MONOCULAR 3D OBJECT DETECTION

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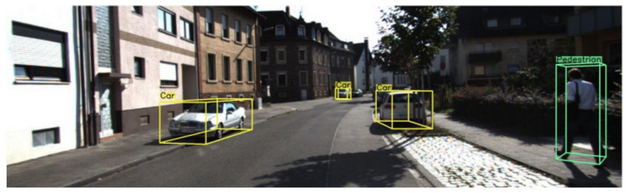
BACKGROUND

3D object detection is crucial for having situational awareness in AVs. Traditionally, stereo vision and LiDAR have been used, but monocular cameras offer a simpler, more cost-effective and easier to integrate alternative. Hence, work in 3D object recognition from this source is relevant.



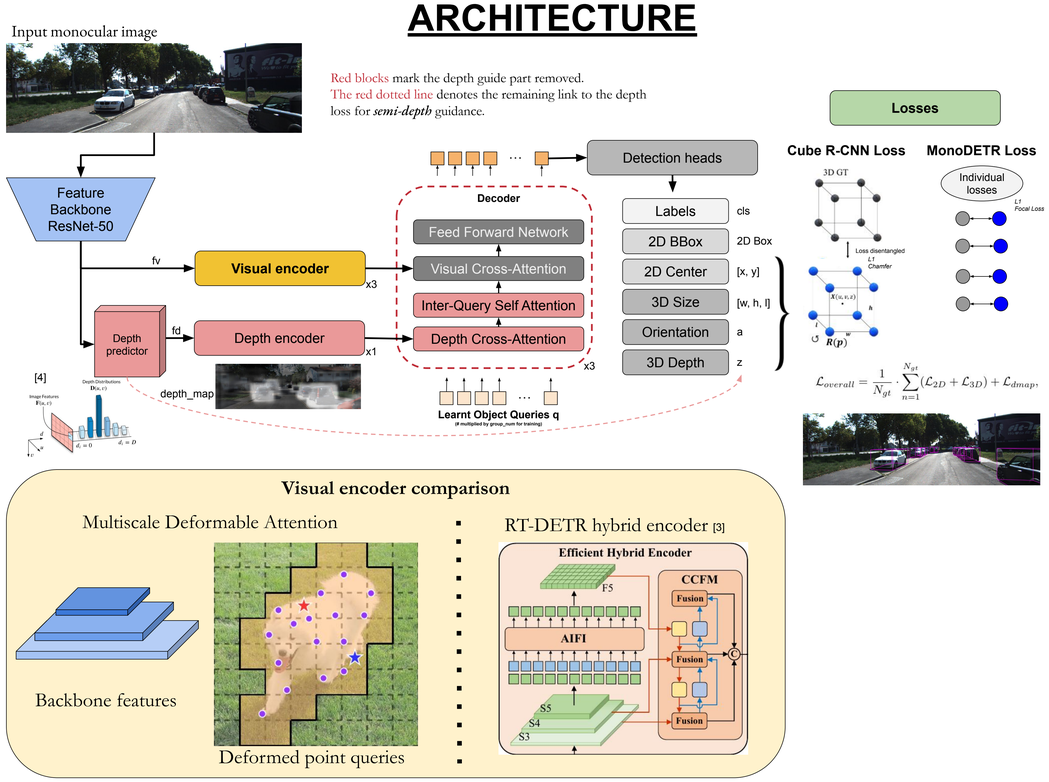
This works investigates modification to the MonoDETR architecture, a model aimed to make monocular camera 3D object detections.
The approaches taken:

- Modifying the information channels in the original model
- Replacing certain parts of the model to assess its impact on inference time, model size and performance (depth guidance, RT-DETR)
- Implementing a different set of losses leveraging on the idea of *disentangled loss.* (Cube R-CNN)

Main contributions:

- Investigation of backbone and depth guidance impact.
- Integration of RT-DETR hybrid visual encoder for improved speed.
- Excluding depth guidance (semi and fully disconnected)
- Training optimization with Cube R-CNN 3D loss
- Inference evaluation with integrated DeepSpeed Profiler.

ARCHITECTURE



TRAINING

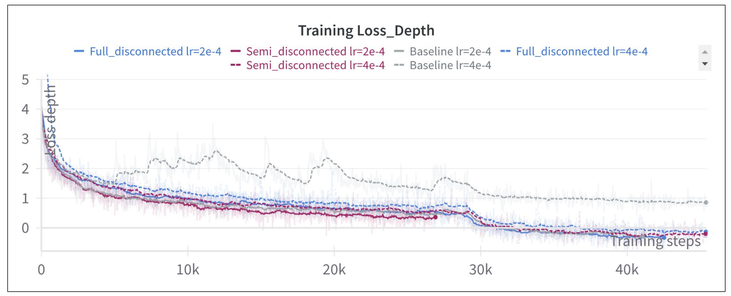
Dataset: ~7500 KITTI rgb images (375x1242)

