

MPDrive: Improving Spatial Understanding with Marker-Based Prompt Learning for Autonomous Driving

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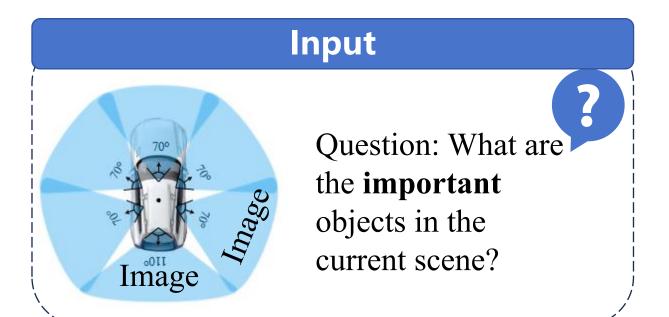
1 Background

- 3 Experimental Results
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Autonomous Driving Visual Question Answering



■ Based on the six-view images of the vehicle, conduct visual question answering in autonomous driving scenarios, with related questions including perception, prediction, and planning.



Output

Answer: There is a brown SUV at the back of the ego vehicle.

Challenges





- Main challenge: Spatial Understanding—semantic gaps between visual coordinate representations and textual descriptions.
- Previous methods enhanced the spatial understanding LLMs through datadriven approaches and the detection experts, but they did not address the semantic gap between spatial information and text coordinates.





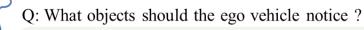
Q: What objects should the ego vehicle notice?



A: Firstly, notice <1018.5,510.8>. The object is stationary, so the ego vehicle should continue ahead at the same speed.









A: Firstly, notice <ID 1>. It is going ahead, so the ego vehicle should slow down and continue ahead. Secondly, notice <ID 2>. It is stationary, so the ego vehicle should slightly maneuver to the right.







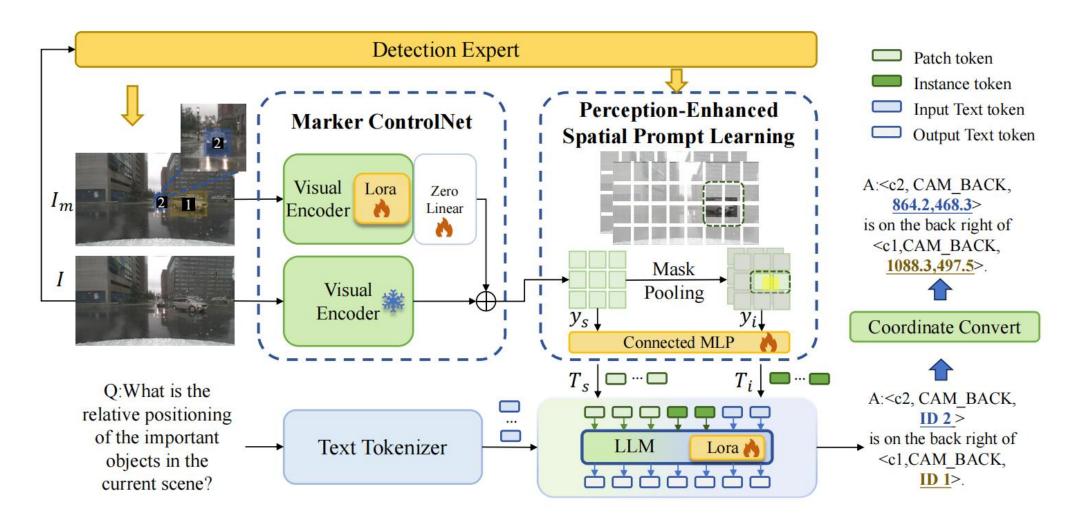
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Overall Pipeline







