

technik autonomer systeme

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informative for a fine-grained segmentation of a scene.

 $\theta = 10.$

C |

14

17

18

19

23

non-drivable vegetation.

Terrain

Vegetation

Level of granularity

Baseline (terrain, vegetation)

→ Asphalt, gravel, soil, sand

ightarrow Drivable, non-drivable

ightarrow Low grass, high grass

tree crown, tree trunk In brackets we compare the performance to the 14 class baseline

ightarrow Bush, forest, misc. vegetation,

Non-drivable vegetation

Drivable vegetation

Boundary Jaccard

The common IoU evaluation metric is known to be biased towards semantic

classes that cover a large image area. A fine-grained segmentation leads to many smaller semantic classes. The Boundary Jaccard (BJ) measure

[6] evaluates scene segmentations along the class borders, which is more

The area of interest evaluated by the BJ metric is within θ pixels to a class border in the ground truth and the prediction. In our experiments, we set

Fine-Grained Semantic Segmentation We analyzed the segmentation performance for different class granularities for the categories terrain and vegetation. We increased the label granularity in each step. Training Fast-SCNN [7] for the different class granularities has shown a drop in segmentation performance when separating the visually similar

low grass and high grass. The same holds for the fine-grained segmentation of

Qualitative Comparison

Val mloU (%)

53.54 (+0.54)

54.77 (+1.77)

52.30 (-0.70)

49.70 (-3.30)

53.00

Val mBJ (%)

54.29 (+1.50)

53.56 (+0.77)

42.88 (-9.91)

50.12 (-2.67)

52.79

Introduction

We introduce TAS500, a novel semantic segmentation dataset for autonomous driving in unstructured outdoor environments. Using TAS500 as our training dataset, we study how a more fine-grained labeling policy affects the overall performance of the semantic segmentation.



Legend: asphalt (■), building (■), bush (■), car (■), ego vehicle (■), forest (■), gravel (■), high grass (■), low grass (■), miscellaneous vegetation (■), person (■), soil (■), sky (■), tree crown (■), tree trunk (

Data Collection

The data was collected using the autonomous vehicle MuCAR-3 [1]. Our vision system is mounted on a multifocal active/reactive camera platform called MarVEye [2]. This allows us to pan the camera when turning into a corner. We cut off most of the sky and ego vehicle hood from all images. The final images have a resolution of 620 px \times 2026 px.



Dataset Comparison

Laying our focus on annotating scenes from unstructured outdoor environments naturally leads to the observation that the scenes in our TAS500 dataset contain more terrain and vegetation pixels per image than other urban scene understanding datasets [3, 4]. We also compare TAS500 to the multimodal Freiburg Forest dataset [5], which also contains scenes in unstructured outdoor environments.

Dataset	Resolution ($H \times W$)	Terrain (%)	Vegetation ‡ (%)
$Cityscapes^\dagger$	1024×2048	38.0	14.1
KITTI [†]	375×1242	10.0	30.3
FreiburgForest	487×880	9.3	25.7 + 39.9
TAS500 (ours)	620×2026	18.4	35.3 + 23.3
[†] The terrain class is composed of the road and sidewalk classes.			

[‡] Vegetation is split into drivable and non-drivable where applicable.



Download the TAS500 dataset at mucar3.de/icpr2020-tas500

Legend: asphalt (), building (), car (), drivable vegetation (), ego vehicle (), gravel (), non-drivable vegetation (), obstacle (),

person (
), pole (
), soil (
), sky (
)

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