxel-based works (Yan, Mao, and Li 2018; Shi et al. 2020; Deng et al. 2020; Xu, Zhong, and Neumann 2022) transform raw point cloud into compact voxel-grid representation and utilize efficient 3D sparse convolution operator so high-resolution voxelization can be adopted during computation. In this work, we mainly refer to voxel-based ones when talking about convolution-based works.

Transformer for 3D Object Detection. Many researchers are motivated by the recent success of Transformer in point cloud processing (Guo et al. 2021; Fan, Yang, and Kankanhalli 2021; Zhao et al. 2021; Fan, Yang, and Kankanhalli 2022) and have tried to introduce Transformer into 3D object detection. Pointformer (Pan et al. 2021) follows their paradigm and designs three Transformers to extract features from different scales. Voxel Transformer (Mao et al. 2021b) combines Transformer with voxel representation and achieves much higher precision. Fan et al. (2022) propose a single-stride Transformer that improves the detection precision on small objects such as pedestrians and cyclists. However, the vanilla Transformer adopted in such works lacks the ability of local structure encoding. Hence we propose SEFormer to better extract local structure.

Extensive experiments prove the advantages of our SEFormer. On the Waymo Open dataset, we achieve 79.02% mAP, which is 1.2% higher than existing works.

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Method

In this section, we first introduce the proposed SEFormer unit, including its motivation and corresponding architecture. Then, we present the proposed detection architecture in the following sections.

Structure Embedding Transformer (SEFormer)

Structure Preserving & Encoding. Before introducing SEFormer, we will first state our primary motivation, achieving simultaneous structure-preserving and encoding. Such motivation comes from one critical insight we have on two existing operators, convolution and Transformer.

Convolution is the most famous operator in computer vision tasks because convolution’s locality and spatial invariance adapt well to the inductive bias in images. While we propose another essential advantage of convolution is that it...
can **encode** the structural information of data. To illustrate such a point, we first formulate convolution as follows:

$$f'_p = \sum_\delta w(\delta(p)) \cdot f_{p+\delta(p)}$$  (1)

Here $f, f'$ represents the input and output feature of a convolution layer at center position $p$, while $\delta$ denotes the relative position between the neighboring points and the center point. We decompose convolution as a two-step operator, transformation and aggregation. Each point will be multiplied during transformation by its corresponding kernel $w(\delta)$. Then these points will be summed with a fixed aggregation coefficient $\alpha = 1$. The kernels are differently learned in convolution based on their directions and distances to the kernel center. Hence convolution can **encode** the local spatial structure into the output. However, in convolution, all neighboring points are equally $(\alpha = 1)$ treated during aggregation. The mainstream convolution operator adopts a static and rigid kernel, but the LiDAR point cloud is often irregular and incomplete. Hence convolution inevitably includes irrelevant or noisy points in the output feature.

Compared with convolution, the self-attention mechanism in Transformer provides a more effective method to **preserve** the irregular objects’ shapes and boundaries in Point Cloud. For a point cloud with $N$ points, $p = [p_1, \ldots, p_N]$, Transformer computes the response of each point as:

$$f'_w = \sum_\delta \alpha(\delta(p)) \cdot W^v f_{p+\delta(p)}$$  (2)

Here $\alpha(\delta)$ represents the self-attention coefficients among points in the neighboring area while $W^v$ means the value transformation. We can still decompose Eq. 2 into a transformation process with a transformation matrix $W^v$ and an aggregation process with attention coefficients $\alpha(\delta)$. The coefficient $\alpha_{ij}$ between point $p_i$ and $p_j$ can be calculated as $\alpha_{ij} = \frac{\exp(e_{ij})}{\sum_k \exp(e_{ik})}$. Here $e_{ij} = \frac{(W^q f_i)(W^k f_j)^T}{\sqrt{d}}$ is the scaled dot-produce attention between $p_i$ and $p_j$ and $W^q, W^k$ represent the transformation matrix for query and key. Compared with the static $\alpha = 1$ in convolution, the self-attention coefficients allow the Transformer to adaptively choose the points for aggregation and exclude the influence of unrelated points. We call Transformer’s such ability as **structure preserving**. However, according to Eq. 2, the same transformation for value is shared among all the points in Transformer. It means that the Transformer misses the **structure encoding** ability, which convolution has.