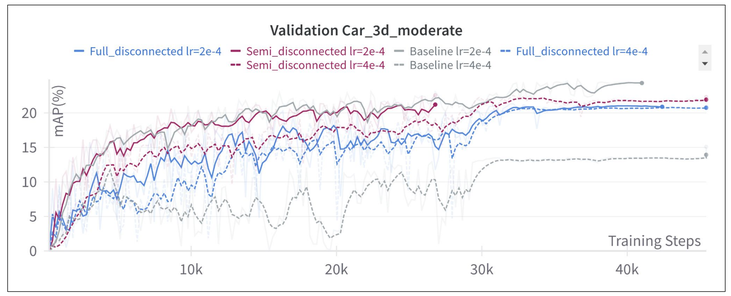
- Training: 49.6%, Validation: 50.4%

Infrastructure:

- DTU's HPC + Weights & Biases + Hydra

Batch Size	16	Epochs	195
Learning Rates	2e-4 4e-4	Weight Decay	1e-4



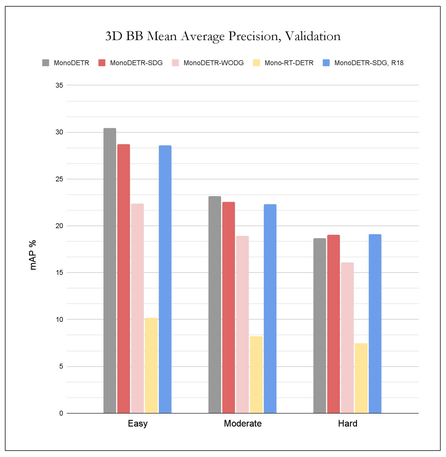


RESULTS - Quantitative

Model validation performance 3D Bounding Box

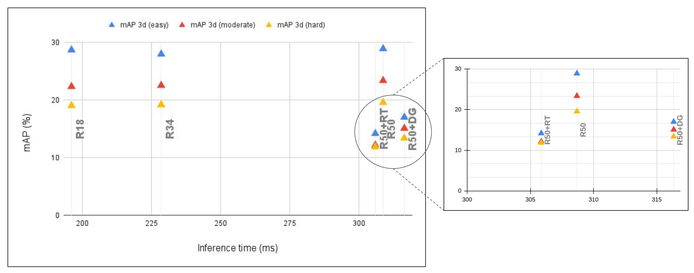
Method (from papers)	Val, AP 3D BB Easy - Mod - Hard
Cube R-CNN [2]	23.59 - 15.01 - 12.56
MonoDETR [1]	25.00 - 16.47 - 13.58

Method (ours)	Val, AP 3D BB Easy - Mod - Hard
MonoDETR *(lr=2e-4)*	30.46, 23.18, 18.65
MonoDETR *(lr=4e-4)*	18.75 - 14.96 - 13.70
MonoDETR-SDG *(lr=2e-4)* (w. semi depth guidance)	28.73 - 22.55 - 19.06
MonoDETR-SDG *(lr=4e-4)*	27.22 - 22.30 - 18.90
MonoDETR-WODG (lr=2e-4) (w/o depth guidance)	22.35 - 18.94 - 16.11
MonoDETR-WODG (lr=4e-4)	25.46 - 20.89 - 18.19
Mono-RT-DETR (lr=4e-4)	10.19 - 08.21 - 07.47
MonoDETR-SDG Resnet18 (lr=4e-4)	28.61 - 22.32 - 19.09
MonoDETR-SDG Resnet34 (lr=4e-4)	25.72 - 22.60 - 19.19

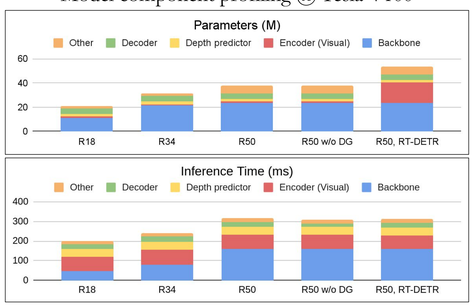


RESULTS - Inference

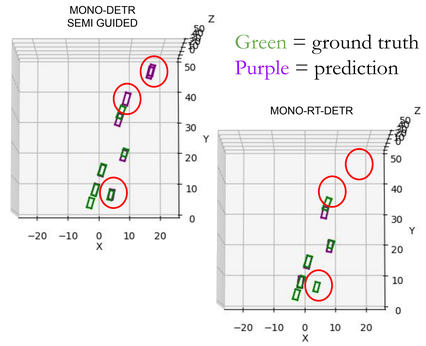
Precision versus inference performance



Model component profiling @ Tesla V100



RESULTS - Qualitative



CONCLUSIONS

- Successfully trained and evaluated monocular 3D object detection models based on MonoDETR.
- The semi-depth guided model is more stable in training across learning rates with similar best precision (mAP). This is related to the depth predictor's training loss gradient paths.
- The ResNet 50 backbone represented ~50% of the parameters and inference time in the baseline.
- ResNet 34 and 18 greatly reduces inference time without significantly affecting precision (mAP).
- The bipartite matching involved in the loss makes DETR models training unstable.
- The RT-DETR hybrid visual encoder results in worse visual queries, reducing performance.

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[4] Reading, C., Harakeh, A., Chae, J., & Waslander, S. L. (2021). *Categorical Depth Distribution Network for Monocular 3D Object Detection*. arXiv preprint arXiv:2103.01100.