

PETrv2: A Unified Framework for 3D Perception from Multi-Camera Images

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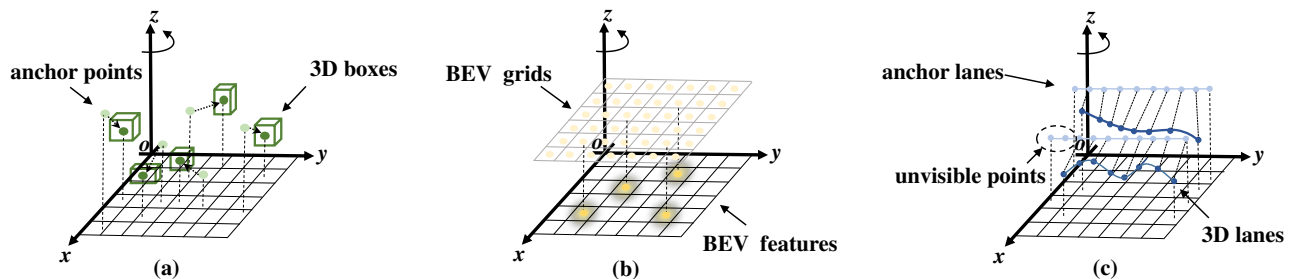


Figure 1. Three kinds of task-specific queries for multi-tasks: (a) 3D object detection (b) BEV segmentation (c) 3D lane detection. The detection queries are defined in the whole 3D space and initialized with anchor points. The segmentation queries are initialized with BEV grid points and represent different BEV patches. The lane queries are denoted as the anchor lanes constructed with several sample points.

Abstract

In this paper, we propose *PETrv2*, a unified framework for 3D perception from multi-view images. Based on *PETR* [25], *PETrv2* explores the effectiveness of temporal modeling, which utilizes the temporal information of previous frames to boost 3D object detection. More specifically, we extend the 3D position embedding (3D PE) in *PETR* for temporal modeling. The 3D PE achieves the temporal alignment on object position of different frames. To support for multi-task learning (e.g., BEV segmentation and 3D lane detection), *PETrv2* provides a simple yet effective solution by introducing task-specific queries, which are initialized under different spaces. *PETrv2* achieves state-of-the-art performance on 3D object detection, BEV segmentation and 3D lane detection. Detailed robustness analysis is also conducted on *PETR* framework. Code is available at <https://github.com/megvii-research/PETR>.

1. Introduction

Recently, 3D perception from multi-camera images for autonomous driving system has drawn a great attention. The multi-camera 3D object detection methods can be divided into BEV-based [13, 12] and DETR-based [43, 25, 21] approaches. BEV-based methods (e.g., BEVDet [13]) explicitly transform the multi-view features into bird-eye-

view (BEV) representation by LSS [34]. Different from these BEV-based counterparts, DETR-based approaches [43] models each 3D object as an object query and achieve the end-to-end modeling with Hungarian algorithm [17]. Among these methods, *PETR* [25], based on DETR [4], converts the multi-view 2D features to 3D position-aware features by adding the 3D position embedding (3D PE). The sparse queries, initialized from 3D space (see Fig. 1(a)), can directly perceive the 3D object information by interacting with the produced 3D position-aware features.

Recently, several works [21, 12] explore the effectiveness of temporal cues to improve the speed estimation of surrounding objects. Except for the 3D object detection, some followers [50, 21] further extend the BEV representation for multi-task learning, e.g. BEV segmentation and motion prediction. Considering the simplicity of *PETR*, we wonder if it is possible for the sparse-query paradigm in *PETR* to follow the success of BEV-based methods. In this paper, we aim to build a strong and unified framework by extending the *PETR* with temporal modeling and the support for multi-task learning.

For temporal modeling, the main problem is how to align the object position of different frames in 3D space. Existing works [12, 21] solved this problem from the perspective of feature alignment. For example, BEVDet4D [12] explicitly aligns the BEV feature of previous frame with current frame by pose transformation. However, *PETR* implicitly encodes the 3D position into the 2D image features and fails to perform the explicit feature transformation. Since *PETR* has

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demonstrated the effectiveness of 3D PE (encoding the 3D coordinates into 2D features) in 3D perception, we wonder if 3D PE still works on temporal alignment. In PETR, the meshgrid points of camera frustum space, shared for different views, are transformed to the 3D coordinates by camera parameters. The 3D coordinates are then input to a simple multi-layer perception (MLP) to generate the 3D PE. In our practice, we find that PETR works well under temporal condition by simply aligning the 3D coordinates of previous frame with the current frame.

For multi-task learning, BEVFormer [21] provides a unified solution with dense BEV representation. It defines each point on BEV map as one BEV query. Thus, the BEV query can be employed for both 3D object detection and BEV segmentation. However, the number of BEV query tends to be huge especially when BEV map is large for long-distance perception. Such definition on object query is obviously not suitable for sparse-query design in PETR due to the global attention transformer. In this paper, we design a unified sparse-query solution for multi-task learning. For different tasks, we define sparse task-specific queries under different spaces. For example, the lane queries for 3D lane detection are defined in 3D space with the style of anchor lane while seg queries for BEV segmentation are initialized under the BEV space, as shown in Fig. 1(b-c). Those sparse task-specific queries are input to the same transformer to update their representation and further injected into different task-specific heads to produce high-quality predictions.