Given the above discussion, we can find that convolution can **encode** data structure while Transformer can well **preserve** the structure. Hence, the straightforward idea is to design a new operator with both convolution and Transformer advantages. Hence we propose a new Transformer, SEFormer, which can be formulated as follows:

$$f'_p = \sum_\delta \alpha_\delta(p) \cdot W^v f_{p+\delta(p)}$$  (3)

If we compare Eq. 3 with Eq. 2, we can find the most difference between SEFormer and vanilla Transformer is that different transformations for value points are learned based on the relative positions between points.

**Architecture of SEFormer.** Fig. 3 provides a comparison between the vanilla Transformer and the proposed SE-
SEFormer Based 3D Object Detection

The whole detection framework is shown in Fig. 2. We first construct a 3D CNN backbone for multi-scale voxel features extraction and initial proposals generation. Then a multi-scale SEFormer network is applied to extract richer local structure features from the voxel features. It contains a SEFormer-based spatial structure module for point-level structure features and a SEFormer-based ROI head for object-level structure features.

3D CNN Backbone. The CNN backbone transforms the input into multiple voxel features with $1 \times 2 \times 4$ and $8 \times 8$ downsampling sizes. After the feature extraction, the $8 \times 3D$ feature volume will be compressed along the $Z$-axis and converted into a 2D BEV feature map. Then a center-based approach (Yin, Zhou, and Krahenbuhl 2021) is applied to predict first-stage proposals based on the BEV feature map.

SEFormer Based Spatial Structure module. Then the proposed spatial structure module aggregates the multi-scale features $[\text{F}^{(1)}, \text{F}^{(2)}, \text{F}^{(3)}, \text{F}^{(4)}]$ into several point-level embedding $\text{E}$. Starting from $\text{E}_{\text{final}}$, we first integrate the finest-grained features $\text{F}^{(1)}$. Each embedding point’s corresponding key points are interpolated from $\text{F}^{(1)}$. We use $m$ different grid distance $d$ to generate sets of multi-scale key features as $\text{F}_{1}^{(1)}, \text{F}_{2}^{(1)}, \ldots, \text{F}_{m}^{(1)}$. Such a multi-radii strategy can better handle the sparse and irregular point distribution in LiDAR. Then $m$ parallel SEFormer blocks which contain multiple SEFormer units are applied and result in $m$ new embedding $\text{E}_{1}^{(1)}, \text{E}_{2}^{(1)}, \ldots, \text{E}_{m}^{(1)}$. In the end of the block, $\text{E}_{1}^{(1)}, \text{E}_{2}^{(1)}, \ldots, \text{E}_{m}^{(1)}$ are concatenated and transformed into embedding $\text{E}^{(1)}$ with a vanilla Transformer. Then $\text{E}^{(1)}$ repeats the above process and aggregates $[\text{F}^{(2)}, \text{F}^{(3)}, \text{F}^{(4)}]$ into the final embedding $\text{E}_{\text{final}}^{(4)}$. Compared with the original voxel features $\text{F}$, the embedding $\text{E}_{\text{final}}^{(4)}$ aggregated contains a richer structural description of the local neighboring area.

SEFormer Based ROI Head. Based on the point-level embeddings $\text{E}_{\text{final}}^{(4)}$, the proposed head aggregates it into several object-level embeddings to generate final proposals. Specifically, we divide each proposal from the first-stage center-based head into multiple cubic sub-regions and interpolate each sub-region with surrounding point-level embedding features. Due to the sparsity of the point cloud, some sub-regions are often empty. Traditional works simply sum the features from the non-empty parts. However, the car side away from the LiDAR source is often sparse. Hence the relative positions of the empty sub-regions can provide a useful object-level structure feature for direction recognition. In contrast, the proposed SEFormer can utilize such information by embedding both the full and empty sub-regions. As shown in part III of Fig. 2, a SEFormer block takes in both the empty and non-empty sub-regions and integrates their features into a proposal embedding $\text{OE}_{\text{final}}^{(4)}$. The stronger structure embedding ability of SEFormer can provide a better description of the object-level structure and then generates more accurate 3D proposals.
Table 1: Performance comparison on the Waymo Open Dataset with 202 validation sequences for the 3D vehicle detection. Only one frame is used for training and testing. * is re-implemented by (Zhou et al. 2020). 20% training data are used for most methods. While † denotes methods that use the whole 100% training dataset.

