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UniTR: A Unified and Efficient Multi-Modal Transformer for Bird's-Eye-View Representation

Haiyang Wang1 Hao Tang1,4* Shaoshuai Shi2† Aoxue Li3 Zhenguo Li3 Bernt Schiele2 Liwei Wang*

- Problem/Objective
  - Bird's eye view representation (3D OD & segmentation)
  - Reduce model size(fusion model) and fast inference time

- Contribution/Key Idea
  - Modality-agnostic Transformer that interact cross-modal
  - Geometry-aware sparse neighborhood relations (2D & 3D)
  - NDS +1.1% & mIoU +12.0%

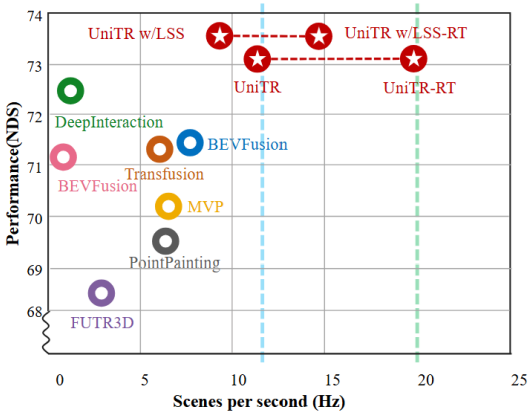

Figure 1. 3D object detection performance (NDS) vs speed (Hz) on nuScenes [3] validation set. Latency is measured on an A100 GPU with AMD EPYC 7513 CPU. Blue and green lines are the operating frequency of the camera and LiDAR in nuScenes.

김범준

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- **Remaining Method**

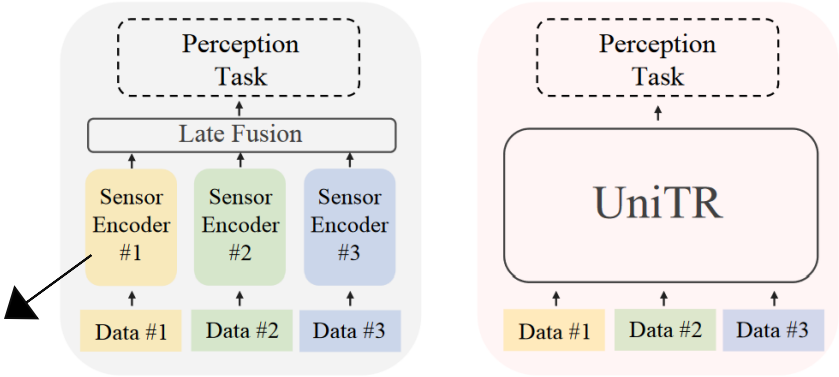

Figure 2. Comparison between sequential modality-specific encoders and our proposed UniTR, which processes various modalities in parallel with a single model and shared parameters.

- 기존의 모델 → 각각의 sensor data를 각자의 encoding layer를 통과하여 Fusion
- UniTR → 데이터를 fusion 하는 early fusion 방식 채택
  - but) 다른점은 modality에 관계없는 (modality-agnostic transformer 제안)