Besides, we also improve the generation of 3D PE and provide a detailed robustness analysis on PETRv2. As mentioned above, 3D PE in PETR is generated based on the fixed meshgrid points in camera frustum space. All images from one camera view share the 3D PE, making 3D PE data-independent. In this paper, we further improve the original 3D PE by introducing a feature-guided way. Concretely, the projected 2D features are firstly injected into a small MLP network and a Sigmoid layer to generate the attention weight, which is used to reweight the 3D PE in an element-wise manner. The improved 3D PE is data-dependent, providing the informative guidance for the query learning in transformer decoder. For comprehensive robustness analysis on PETRv2, we consider multiple noise cases, including the camera extrinsics noise, camera miss and time delay.

To summarize, our contributions are:

- We study a conceptually simple extension of position embedding transformation to temporal representation learning. The temporal alignment can be achieved by the pose transformation on 3D PE.
- A simple yet effective solution is introduced for PETR to support the multi-task learning. BEV segmentation and 3D lane detection are supported by introducing task-specific queries.

- Experiments show that the proposed framework achieves state-of-the-art performance on both 3D object detection, BEV segmentation and 3D lane detection. Detailed robustness analysis is also provided for comprehensive evaluation on PETR framework.

2. Related Work

2.1. Multi-View 3D Object Detection

Previous works [6, 30, 15, 16, 36, 14, 44, 2, 42, 41] perform 3D object detection mainly under the mono setting. Recently, 3D object detection based on multi-view images has attracted more attention. ImVoxelNet [35] and BEVDet [13] projected the multi-view image features into BEV representation. Then the 3D object detection can be performed using the methods from 3D point cloud, like [49]. DETR3D [43] and PETR [25] conduct the 3D object detection mainly inspired by the end-to-end DETR methods [4, 54, 39, 48, 29, 24]. The object queries are defined in 3D space and interact with the multi-view image features in transformer decoder. BEVFormer [21] further introduces the temporal information into vision-based 3D object detection. The spatial cross-attention is adopted to aggregate image features, while the temporal self-attention is used to fuse the history BEV features. BEVDet4D [12] extends the BEVDet [13] by the temporal modeling and achieves good speed estimation. Both BEVFormer [21] and BEVDet4D [12] align the multi-frame features in BEV space. Different from them, we extend the temporal version from PETR and achieve the temporal alignment from the perspective of 3D position embedding (3D PE).

2.2. BEV Segmentation

BEV segmentation focus on the perception in the BEV view. It takes the multi-view images as input and rasterizes output onto a map view. VPN [31] proposes a view parsing network under the simulated environments and then transfers it to real-world environments to perform cross-view semantic segmentation. LSS [34] transforms the 2D features into 3D space by implicit estimation of depth and employs different heads for BEV segmentation and planning. M²BEV [46] further uses the camera parameters to project the features extracted from backbone to the 3D ego-car coordinate to generate the BEV representation. Then multi-task heads are used for 3D detection and segmentation. BEVFormer [21] generates the BEV features from multi-camera inputs by interacting the predefined grid-shaped BEV queries with the 2D image features. CVT [51] uses cross-view transformer to learn geometric transformation implicitly. HDMapNet [20] transforms multi-view images to the BEV view and produces a vectorized local semantic map. BEVSegFormer [33] proposes multi-camera deformable attention to construct semantic map.

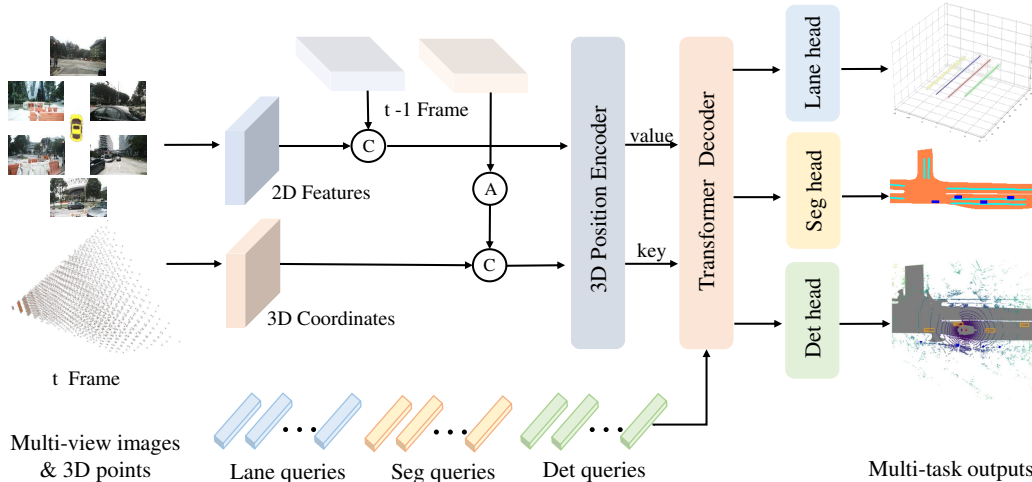


Figure 2. The paradigm of the proposed PETRv2. The 2D features are extracted by the backbone network from the multi-view images and the 3D coordinates are generated following the same way as PETR. To achieve the temporal alignment, the 3D coordinates in PETR of previous frame $t - 1$ are firstly transformed through pose transformation. Then 2D image features and 3D coordinates of two frames are concatenated together and injected to 3D position encoder to generate the key and value components for the transformer decoder. The detection, segmentation and lane queries, initialized under different spaces, interact with the key and value components in transformer decoder. The updated queries are further used to predict the 3D bounding boxes, BEV segmentation map and the 3D lanes with task-specific heads. (A) is 3D coordinates alignment from frame $t - 1$ to frame t . (C) is concatenation operation along the batch axis.