| Methods                  | LEVEL_1 (IoU=0.7) | LEVEL_2 (IoU=0.7) | LEVEL_1 3D mAP/mAPH by Distance |
|--------------------------|-------------------|-------------------|-----------------------------|
|                          | 3D mAP/mAPH       | 3D mAP/mAPH       | 0-30m | 30-50m | 50m-Inf |
| PointPillars (Lang et al. 2019)* | 56.62/- | -/- | 81.01/- | 51.75/- | 27.94/- |
| MVF (Zhou et al. 2020)   | 62.93/- | -/- | 86.30/- | 60.02/- | 36.02/- |
| AFDet (Ge et al. 2020)   | 63.69/- | -/- | 87.38/- | 62.19/- | 29.27/- |
| Pillar-OD (Wang et al. 2020) | 69.8/- | -/- | 88.5/- | 66.5/- | 42.9/- |
| CVCNet (Chen et al. 2020) | 65.2/- | -/- | 86.80/- | 62.19/- | 29.27/- |
| SVGA-Net (He et al. 2022b) | 73.45/- | 66.65/- | 92.53/- | 69.44/- | 42.08/- |
| VoTr-SSD (Mao et al. 2021b) | 68.99/68.39 | 60.22/59.69 | 88.18/87.62 | 66.73/66.05 | 42.08/41.38 |
| PV-RCNN (Shi et al. 2020) | 70.3/69.7 | 65.4/64.8 | 91.9/91.3 | 69.2/68.5 | 42.2/41.3 |
| VoTr-TSD (Mao et al. 2021b) | 74.95/74.25 | 65.9/65.29 | 92.28/91.73 | 73.36/72.56 | 51.09/50.01 |
| RSN (Sun et al. 2021a)† | 75.1/74.6 | 66.0/65.5 | 91.8/91.4 | 73.5/73.1 | 53.1/52.5 |
| VoxeRCNN (Deng et al. 2020) | 75.59/- | 66.59/- | 92.49/- | 74.09/- | 53.15/- |
| SCIR-Net(He et al. 2022c) | 75.63/- | 66.73/- | 92.55/- | 74.42/- | -/- |
| LiDAR RCNN(Li, Wang, and Wang 2021)† | 76.0/75.5 | 68.3/67.9 | 92.1/91.6 | 74.6/74.1 | 54.5/53.4 |
| SST_TS (Fan et al. 2022)† | 76.22/75.79 | 68.0/67.64 | -/- | -/- | -/- |
| CT3D (Sheng et al. 2021) | 76.30/- | 69.04/- | 92.51/- | 75.07/- | 55.36/- |
| Pyramid RCNN(Mao et al. 2021a) | 76.30/75.68 | 67.23/66.82 | 92.67/92.20 | 74.91/74.24 | 54.54/54.45 |
| CenterPoint(Yin, Zhou, and Krahenbuhl 2021)† | 76.76/68.8 | 76.2/68.3 | -/- | -/- | -/- |
| PDV (Hua, Kuai, and Waslander 2022) | 76.85/76.33 | 69.30/68.81 | 93.13/92.71 | 75.49/74.91 | 54.75/53.90 |
| Vox-to-Point(Li et al. 2021b) | 77.24/- | 69.77/- | 93.23/- | 76.21/- | 55.79/- |
| PV-RCNN++(Shi et al. 2022) | 77.32/- | 68.62/- | -/- | -/- | -/- |
| VoxSet (He et al. 2022a) | 77.82/- | 70.21/- | 92.78/- | 77.21/- | 54.41/- |
| Ours                      | 79.02/78.52 | 70.31/69.85 | 93.10/92.66 | 78.07/77.54 | 57.60/56.87 |

Experiment

In this work, we mainly evaluate the proposed SEFormer on Waymo. Because its large data scale can provide much more convincing evaluation than other benchmarks. We will first introduce Waymo and describe the details of our implementation. Then we will compare with state-of-the-art works on Waymo Open and provide an ablation analysis for the proposed method.

Implementation Details

Waymo Open Dataset. The Waymo dataset contains 1000 LiDAR sequences in total. These sequences are further split into 798 training sequences (including around 158k LiDAR samples) and 202 validation sequences (including around 40k LiDAR samples). Waymo provides object annotations in the entire 360° field. Its Official evaluation metrics include the standard 3D mean Average Precision (mAP) and mAP weighted by heading accuracy (mAPH). In this work, we present such two metrics mainly from two aspects: difficulty levels and object distance. For the first way, the ground-truth boxes are divided into two groups: LEVEL_1 (number of points is more than five) and LEVEL_2 (the box contains at least one point). For the second way, apart from the overall mAP, we will also show respective mAP for objects located in 0 – 30m, 30 – 50m, and > 50m.