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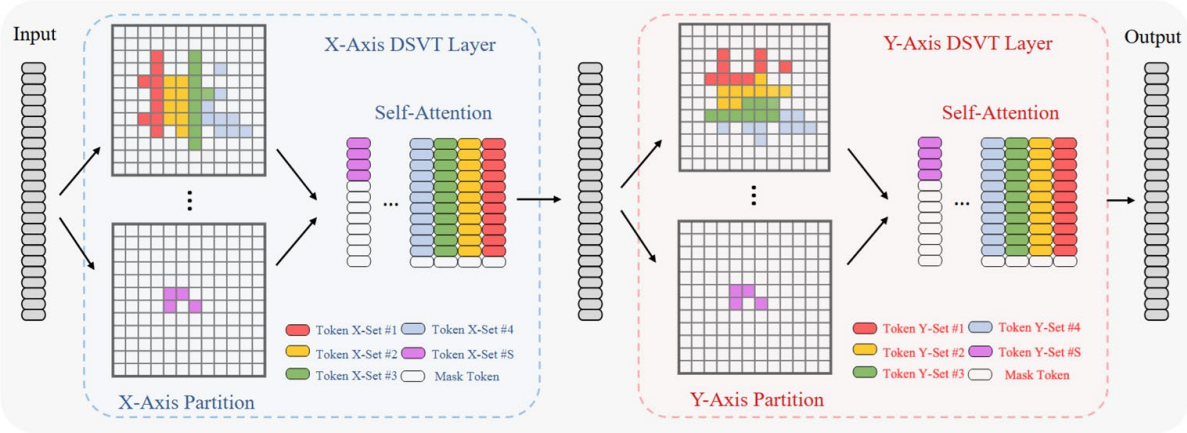
- **DSVT (Dynamic Sparse Window attention) - CVPR 2023**



- VFE (voxel feature encoder) 통과한 feature들을 token → token이 비어있는 것이 LiDAR의 특징
  - Window 내부 X-axis 방향으로 non-empty token n개를 concat하여 같은 색으로 지정
  - Self-Attention
  - Y-axis 반복
  - 이것을 여러 Window size에서 반복 (L x W x H size)

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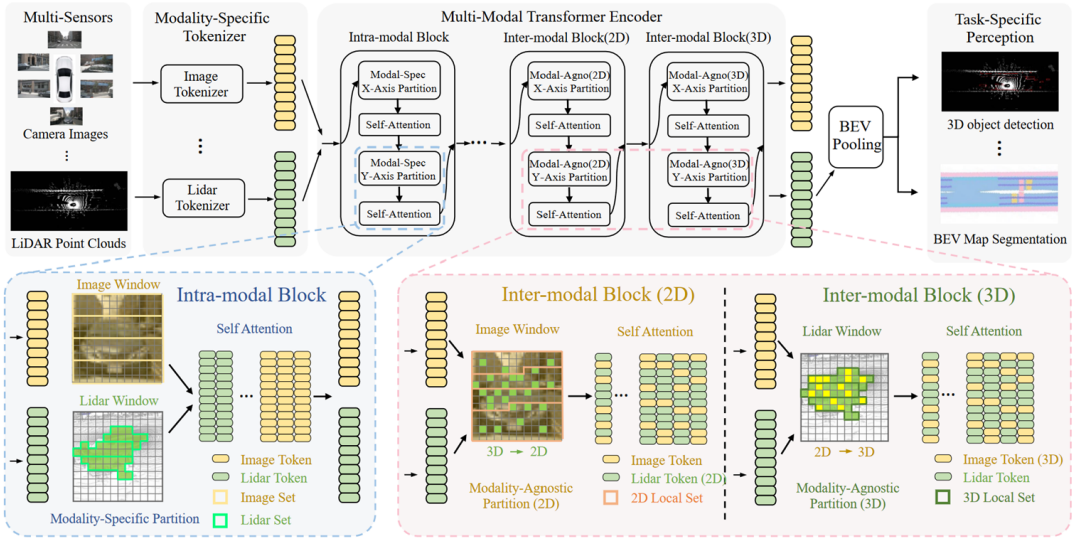
- **Method**



- 기존 모델들 처럼 각 모달리티에 대한 별도의 처리 네트워크 x
- Image Tokenize & LiDAR Tokenizer만 개별로 통과 후 Block들 통과