2.3. 3D Lane Detection

BEV segmentation can reconstruct the elements of local map. However, it fails to model the spatial association between different instances. Recently, the 3D lane detection task has attracted more and more attention [8, 5, 45]. 3D-LaneNet [8] is the first method that makes the 3D lane prediction. It uses inverse perspective mapping (IPM) to transform feature from front view to BEV. Gen-LaneNet [9] introduces a new anchor lane representation to align the perspective anchor representation and BEV feature. PersFormer [5] employs the deformable attention to generate BEV features by attending local context around reference points. CurveFormer [1] introduces a curve cross-attention module to compute the similarities between curve queries and image features. It employs deformable attention to obtain the image features corresponding to the reference points.

3. Method

3.1. Overall Architecture

As illustrated in Fig. 2, overall architecture of PETRv2 is built upon PETR [25] and extended with temporal modeling and multi-task learning. The 2D image features are extracted from multi-view images with the 2D backbone (e.g., ResNet-50), and the 3D coordinates are generated from camera frustum space as described in PETR. Considering the ego motion, 3D coordinates of the previous frame $t - 1$ are first transformed into the coordinate system of current frame t through the pose transformation. Then, the

2D features and 3D coordinates of adjacent frames are respectively concatenated together and input to the 3D position encoder, which generates the key and value components for the transformer decoder. Further, task-specific queries including the detection queries (det queries), segmentation queries (seg queries) and lane detection queries (lane queries), which are initialized from different spaces, are fed into the transformer decoder and interact with multi-view image features. Lastly, the updated queries are input to the task-specific heads for final prediction.

3.2. Temporal Modeling

PETR leverages image features and projected 3D points to generate implicit 3D features for multi-view 3D detection. In this section, we extend it with the temporal modeling, which is realized by the 3D coordinates alignment (CA) and a modified 3D position encoder for better localization and speed estimation.

3D Coordinates Alignment The temporal alignment is to transform the 3D coordinates of frame $t - 1$ to the coordinate system of frame t (see Fig. 3). For clarity, we first denote some coordinate systems: camera coordinate as $c(t)$, lidar coordinate as $l(t)$, and ego coordinate as $e(t)$ at frame t . What's more, global coordinates as g . We define T_{src}^{dst} as the transformation matrix from the source coordinate system to the target coordinate system.

We use $l(t)$ as the default 3D space for multi-view camera 3D position-aware feature generation. The 3D points

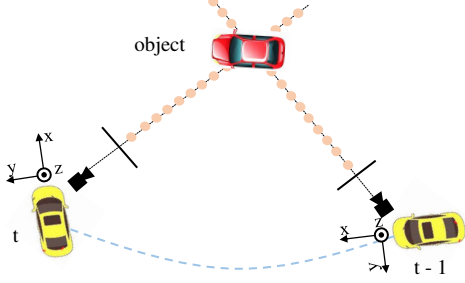


Figure 3. The illustration of the coordinate system transformation from frame $t - 1$ to frame t .

$P_i^{l(t)}(t)$ projected from i -th camera can be formulated as:

$$P_i^{l(t)}(t) = T_{c_i(t)}^{l(t)} K_i^{-1} P^m(t) \quad (1)$$

where $P^m(t)$ is the points set in the meshgrid of camera frustum space at frame t . $K_i \in R^{4 \times 4}$ is the camera intrinsic matrix of the i -th camera. Given the auxiliary frame $t - 1$, we align the coordinates of 3D points from frame $t - 1$ to frame t :

$$P_i^{l(t)}(t - 1) = T_{l(t-1)}^{l(t)} P_i^{l(t-1)}(t - 1) \quad (2)$$

With *global* coordinate space acting as a bridge between frame $t - 1$ and frame t , $T_{l(t-1)}^{l(t)}$ can be easily calculated:

$$T_{l(t-1)}^{l(t)} = T_{e(t)}^{l(t)} T_g^{e(t)} T_g^{e(t-1)-1} T_{e(t-1)}^{l(t-1)-1} \quad (3)$$

The aligned point sets $[P_i^{l(t)}(t - 1), P_i^{l(t)}(t)]$ are used to generate the 3D PE, as described below.

3D Position Encoder PETR transforms the 3D coordinates into 3D position embedding (3D PE). The generation of 3D PE can be formulated as:

$$PE_i^{3d}(t) = \psi(P_i^{l(t)}(t)) \quad (4)$$

where $\psi(\cdot)$ is a simple multi-layer perception (MLP). The 3D PE in PETR is independent with input image. In this paper, we make a minor modification, which implicitly introduces the vision prior. The generation of 3D PE is guided by 2D feature and can be formulated as:

$$PE_i^{3d}(t) = \xi(F_i^{2d}(t)) * \psi(P_i^{l(t)}(t)) \quad (5)$$

where ξ is a small MLP network. $F_i^{2d}(t)$ is the 2D image features of the i -th camera. As illustrated in Fig. 4, the 2D image features projected by a 1×1 convolution are fed into a small MLP network ξ and Sigmoid function to obtain the attention weights. The 3D coordinates are transformed by another MLP network ψ and multiplied with the attention weights to generate the 3D PE.

For the t -th frame, $PE^{3d}(t)$ is added with 2D features $F^{2d}(t)$ to obtain 3D-aware features $F^{3d}(t)$. We can obtain

the 3D-aware features of last frame $F^{3d}(t - 1)$ as well. We simply concatenate the 3D-aware features and 2D features of two frames to produce the temporal 3D-aware features F^{3d} and temporal 2D features F^{2d} . F^{3d} and F^{2d} serve as the *key* and *value* components in transformer decoder for multi-task learning (see Sec. 3.3).