Network Architecture. First, the points within the range of [−75.2, 75.2]m, [−75.2, 75.2]m, and [−2, 4]m for the X, Y, and Z-axis are extracted. Then they are voxelized with a (0.05m, 0.05m, 0.1m) step. Our first-stage convolution backbone and the BEV neck follow the same architecture in (Yan, Mao, and Li 2018). The 3D backbone transforms the input into 1 × 2 × 4 × 8 downsampled voxel volumes with 16, 32, 64, 64 dimensions respectively. In the SEFormer based spatial structure module, 4096 query points are selected for each scene. In the SEFormer head, each proposal is divided into 6 × 6 × 6 sub-regions.

Training and Inference. We use 4 RTX 3090 GPUs to train the entire network with batch size 8. We keep most training and inference hyper-parameters same with existing works (Mao et al. 2021a; Shi et al. 2022; Deng et al. 2020; Mao et al. 2021b; Sheng et al. 2021) for a fair comparison. We adopt AdamW optimizer and one-cycle policy (Smith and Topin 2019) with division factor 10 and momentum ranges from 0.95 to 0.85 to train the model. The learning rate is initialized with 0.003. The training time is 40 epochs. Given the large scale of Waymo dataset, we uniformly use 20% training samples for training but use the whole validation set for evaluation.

Detection Results on Waymo Detection Dataset

Fig. 4 illustrates a qualitative presentation of our detection results on Waymo dataset. Table 1 and Table 2 show the 3D detection results on Waymo Open Dataset. 0.7 IoU threshold is adopted for both evaluations. We mainly compare the one-frame detection results here.

In Table 1, it can be found further improvement of current 3D object detection has become more and more difficult. However, our SEFormer can still achieve a significant improvement compared with prior works. For the commonly
used LEVEL\textsubscript{1} mAP/mAPH, we achieve 79.02%/78.52%, which exceeds state-of-the-art works by 1.2% for the LEVEL\textsubscript{1} mAP. For the difficult LEVEL\textsubscript{2} result, we can still get the SOTA results and achieve 70.31%/69.85% for mAP/mAPH. Such results demonstrate the effectiveness of the proposed SEFormer. To evaluate the influence of object distance, we also provide the range-based LEVEL\textsubscript{1} mAP/mAPH. Although we show lower precision on near objects (<30m), 93.10% mAP vs 93.23% mAP, our improvement for distant objects is much more significant. The improvement for 30 – 50m and 50m – Inf targets achieves 0.86% and 3.19% mAP respectively. In most cases, the distant objects are often sparse and only show part of the outline of the objects, which makes extracting useful structure information much more difficult. While SEFormer’s structure preserving and encoding ability alleviates such problem.

In Table 2, SEFormer also outperforms prior works on BEV precision. 91.73% LEVEL\textsubscript{1} and 85.18% LEVEL\textsubscript{2} BEV mAP are achieved. It can be found that the LEVEL\textsubscript{2} improvement is higher. Compared with LEVEL\textsubscript{1}, LEVEL\textsubscript{2} contains objects that have very few points. Hence such BEV results also support the above claim that SEFormer has more advantages for sparse objects.

### Ablation Study

**Comparison between vanilla Transformer and SEFormer.** In this work, we propose a new Transformer, SEFormer, to encode the local spatial structure. Hence we compare the performance of the vanilla Transformer and the proposed SEFormer in Table 3. The T and S represent vanilla Transformer and out SEFormer respectively. In this work, we propose a SEFormer based spatial structure module (SSM) and a SEFormer based head to extract point- and object-level structure features. Hence we use Transformer based SSM and head as the baseline. It can be found vanilla Transformer only achieves 76.10%/75.61% and 68.24%/67.78% for LEVEL\textsubscript{1} and LEVEL\textsubscript{2} mAP/mAPH. Replacing Transformer in SSM with SEFormer improves the performance to 77.54%/77.05% LEVEL\textsubscript{1} mAP/mAPH and 68.82%/68.38% LEVEL\textsubscript{2} mAP/mAPH. If we further replace the Transformer in the head with SEFormer, we can further get 1.48% LEVEL\textsubscript{1} mAP and 1.49% LEVEL\textsubscript{2} mAP improvement respectively. The results illustrate that the proposed SEFormer has a better ability to capture the structural features of local areas than Transformer. In most Transformer based works, relative position encoding is often used as a method to introduce the relative spatial relationship. Hence we use relative position encoding in both the Transformer based baseline and our SEFormer for a fair comparison. Hence the improvement of SEFormer over Transformer shows that simple relative position encoding cannot fully encode the structure information.