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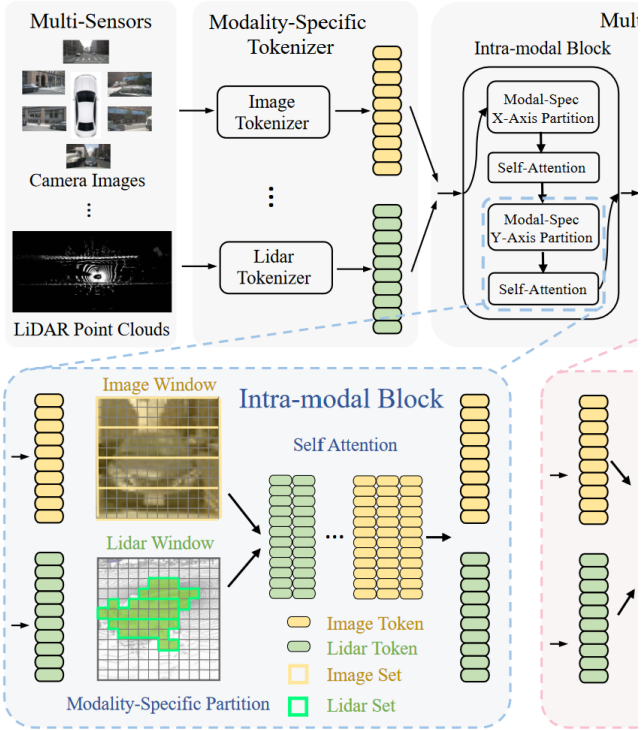
- **Method**



- 첫번째 모듈에서는 sensor의 raw-data를 tokenization하는 과정
  - LiDAR data → voxelization & dynamic 하게 encoding하는 VFE 과정
  - Image data → ViT에서 사용하는 image patch tokenizer

$$\mathcal{T}^P = \{t_i^P | t_i^P = [(x_i^P, y_i^P, z_i^P); f_i^P]\}_{i=1}^N,$$
$$\mathcal{T}^I = \{t_i^I | t_i^I = [(x_i^I, y_i^I, b_i^I); f_i^I]\}_{i=1}^M,$$

- Image: 6x256x704x3 (b,h,w,c) → m x c 개의 patch
- pointcloud : voxel size (0.3, 0.3, 8.0)m → n x c 개의 patch with Dynamic Set partition

$$\{\mathcal{Q}_n^P\}_{n=0}^{\mathcal{N}} = \mathrm{DSP}(\mathcal{T}^P, L^P \times W^P \times H^P, \tau),$$
$$\{\mathcal{Q}_m^I\}_{m=0}^{\mathcal{M}} = \mathrm{DSP}(\mathcal{T}^I, L^I \times W^I \times 1, \tau),$$

- Intra-modal Block 에서 self-attention 하는 과정 (각 센서별로)
  - Image는 Swin-Transformer 처럼
  - LiDAR는 DSVT 처럼

$$\mathcal{F}_l, \mathcal{C}_l = \mathrm{INDEX}([\mathcal{T}_{l-1}^P, \mathcal{T}_{l-1}^I], [\{\mathcal{Q}_n^P\}_{n=0}^{\mathcal{N}}, \{\mathcal{Q}_m^I\}_{m=0}^{\mathcal{M}}]),$$
$$\widetilde{\mathcal{T}}_l^P, \widetilde{\mathcal{T}}_l^I = \mathrm{MHSA}(\mathcal{F}_l, \mathrm{PE}(\mathcal{C}_l)),$$