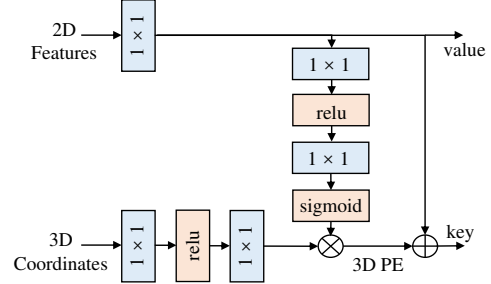


Figure 4. Architecture of 3D position encoder. Different from PETR, 3D PE in PETRv2 is generated in a data-dependent way.

3.3. Multi-task Learning

In this section, we aim to equip PETR with det queries, seg queries and lane queries to support high-quality 3D object detection, BEV segmentation and 3D Lane detection. **3D Object Detection** Similar to previous practice in PETR, we model each 3D object as a det query and initialize the det queries with anchor points. The anchor points are projected into initial det queries Q_{det}^0 by a simple MLP with two linear layers. The det queries are input to the transformer decoder and interact with the multi-frame 3D-aware features:

$$Q_{det}^l = D_l(F^{3d}, F^{2d}, Q_{det}^{l-1}), \quad l = 1, \dots, L \quad (6)$$

where D_l is the l -th transformer decoder. L is the number of decoders. The updated det queries Q_{det}^L is further input to the detection head, implemented by a simple MLP, for classification and regression. We use the Focal loss [22] and L1 loss to supervise the classification and regression predictions, respectively.

BEV Segmentation A high-resolution BEV map can be partitioned into a small number of patches. We introduce the seg query for BEV segmentation and each seg query corresponds to a specific patch (e.g., top-left 25×25 pixels of the BEV map). As shown in Fig. 1 (b), the seg queries are initialized with fixed grid points in BEV space, similar to the generation of detection query (det query) in PETR. These anchor points are projected to the initial seg queries Q_{seg}^0 by a simple MLP with two linear layers. After that, the seg queries are input to the transformer decoder and interact with the temporal 2D and 3D features.

$$Q_{seg}^l = D_l(F^{3d}, F^{2d}, Q_{seg}^{l-1}), \quad l = 1, \dots, L \quad (7)$$

Then the updated seg queries are finally fed into the segmentation head, similar to the decoder in CVT [51], to predict the final segmentation results. We use the Focal loss to supervise the predictions of each category separately.

3D Lane Detection We further add the lane queries on the PETR framework to support for the 3D lane detection (see Fig. 1 (c)). We define the 3D anchor lanes, each of which is represented as an ordered set of 3D coordinates: $l = \{(x_1, y_1, z_1), (x_2, y_2, z_2), \dots, (x_n, y_n, z_n)\}$, where n is the number of the sample points of each lane. In order to improve the prediction ability for 3D lanes, we use a fixed sampling point set uniformly sampled along the Y-axis, similar to PersFormer [5]. Different from PersFormer, our anchor lanes are parallel to the Y-axis while PersFormer predefines different slopes for each anchor line. The anchor lanes are also projected into the initial lane queries Q_{lane}^0 by a simple MLP with two linear layers. The lane queries interact with the temporal 2D and 3D features in the transformer decoder as well.

$$Q_{lane}^l = D_l(F^{3d}, F^{2d}, Q_{lane}^{l-1}), \quad l = 1, \dots, L \quad (8)$$

The updated lane queries Q_{lane}^L are further input to 3D lane head for 3D lane prediction. The 3D lane head predicts the lane class C as well as the relative offset $(\Delta x, \Delta z)$ along the X-axis and Z-axis compared to the anchor lanes. Since the length of 3D lane is not fixed, we also predict the visibility vector T_{vis} of size n to control the start and end points of the lane. We use focal loss to supervise the predictions of the lane category and visibility. We also use L1 loss to supervise the predictions of the offset.

3.4. Robustness Analysis

Though recently there are lots of works on autonomous driving systems, only a few works [34, 21] explore the robustness of proposed methods. LSS [34] presents the performance under extrinsics noises and camera dropout at test time. Similarly, BEVFormer [21] demonstrates the robustness of model variants to camera extrinsics. In practice, there are diverse sensor errors and system biases, and it is important to validate the effect of these circumstances due to the high requirements of safety and reliability. We aim to give an extensive study of our method under different conditions. As shown in Fig. 5, we focus on three common types of sensor errors as follows:

Extrinsics noise: Extrinsics noises are very common in reality, such as the camera shake caused by a car bump or camera offset by the environmental forces. In these cases, extrinsics provided by the system is not that accurate and the perception results will be affected.

Camera miss: Camera image miss occurs when one camera breaks down or is occluded. Multiview images provide panoramic visual information, yet the possibility exists that one of them is absent in the real world. It is necessary to

evaluate the importance of these images so as to prepare the strategy of sensor redundancy in advance.

Camera time delay: Camera time delay is also a challenge due to the camera exposure time, especially in night. The long exposure time causes the system is fed with images from the previous time, and brings the significant output offsets.

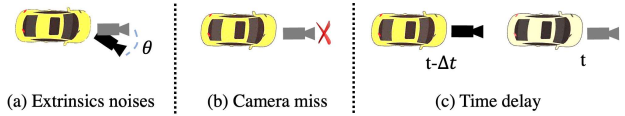


Figure 5. We analyze the system robustness of PETR series under three simulated sensor errors: (a) extrinsics noise, (b) camera miss and (c) camera time delay.

3.5. Discussion on Sparse-Query Design

In autonomous driving, the objects (e.g. vehicles and 3D lanes) are sparsely distributed in 3D environment. Overall, the sparse-query solution in PETRv2 has two typical advantages compared to those dense-query design. (i) BEV-based methods, are limited by the excessive cost of BEV features especially when perceiving long-distance objects (e.g. Waymo dataset) for spatial attention in BEVFormer. PETRv2 consumes constant FLOPs and is not restricted by the perception distance. (ii) Dense BEV-based methods tend to compress Z-axis information, which introduces the Z-axis error for 3D lane detection.