**Effect of the number of parallel SEFormer blocks.** As noted in Section 5, multiple parallel SEFormer blocks with different search radii are established. Hence, we investigate the effects of the number of parallel SEFormer blocks in Table 4. In implementation, the parallel SEFormer blocks have gradually doubled search radii. While we set the initial radii as 0.4/0.8/1.2/2.4 for the multi-scale features. According to the results, it can be found that 2 parallel SEFormer blocks achieve the best performance. Increasing or decreasing the block number causes about 0.2% LEVEL\textsubscript{1} mAP reduction.

**Effect of the number of heads.** Multi-head Transformer often has better performance than single-head Transformer. Hence, we provide an investigation of the effects of head number in Table 5. It can be found that single-head SEFormer achieves 78.87%/78.37% and 70.14%/69.09% for LEVEL\textsubscript{1} and LEVEL\textsubscript{2} mAP/mAPH respectively. Adopting double-head SEFormer can reach 79.02%/78.52% LEVEL\textsubscript{1} and 70.31%/69.85% LEVEL\textsubscript{2} mAP/mAPH. But the results reduce if we further increase the head number. Hence we choose head number $h = 2$ in this work.

**Effect of multi-scale features.** Table 6 demonstrates the effects of using multi-scale features. Only using the single-scale feature (conv1) only achieves 78.54% and 69.94%

### Table 2: Comparison of BEV vehicle detection on the WOD with 202 validation sequences. * is re-implemented by (Zhou et al. 2020). We only use 20% training data.

| Diff. | Methods | Overall | 0-30m | 30-50m | 50m-Inf |
|-------|---------|---------|-------|--------|---------|
| LV\textsubscript{1} | PointPillars(2019)* | 75.57 | 92.10 | 74.06 | 55.47 |
| | MVF(2020) | 80.40 | 93.59 | 79.21 | 63.09 |
| | Pillar-OD (2020) | 87.11 | 95.78 | 84.87 | 72.12 |
| | PV-RCNN (2020) | 82.96 | 97.35 | 82.99 | 64.97 |
| | SVGA-Net (2022b) | 83.52 | 97.60 | 83.14 | 64.52 |
| | Voxel RCNN (2020) | 88.19 | 97.62 | 87.34 | 77.70 |
| | SCIR-Net (2022c) | 88.45 | 97.71 | 88.41 | 78.9 |
| | LiDAR RCNN (2021) | 90.1 | 97.0 | 89.5 | 78.9 |
| | Vox-to-Point(2021b) | 89.93 | 98.05 | 88.25 | 79.19 |
| | VoxSet(2022a) | 90.31 | 96.11 | 88.12 | 77.98 |
| | Ours | 91.73 | 98.13 | 91.23 | 82.12 |
| LV\textsubscript{2} | PV-RCNN (2020) | 77.45 | 94.64 | 80.39 | 55.39 |
| | SVGA-Net (2022b) | 80.97 | 95.54 | 81.58 | 60.18 |
| | Voxel RCNN (2020) | 81.07 | 96.99 | 81.37 | 63.26 |
| | SCIR-Net (2022c) | 81.65 | 96.88 | 81.34 | - |
| | LiDAR RCNN (2021) | 81.7 | 94.3 | 82.3 | 65.8 |
| | Vox-to-Point(2021b) | 82.18 | 97.48 | 82.51 | 64.86 |
| | VoxSet(2022a) | 80.56 | 96.79 | 80.44 | 62.37 |
| | Ours | 85.18 | 97.55 | 85.99 | 69.48 |

### Table 3: Comparison between vanilla Transformer and SEFormer. Here SSM and Head respectively denote the spatial structure module and the detection head while T and S represent vanilla Transformer and SEFormer respectively.

| Block Num (m) | LV\textsubscript{1} (IoU=0.7) | LV\textsubscript{2} (IoU=0.7) |
|---------------|-----------------|-----------------|
|               | 3D mAP/mAPH     | 3D mAP/mAPH     |
| 1             | 76.10/75.61     | 68.24/67.78     |
| 2             | 79.02/78.52     | 70.31/69.85     |
| 3             | 79.02/78.52     | 70.31/69.85     |