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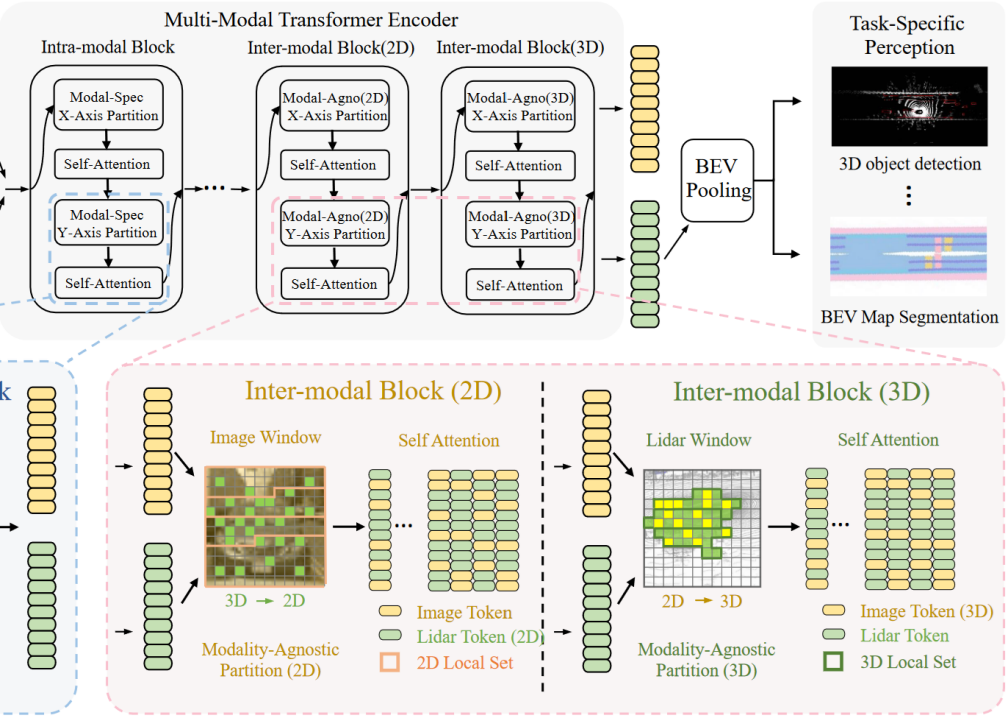
- **Method**



- Multi-sensor의 경우 view-discrepant 문제를 해결하기 위함
  - 하나의 model에서 여러 sensor의 feature를 뽑을 수 있어서 굉장한 시간 이점이라고 주장

- LiDAR token을 calibration parameter를 이용해서 투영 (L→C)
  - image token과의 unify는 동일 채널을 가지기에 sum or interpolation
  - X-axis / Y-axis에서 self-attention

$$\mathcal{T}^P \rightarrow \mathcal{T}^P_{2D} : (x^P, y^P, z^P) \rightarrow (x^P_{2D}, y^P_{2D}, b^P_{2D}),$$

$$\{\mathcal{Q}^{2D}_m\}^{\widetilde{\mathcal{M}}}_{m=0} = \text{DSP}([\mathcal{T}^P_{2D}, \mathcal{T}^I], L^I \times W^I \times 1, \tau),$$

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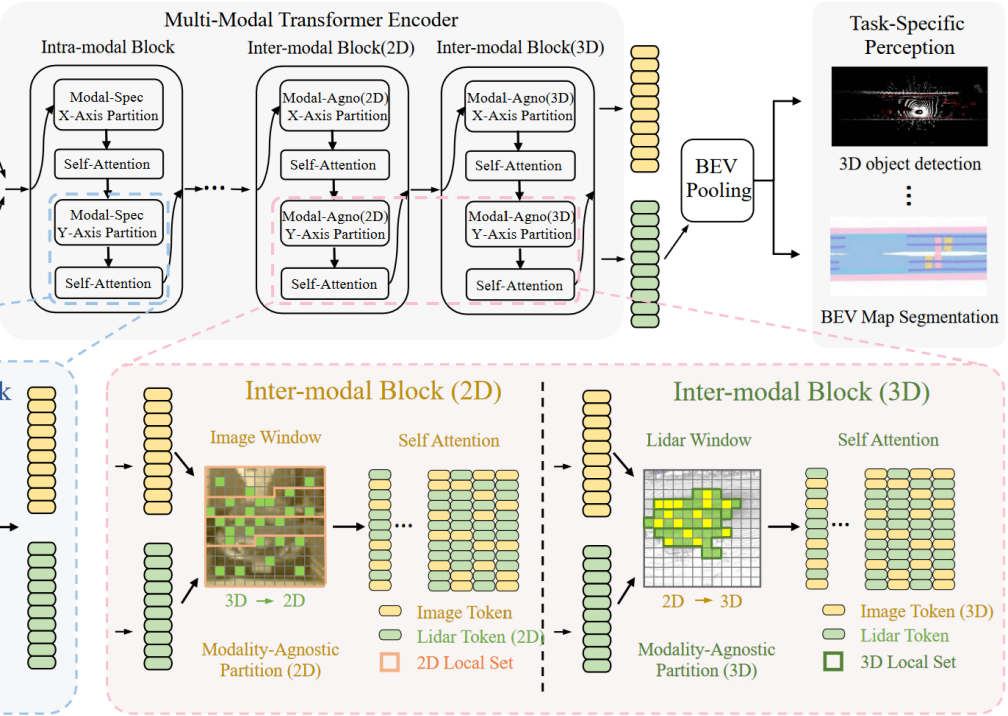
- **Method**