MPDrive represents spatial coordinates using concise visual markers

Method Details

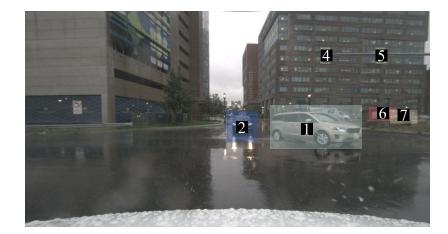




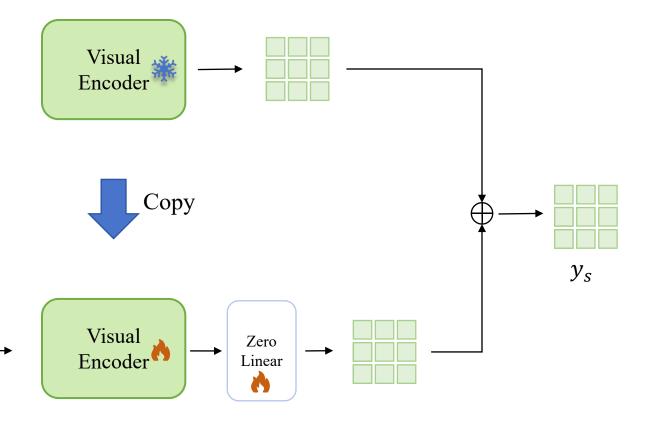
Visual Marker



Detection Expert



Marker ControlNet

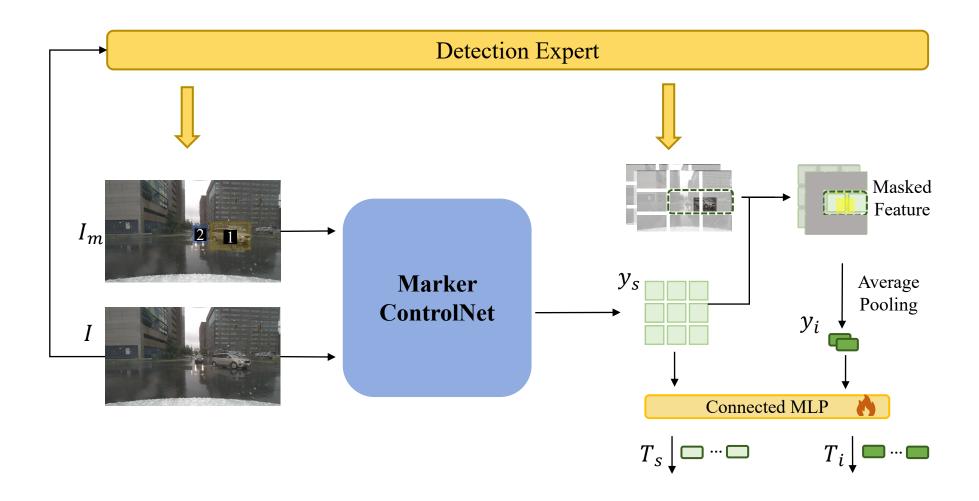


Method Details





Perception-Enhanced Spatial Prompt Learning







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Experimental Results





Quantitative evaluation on the DriveLM dataset

Method	Inference Schema	Spatial↑ Perception	Language↑				
		Match	Accuracy	BLEU-4	ROUGE_L	CIDEr	METEOR
DriveLM-Agent [39]	Graph	-	-	53.09	66.79	2.79	36.19
EM-VLM4AD [14]	Single	, - ,	-	45.36	71.98	3.20	34.49
MiniDrive [58]	Single	-	_	50.20	73.50	3.32	<u>37.40</u>
LLaMA-Adapter [59]	Single	1.48	66.66	45.96	69.78	3.07	33.66
InternVL-2 [6]	Single	7.59	82.54	51.42	77.08	3.53	37.12
Ours: MPDrive	Single	13.43	85.18	<u>52.71</u>	<u>76.98</u>	3.56	38.31

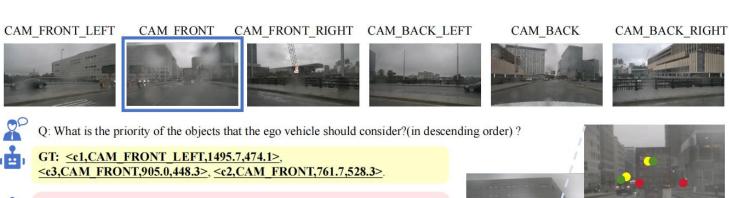
■ MPDrive outperforms existing single-round reasoning methods in both spatial awareness and language understanding, with spatial positioning metrics exceeding the second place by 76%.

Experimental Results



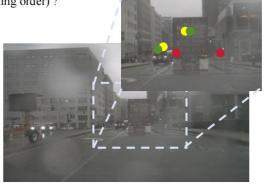


Qualitative evaluation on the DriveLM dataset



InternVL2: The priority of the objects that the ego vehicle should consider (in descending order) is <c4,CAM_FRONT,1020.0,515.8>,<c1,CAM_FRONT,810.0,530.0>, <c3,CAM_FRONT,13.3,565.8>,<c2,CAM_BACK,860.8,510.0>,

MPDrive: The priority of the objects that the ego vehicle should consider (in descending order) is <c1,CAM_FRONT_LEFT,1504.0,482.0>, <c3,CAM_FRONT,873.0,441.0>, <c2,CAM_FRONT,764.0,517.0>.

















Q: What actions taken by the ego vehicle can lead to a collision with <c3,CAM FRONT RIGHT,1022.5,540.0>?



GT: Moderate right turn.



InternVL2: No such action will lead to a collision.



MPDrive: Moderate right turn.







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Contributions

- We introduce MPDrive, a marker-based prompt learning framework that enhances spatial understanding in AD-VQA tasks using visual marker.
- We propose MCNet to fuses visual marker images for scene features.
- We propose Perception-Enhanced Spatial Prompt Learning (PSPL) to integrates scene- and instance-level visual prompts for multi-level spatial understanding.

Future work

■ Long-Horizon Temporal Perception

The End

Thanks for watching!