### Table 4: Effects of the number of parallel SEFormer blocks.

| Head | LV\textsubscript{1} (IoU=0.7) | LV\textsubscript{2} (IoU=0.7) |
|------|-----------------|-----------------|
|      | 3D mAP/mAPH     | 3D mAP/mAPH     |
| T    | 78.76/78.25     | 70.08/69.62     |
| S    | 79.02/78.52     | 70.31/69.85     |
| T    | 79.02/78.52     | 70.31/69.85     |
| S    | 78.81/78.32     | 70.00/69.55     |

### Table 5: Effects of the number of parallel SEFormer blocks.

| Head | LV\textsubscript{1} (IoU=0.7) | LV\textsubscript{2} (IoU=0.7) |
|------|-----------------|-----------------|
|      | 3D mAP/mAPH     | 3D mAP/mAPH     |
| T    | 78.76/78.25     | 70.08/69.62     |
| S    | 79.02/78.52     | 70.31/69.85     |
| T    | 79.02/78.52     | 70.31/69.85     |
| S    | 78.81/78.32     | 70.00/69.55     |
**Conclusion**

This work proposes a new Transformer, SEFormer. In vanilla Transformer, all the value points share the same transformation. Hence it lacks the ability to encode the distance-direction-oriented local spatial structure. To solve such problem, SEFormer learns different transforms for value points based on their relative directions and distances to the center query point. Based on the proposed SEFormer, we establish a new 3D detection network including a SEFormer based spatial structure module to extract point-level structure information and a SEFormer based head to capture object-level structure features. Compared with state-of-the-art solutions, our SEFormer achieves higher detection precision on the Waymo Open dataset.

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**Table 5: Effects of the head number in SEFormer.**

| Head Num (h) | LV.1 (IoU=0.7) 3D mAP/mAPH | LV.2 (IoU=0.7) 3D mAP/mAPH |
|--------------|-------------------------------|-------------------------------|
| 1            | 78.87/78.37                  | 70.14/69.69                  |
| 2            | 79.02/78.52                  | 70.31/69.85                  |
| 4            | 79.00/78.51                  | 70.30/69.85                  |

**Table 6: Effects of multi-scale features.**

| conv1 conv2 conv3 conv4 | LV.1 (IoU=0.7) 3D mAP/mAPH | LV.2 (IoU=0.7) 3D mAP/mAPH |
|-------------------------|-------------------------------|-------------------------------|
| ✓ ✓ ✓ ✓                  | 78.77/78.29                  | 69.98/69.52                  |

**Table 7: Effects of grid interpolation.**

| SSM Structure | LEVEL.1 (IoU=0.7) 3D mAP/mAPH | LEVEL.2 (IoU=0.7) 3D mAP/mAPH |
|---------------|-------------------------------|-------------------------------|
| w/o GI        | 78.83/78.14                  | 69.83/69.38                  |
| w/ GI         | 79.02/78.52                  | 70.31/69.85                  |

**Table 8: Comparison among different SSM structures.**

| (a)           | 78.70/78.23                  | 70.04/69.36                  |
| (b)           | 78.86/78.39                  | 70.12/69.68                  |
| (c)           | 79.02/78.52                  | 70.31/69.85                  |

LEVEL.1 and LEVEL.2 mAP. Introducing more features of different scales gradually improves the performance while using features of all 4 scales reduces the precision to some extent. Please see our supplementary material for more results.

**Effect of grid interpolation.** Table 7 illustrates the effects of grid interpolation. For the control group, grid interpolation is replaced with random sampling within a radius. Please see our supplementary material for more results and discussions.

**Structure of the spatial structure module.** In the spatial structure module, we aggregate the multi-scale features one by one. While multiple SEFormer blocks with different radii are adopted to extract structure information from one feature. To show the effects of such strategy, we design three different structures for the spatial structure module, fully parallel, full chained, and half parallel half chained. Fig. 5 illustrates the difference among such three structures. Half parallel half chained denotes the structure used in this work. Their effects on model performance are shown in Table 8. It can be found that the half parallel half chained structure has better results than others.

**Figure 4:** Qualitative visualization on WOD. The green boxes denote the groundtruth.

**Figure 5:** Illustration of (a) fully parallel (b) fully chained and (c) half parallel half chained spatial structure module.
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