4. Experiments

4.1. Datasets and Metrics

We evaluate our approach on nuScenes benchmark [3], OpenLane benchmark [5] and Waymo benchmark [37]. nuScenes [3] is a large-scale multi-task dataset covering 3D object detection, BEV segmentation, 3D object tracking, etc. The dataset is officially divided into training/validation/testing sets with 700/150/150 scenes, respectively. We mainly focus on two sub-tasks: 3D object detection and BEV segmentation. We also conduct the 3D lane detection experiments on OpenLane benchmark [5]. Openlane [5] is a large-scale real world 3D lane dataset. It has 200K frames and over 880K carefully annotated lanes and covers a wide range of lane types using 14 lane categories. Waymo dataset collects data from 5 camera views that cover about 230 degrees of field of vision (FOV). It can be divided into training, validation, and testing sets that including 798, 202 and 80 video respectively. Following BEVFormer, we use train-mini set (about 20% of the training set) to train the model and test on val set.

For 3D object detection, each scene has 20s video frames and is annotated around 40 key frames. We report the official evaluation metrics including nuScenes Detection Score

Table 1. Comparison of recent works on the nuScenes val set. The results of FCOS3D and PGD are fine-tuned and tested with test time augmentation. The DETR3D, BEVDet and PETR are trained with CBGS [53]. Inference speed of PETRv2 on a single 3090 GPU, "v" is tested on a single V100 GPU.

Methods	Backbone	Prerained	Size	NDS \uparrow	mAP \uparrow	mATE \downarrow	mASE \downarrow	mAOE \downarrow	mAVE \downarrow	mAAE \downarrow	FPS
CenterNet [52]	DLA	\times	-	0.328	0.306	0.716	0.264	0.609	1.426	0.658	-
FCOS3D [42]	Res-101-D	\times	1600 \times 900	0.415	0.343	0.725	0.263	0.422	1.292	0.153	1.7(v)
PGD [41]	Res-101-D	\times	1600 \times 900	0.428	0.369	0.683	0.260	0.439	1.268	0.185	1.4(v)
BEVDet [13]	Swin-T	\times	1408 \times 512	0.417	0.349	0.637	0.269	0.490	0.914	0.268	15.6
DETR3D [43]	Res-101-D	\checkmark	1600 \times 900	0.434	0.349	0.716	0.268	0.379	0.842	0.200	6.3
PETR [25]	Res-101-D	\checkmark	1408 \times 512	0.441	0.366	0.717	0.267	0.412	0.834	0.190	5.7
BEVFormer [21]	Res-101-D	\checkmark	1600 \times 900	0.517	0.416	0.673	0.274	0.372	0.394	0.198	3.0
BEVDet4D-T [12]	Swin-T	\times	704 \times 256	0.453	0.323	0.674	0.272	0.503	0.429	0.208	15.5
BEVDet4D-B [12]	Swin-B	\times	1600 \times 640	0.515	0.396	0.619	0.260	0.361	0.399	0.189	1.9
PETRv2	Res-50	\times	704 \times 256	0.456	0.349	0.700	0.275	0.580	0.437	0.187	18.9
PETRv2	Res-101-D	\checkmark	1600 \times 640	0.524	0.421	0.681	0.267	0.357	0.377	0.186	3.5

Table 2. Comparison of recent works on the nuScenes test set. * are trained with external data. \ddagger is test time augmentation. "ms" indicates using the resolution of 800 \times 320 and 1600 \times 640 as the inputs.

Methods	Backbone	NDS \uparrow	mAP \uparrow	mATE \downarrow	mASE \downarrow	mAOE \downarrow	mAVE \downarrow	mAAE \downarrow
CenterNet [52]	DLA	0.400	0.338	0.658	0.255	0.629	1.629	0.142
FCOS3D \ddagger [42]	Res-101-D	0.428	0.358	0.690	0.249	0.452	1.434	0.124
PGD \ddagger [41]	Res-101-D	0.448	0.386	0.626	0.245	0.451	1.509	0.127
DD3D* \ddagger [32]	V2-99	0.477	0.418	0.572	0.249	0.368	1.014	0.124
DETR3D* [43]	V2-99	0.479	0.412	0.641	0.255	0.394	0.845	0.133
BEVDet [13]	Swin-S	0.463	0.398	0.556	0.239	0.414	1.010	0.153
BEVDet* [13]	V2-99	0.488	0.424	0.524	0.242	0.373	0.950	0.148
M ² BEV [46]	X-101	0.474	0.429	0.583	0.254	0.376	1.053	0.190
PETR* [25]	V2-99	0.504	0.441	0.593	0.249	0.383	0.808	0.132
BEVFormer* [21]	V2-99	0.569	0.481	0.582	0.256	0.375	0.378	0.126
BEVDet4D \ddagger [12]	Swin-B	0.569	0.451	0.511	0.241	0.386	0.301	0.121
PETRv2*	V2-99	0.592	0.506	0.536	0.243	0.359	0.349	0.120
PETRv2* ms	V2-99	0.601	0.519	0.527	0.242	0.358	0.341	0.118

(NDS), mean Average Precision (mAP), and five True Positive (TP) metrics: mean Average Translation Error (mATE), mean Average Scale Error (mASE), mean Average Orientation Error(mAOE), mean Average Velocity Error(mAVE), mean Average Attribute Error(mAAE). NDS is a comprehensive indicator to evaluate the detection performance.