- Image token을 LiDAR token에 투영 (C→L)
  - depth estimation (오차 발생, ill-posed problem)
    → MVP [1] 아이디어 차용
    : L→C 매칭쌍 이용하여 depth retrieval,

매칭 안된거는

가장 가까운 depth를 retrieve

  - X-axis / Y-axis에서 self-attention

$$\{v_i^{\text{nearest}} | (x_i, y_i); b_i; d_i\}_{i=0}^{M} = \text{Nearest}(\mathcal{V}^I, \mathcal{T}^I),$$

$$\mathcal{T}^I \rightarrow \mathcal{T}_{3D}^I : (x^I, y^I, b^I) \rightarrow (x_{3D}^I, y_{3D}^I, z_{3D}^I),$$
$$f^I \rightarrow f^I + \text{MLP}(||v^{\text{nearest}}(x, y) - (x^I, y^I)||).$$

$$\{\mathcal{Q}_n^{3D}\}_{n=0}^{\tilde{\mathcal{N}}} = \text{DSP}([\mathcal{T}^P, \mathcal{T}_{3D}^I], L^P \times W^P \times H^P, \tau),$$

[1] Yin, Tianwei, Xingyi Zhou, and Philipp Krähenbühl. "Multimodal virtual point 3d detection." Advances in Neural Information Processing Systems 34 (2021): 16494-16507.

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- **Experiment**

Modality	Intra-B	Inter-B (2D)	Inter-B (3D)	BEVLSS	NDS	mAP
L	4	0	0		70.5	65.9
C+L	3	0	1		72.0	68.5
C+L	3	1	0		72.5	69.0
C+L	2	1	1		72.9	69.8
C+L	1	2	1		73.1	70.0
C+L	1	2	1	✓	73.3	70.5

Table 10. The number of the intra- and inter-modal blocks on the ablation of 2D & 3D fusion. Camera (C), LiDAR (L).