For BEV segmentation, we follow LSS [34] and use IoU score as the metric. The ground-truth includes three different categories: Driveable area, Lane and Vehicle. The lane category is formed by two map layers: lane-Divider and Road-Divider. For Vehicle segmentation, we obtain the BEV ground truth by projecting 3D bounding boxes into the BEV plane[34]. The Vehicle segmentation ground truth refers to all bounding boxes of meta-category Vehicle, which contains bicycle, bus, car, construction, motorcycle, trailer and truck.

For 3D lane detection, we follow PersFormer [5] using F1-Score and category accuracy as the metrics. When 75% points of a predicted lane instance have the point-wise euclidean distance less than 1.5 meters, the lane instance is considered to be correctly predicted. We also report X error near, X error far, Z error near, Z error far to evaluate the models. These four metrics are used to evaluate the average error of the results in specified ranges.

4.2. Implementation Details

In our implementation, ResNet [10], VoVNetV2 [18] and EfficientNet [38] are employed as the backbone for feature extraction. The P4 feature (merging the C4 and C5 features from backbone) with 1/16 input resolution is used as the 2D feature. The generation of 3D coordinates is consistent with PETR [25]. Following BEVDet4D [12], we randomly sample a frame as previous frame ranging from [3T, 27T] during training, and sample the frame at 15T during inference. T(≈ 0.083) is the time interval between two sweep frames. Our model is trained using AdamW [28] optimizer with a weight decay of 0.01. The learning rate is initialized with 2.0×10^{-4} and decayed with cosine annealing policy [27]. All the experiments are trained for 24 epochs ($2 \times$ schedule) on 8 Tesla A100 GPUs with a total batch size of 8 except for the test set. No test time augmentation methods are used during inference.

For 3D object detection, we perform experiments with 1500 det queries on nuScenes test dataset. Following the settings in PETR [25], we initialize a set of learnable anchor points in 3D world space, and generate these queries through a small MLP network. Similar to FCOS3D [42], we add extra disentangled layers for regression targets. We

Table 3. Results on Waymo v1.4 dataset with LET-mAPL metrics. These model are trained on ResNet101 backbone.

Methods	LET-mAPL	LET-mAP	LET-mAPH
BEVFormer-MS	35.4	51.1	47.1
MV-FCOS3D++	35.1	48.0	45.5
PETrv2	36.6	51.9	48.0

Table 4. Comparison of recent BEV segmentation works on the nuScenes val set. * are trained with external data. The performance of M²BEV is reported with X-101 [47] backbone.

Methods	Backbone	Drive	Lane	Vehicle
Lift-Splat [34]	Res-101	0.729	0.200	0.321
FIERY [11]	Res-101	-	-	0.382
M ² BEV [46]	X-101	0.759	0.380	-
BEVFormer [21]	Res-101	0.801	0.257	0.448
PETrv2	Res-101	0.833	0.448	0.434
PETrv2*	V2-99	0.856	0.490	0.463

extend query denoise of DN-DETR [19] to accelerate convergence of 3D object detection. For each ground-truth 3D box, the center is shifted by a random noise less than $(w/2, l/2, h/2)$, where (w, l, h) is the size of object. The Hungarian algorithm [17] is used for label assignment between ground-truths and predictions. For BEV segmentation, we follow the settings in [34]. We use the map layers provided by the nuScenes dataset to generate the 200×200 BEV map ground truth. We set the patch size to 25×25 and 625 seg queries are used to predict the final BEV segmentation result. For 3D lane detection, we follow the settings in [5]. The input size of images is 360×480 . We use 100 lane queries to predict the 3D lanes. We set the number of points in each anchor lane to 10 and the prediction range is $[3m, 103m]$ on Y-axis and $[-10m, 10m]$ on X-axis. The distance is calculated at several fixed positions along the Y-axis: [5, 10, 15, 20, 30, 40, 50, 60, 80, 100] for 3D anchor lanes.

To simulate extrinsic noises and evaluate the effect, we choose to randomly apply 3D rotation to camera extrinsics. 3D rotation is very common and typical in real scenarios, and we ignore other noisy patterns such as translation to avoid multi-variable interference. Specifically, we randomly choose one from multiple cameras to apply 3D rotation. Denoting α, β, γ as angles (in degree) along X, Y, Z axes respectively, we investigate in several rotation settings with maximum amplitudes $\alpha_{max}, \beta_{max}, \gamma_{max} \in \{2, 4, 6, 8\}$, where $\alpha_{max} = 2$ means that α is uniformly sampled from $[-2, 2]$, for example. In experiment, we use $R_{max} = M$ to denote $\alpha_{max} = \beta_{max} = \gamma_{max} = M$.

4.3. State-of-the-art Comparison

Tab. 1 compare the performance with recent works on nuScenes val set. Our method achieves state-of-the-art performance among public methods. PETrv2 achieves 34.9% mAP and 45.6% NDS even with ResNet-50. Tab. 2

Table 5. Comparison of recent 3D lane detection works on OpenLane benchmark. PETrv2-V and PETrv2-E are our method with VoV-99 [18] and EfficientNet [38] backbones. PersFormer is reported with EfficientNet backbone. ‡ denotes projecting 2D lane results from CondLaneNet [23] to BEV using IPM.

Methods	F-score(%) [↑]	X-near [↓]	X-far [↓]	Z-near [↓]	Z-far [↓]
3D-LaneNet [8]	44.1	0.479	0.572	0.367	0.443
Gen-LaneNet [9]	32.3	0.591	0.684	0.411	0.521
Cond-IPM [‡]	36.6	0.563	1.080	0.421	0.892
PersFormer [5]	50.5	0.485	0.553	0.364	0.431
PETrv2-E	51.9	0.493	0.643	0.322	0.463
PETrv2-V	61.2	0.400	0.573	0.265	0.413

shows the performance comparison on nuScenes test set. Our PETrv2 with VoVNet surpasses the PETR by a large margin (9.7% NDS and 7.8% mAP). Benefiting from the temporal modeling, the mAVE can achieved with 0.341m/s compared to the 0.834m/s of PETR. When compared with other temporal methods, PETrv2 surpasses the BEVDet4D [12] with Swin-Base [26] and BEVFormer [21] V2-99 [18] by 3.2% NDS. It shows that the temporal alignment by 3D PE can also achieve remarkable performance. It should be noted that PETrv2 can be easily employed for practical application without the explicit feature alignment. Tab. 3 further shows the performance comparison on Waymo val set. Since the methods for comparison are mainly from Waymo Challenge, all the results are reported any without bells and whistles. It shows that PETrv2 outperforms BEVFormer and MV-FCOS3D++ [40] by 1.2% and 1.5% mAPL respectively.

We also compare the BEV segmentation performance on nuScenes dataset. As shown in Tab. 4, we conduct the experiments with ResNet-101 and VoV-99 backbones. Since PETrv2 is the temporal extension of PETR so we mainly compare the performance with BEVFormer for fair comparison. With ResNet-101 backbone, our PETrv2 outperforms BEVFormer on IoU-lane and IoU-Drive metrics by a large margin and achieves comparable performances on IoU-Vehicle metric. With the pretrained VoV-99 backbone, our PETrv2 achieves state-of-the-art performance.

As shown in Tab. 5, we compare the performance with other state-of-the-art 3D lane detection methods. Since PersFormer [5] with EfficientNet backbone is a static method, we do not use the temporal information for fair comparison. With the same EfficientNet backbone, our method achieves 51.9% F1-score compared to the 50.5% in Performer. With the strong pretrained VoV-99 backbone, the performance of our method is greatly improved.

4.4. Ablation Study

In this section, we conduct the ablations with VoVNet-99 backbone. The backbone is pretrained on DDAM15M dataset [32] and train set of Nuscenes [3]. The input image size is 800×320 and the model is trained with 24 epochs.

Table 6. The impact of 3D coordinates alignment (CA) and temporal information (Tem).

CA	Tem	NDS \uparrow	mAP \uparrow	mATE \downarrow	mAOE \downarrow	mAVE \downarrow
		0.437	0.372	0.757	0.479	0.782
	✓	0.426	0.329	0.819	0.500	0.593
✓	✓	0.487	0.396	0.759	0.464	0.423

Table 7. The number of sample points for each anchor lane in 3D lane detection.

Sample Points	F-score($\%$) \uparrow	X-near \downarrow	X-far \downarrow	Z-near \downarrow	Z-far \downarrow
10	57.8	0.427	0.582	0.293	0.421
400	61.2	0.400	0.573	0.265	0.413

Table 8. Result of different loss weights on the nuScenes val set.

Det	Seg	NDS \uparrow	mAP \uparrow	Drive \uparrow	Lane \uparrow	Vehicle \uparrow
0.0	1.0	-	-	0.836	0.438	0.407
1.0	0.0	0.487	0.396	-	-	-
1.0	1.0	0.488	0.396	0.807	0.388	0.411
1.0	2.0	0.486	0.399	0.814	0.398	0.423

The number of detection queries is set to 900.

Temporal Modeling. For temporal modeling, we explore the effect of two key components in our design: 3D coordinates alignment (CA) and temporal information. For the ablation study, we only trained the 3D detection branch for clarity. As shown in Tab. 8, without CA, the performance drops from 37.2% mAP to 32.9% mAP, since the position embedding is difficult to distinguish different frames and confuses the model learning. With CA, the performance is improved by 5.0% NDS and 2.4% mAP. The mAVE metric is decreased to 0.423m/s, which shows a large margin compared to the original PETR baseline.

Sample Points for Anchor Lane. As shown in Tab. 7, we represent each 3D anchor lane with 400 anchor points and the experimental result shows that increasing the number of anchor points leads to great performance improvements. We argue that 10 anchor points are not enough to model a relatively complex 3D lane, making it difficult to produce accurate prediction. It should be noted that the large number of anchor points only increase marginal computation cost in our method. The increased cost is mainly from the higher dimension of the MLP in 3D lane head.

Analysis on Multi-task Learning. We also perform the analysis on the effect of multi-task learning (see Tab. 8). It can be observed that 3D detection and BEV segmentation tasks do not promote each other, except for the vehicle class. When the loss weights of the detection and segmentation branches are set to the same (1.0), the performance of BEV segmentation on driveable area is decreased by 2.9% compared to the baseline (segmentation only). Recently, some other studies [7, 46] also pointed out that not all the 3D computer vision tasks can benefit from other tasks in joint training setting. While in our practice, good trade-off performance can be achieved when the loss weight of segmentation branch is set to 2.

Table 9. Quantitative results on the nuScenes val set with extrinsics noises. The metrics in each cell are mAP[%]. $R_{max} = M$ denotes the maximum angle of three axes is M in degree.

	baseline	$R_{max} = 2$	$R_{max} = 4$	$R_{max} = 6$
PETR	37.9	\downarrow -1.16	\downarrow -3.29	\downarrow -5.08
BEVFormer	41.6	\downarrow -0.71	\downarrow -2.22	\downarrow -3.72
PETRv2	42.1	\downarrow -0.68	\downarrow -2.25	\downarrow -3.66

Table 10. The performance of our method with pose transformation errors. T_{max} denotes maximum translation distance (m).