- 각 블럭 개수에 대한 ablation study

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- **Experiment**

Methods	Present at	Modality	NDS (*val*)	mAP (*val*)	NDS (*test*)	mAP (*test*)	Latency (*ms*)
BEVFormer [34]	ECCV'22	C	-	-	56.9	48.1	–
BEVDepth [32]	AAAI'23	C	-	-	60.0	50.3	–
BEVFormer v2 [69]	CVPR'23	C	-	-	63.4	55.6	–
SECOND [68]	Sensors'18	L	63.0	52.6	63.3	52.8	53.2
PointPillars [27]	CVPR'19	L	61.3	52.3	–	–	28.1
CenterPoint [74]	CVPR'21	L	66.8	59.6	67.3	60.3	62.7
PointPainting [56]	CVPR'20	C+L	69.6	65.8	-	-	151.8
PointAugmenting [57]	CVPR'21	C+L	-	-	71.0†	66.8†	188.4
MVP [75]	NeurIPS'21	C+L	70.0	66.1	70.5	66.4	148.1
FusionPainting [67]	ITSC'21	C+L	70.7	66.5	71.6	68.1	-
FUTR3D [5]	ArXiv'22	C+L	68.3	64.5	-	-	302.6
AutoAlign [8]	IJCAI'22	C+L	71.1	66.6	-	-	-
TransFusion [1]	CVPR'22	C+L	71.3	67.5	71.6	68.9	164.6
AutoAlignV2 [7]	ECCV'22	C+L	71.2	67.1	72.4	68.4	207.0
UVTR [30]	NeurIPS'22	C+L	70.2	65.4	71.1	67.1	-
BEVFusion (PKU) [35]	NeurIPS'22	C+L	71.0	67.9	71.8	69.2	1231.0
DeepInteraction [71]	NeurIPS'22	C+L	72.6	69.9	73.4	**70.8**	541.1
BEVFusion (MIT) [39]	ICRA'23	C+L	71.4	68.5	72.9	70.2	130.5
UniTR (Ours)	ICCV'23	C+L	**73.1**	**70.0**	**74.1**	70.5	**88.7 (50.2‡)**
UniTR w/ LSS (Ours)	ICCV'23	C+L	**73.3**	**70.5**	**74.5**	**70.9**	**107.5 (69.1‡)**

Table 1. Performance of 3D detection on nuScenes (val and test) dataset [3]. Notion of modality: Camera (C), LiDAR (L). †: with test-time augmentation. ‡: deployed by TensorRT). We highlight the top-2 entries with **bold** font in each column.

- 매우 빠른 Inference & +1.9% 정도의 성능 향상 in 3D object detection

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- **Experiment**

Approach	Clean		Missing F		Preserve F		Stuck	
	mAP	NDS	mAP	NDS	mAP	NDS	mAP	NDS
DETR3D* [64]	34.9	43.4	25.8	39.2	3.3	20.5	17.3	32.3
PointAugmenting [57]	46.9	55.6	42.4	53.0	31.6	46.5	42.1	52.8
MVX-Net [54]	61.0	66.1	47.8	59.4	17.5	41.7	48.3	58.8
TransFusion [1]	66.9	70.9	65.3	70.1	64.4	69.3	65.9	70.2
BEVFusion [35]	67.9	71.0	65.9	70.7	65.1	69.9	66.2	70.3
UniTR (Ours)	70.5	73.3	68.5	72.4	66.5	71.2	68.1	71.8

Table 5. Results on robustness setting of camera failure cases. F denotes the front camera, and * means camera-only inputs. All the experiments are on nuScenes validation set.

Aug	Metrics	LiDAR	BEVFusion[35]	Ours
	mAP	31.3	40.2 (+8.9)	38.3(+7.0)
	NDS	50.7	54.3 (+3.6))	55.6(+4.9)
✓	mAP	-	54.0(+22.7)	60.2(+28.9)
✓	NDS	-	61.6(+10.9)	66.0(+15.3)

Table 6. Results on robustness setting of object failure cases. We refer readers to [35] for more details.

- 일부로 만든 failure case에서도 높은 성능

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- **Experiment**

Modality	Camera	Lidar	Serial	Parallel
C+L(1-beam)	36.2	42.0	57.6	**59.5**
C+L(4-beam)	36.2	62.1	67.3	**68.5**
C+L(16-beam)	36.2	69.1	71.6	**72.2**
C+L(32-beam)	36.2	70.5	73.2	**73.3**

Table 7. Ablation of low beam setting with NDS evaluation metric.

Block config	NDS	mAP
3D → 2D	73.0	70.0
2D → 3D	**73.3**	**70.5**
Inter → Intra	72.9	69.8
Intra → Inter	**73.3**	**70.5**

Table 8. Results of different block configurations.

- Table 7: low beam LiDAR에서도 잘 작동한다.
- Table 8: Block들의 순서를 바꿨을때 현재의 순서가 가장 잘 작동한다.