T_{max}	0.0	0.2	0.4	0.6	0.8	1.0
NDS	52.38	52.38	52.33	52.28	52.17	52.04

Table 11. The performance impact (on mAP metric) of camera time delay. Here, the time delay unit $T \approx 0.083s$.

Time delay	0	T	2T	3T
PETRv2	40.1	36.9 (\downarrow 3.2)	34.0 (\downarrow 6.1)	30.9 (\downarrow 9.2)

Robustness analysis Tab. 9 reports a summary of quantitative results on the nuScenes [3] dataset with extrinsics noises during inference. We compare PETRv2 with PETR [25], and observe that temporal modeling improves the robustness to extrinsics noises. In the extreme noise setting $R_{max} = 6$, PETRv2 drops 3.66% mAP. We perform the robustness analysis on BEVFormer [21] and observe similar performance. When adding the noise on pose transformation as shown in Tab. 10. The performance of PETRv2 only reduces 0.34% NDS when the translation error is 1.0 m.

The effect of camera time delay is demonstrated in Tab. 11. We leverage the unannotated frames between key frames as input images to simulate the time delay. The delay of 0.083s leads to a drop of 3.19% mAP and 8.4% NDS, indicating the significant impact of time delay. When the time delay is increased to over 0.3s, the performance sharply decreases to 26.08% mAP and 36.54% NDS. Since time delay is inevitable in real-world systems and largely affects the detection, more attention is supposed to pay to it.

4.5. Qualitative results

We provide some qualitative results of 3D lane detection in Fig. 6. As seen, our proposed PETRv2 achieves compelling results under various challenging situations, *e.g.*, straight lines, curved lines, night scenes and *etc.*, even when the GTs are not that accurate. Fig. 7 shows some qualitative results of 3D object detection and BEV segmentation. The projected 3D bounding boxes are close to the objects in perspective view and the segmentation of driveable area and lane is fine. However, there are still some failure cases that are marked by red circles. The distant objects have low confidence scores that may be wrongly filtered by the given score threshold. For BEV segmentation, the borders of small vehicles are blurred, which is also reflected in recent works [46, 21].

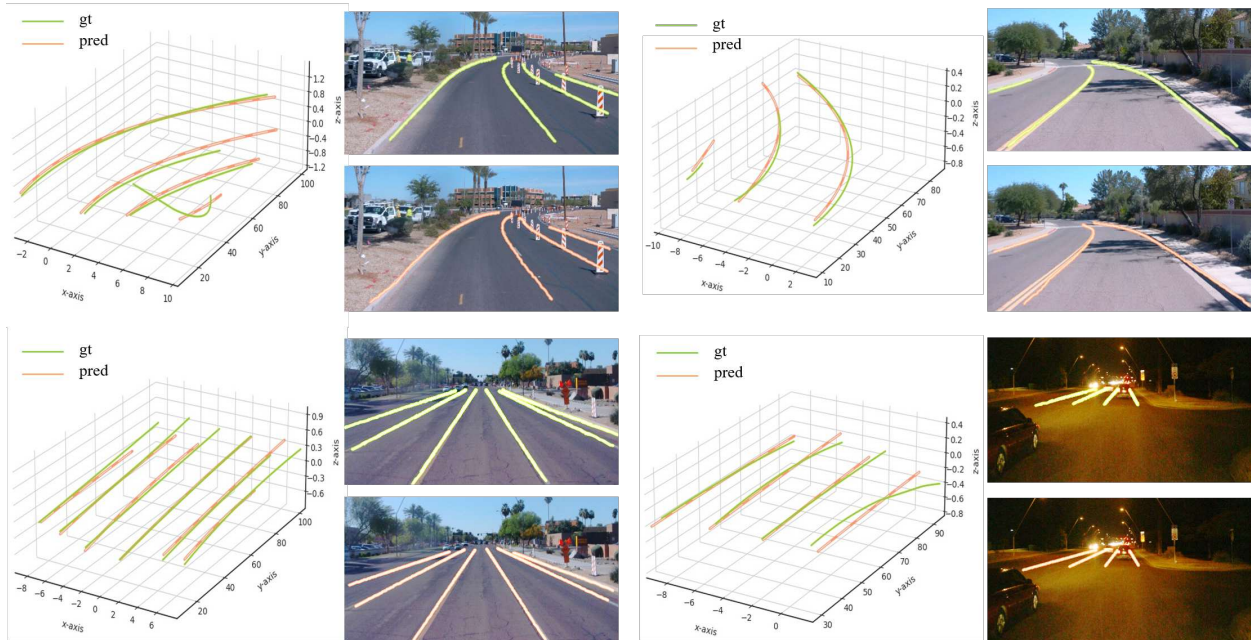


Figure 6. Qualitative results of 3D lane detection on Openlane [5] dataset.



Figure 7. Qualitative analysis of 3D object detection and BEV segmentation. The score threshold of detection is 0.25. The red circles are some failure cases, such as distant objects and blurred borders.

5. Conclusion

In this paper, we introduce PETRv2, a unified framework for 3D perception from multi-camera images. PETRv2 extends the PETR baseline with temporal modeling and multi-task learning. With the temporal alignment on 3D position embedding, PETRv2 naturally achieves the multi-frame modeling and improves the 3D detection performance. For a fully understanding of PETRv2 framework, we further provide a detailed analysis on the robustness of PETRv2 under three types of simulated sensor errors.

Limitations. As described above, one drawback is the blurred borders of small vehicles in BEV segmentation. Another limitation is that 3D lane detection is not included in nuScenes dataset and performed on Openlane dataset alone.

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