Boosting Monocular Depth with Panoptic Segmentation Maps
– Supplemental Material –

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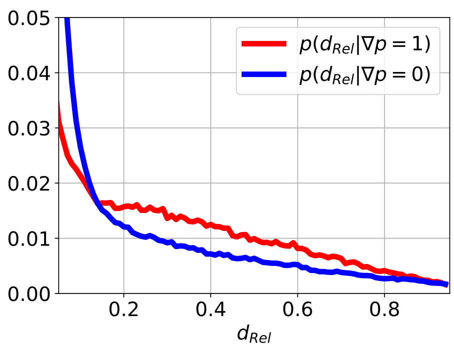

Figure 6. The histogram of $p(d_{rel}|\nabla_p = 0)$ *(blue)* and $p(d_{rel}|\nabla_p = 1)$ *(red)*. Strong depth continuities are more probable to coincide with panoptic boundary locations ($\nabla_p = 1$).

A. Empirical Motivation

To confirm the visual observations in Fig. 1 of the main paper, we take 200 images from the Synscapes dataset [36] and plot the histogram of relative edge strengths conditioned on whether or not they coincide with the edges of the panoptic maps. Fig. 6 shows the results. Here, we identify panoptic discontinuities as

$$\nabla_p = (1 - \delta(\nabla_x p)) \vee (1 - \delta(\nabla_y p)), \quad (11)$$

where ∇_x and ∇_y are the differences between adjacent pixels in x and y direction, respectively. δ is the Dirac delta and $\vee$ denotes the pixel-wise logical OR operator.

We clearly observe that the conditional probability of strong depth edges is higher for panoptic boundaries than away from boundaries, which motivates our panoptic depth boost loss in the main paper.

B. Detailed Experimental Results

Here, we additionally show the full evaluation of the experiments for all our models and the baselines from the main paper in Tables 5 to 8 below. For all models we report values for the absolute relative difference (*Abs. Rel.*), squared relative difference (*Sq. Rel.*), root mean squared error linear (RMSE) and logarithm (RMSE_{log}), $\delta < 1.25$, $\delta < 1.25^2$, and $\delta < 1.25^3$. The first four measures are errors, hence the lower the better. For the last 3 evaluation metrics, the higher value indicates a better accuracy.

Method	Abs. Rel.	Sq. Rel.	RMSE	RMSE_{log}	$\delta < 1.25$	$\delta < 1.25^2$	$\delta < 1.25^3$
Xu *et al*. [38]	0.246	4.060	7.117	0.428	0.786	0.905	0.945
Zhang *et al*. [41]	0.234	3.776	7.104	0.416	0.776	0.903	0.949
Wang *et al*. [33]	0.227	3.800	**6.917**	0.414	**0.801**	0.913	0.950
Ours	**0.1783**	**2.9270**	9.023	**0.248**	0.771	**0.922**	**0.971**

Table 5. Complete results for Table 1 of the main paper.

Method	Abs. Rel.	Sq. Rel.	RMSE	RMSE_{log}	$\delta < 1.25$	$\delta < 1.25^2$	$\delta < 1.25^3$
Godard (M) [11]	0.141	1.186	5.677	0.238	0.809	0.928	0.969
Chen [3]	0.118	0.905	5.096	0.211	0.839	0.945	0.977
M + panoptic	**0.111**	**0.870**	**4.92**	**0.206**	**0.849**	**0.951**	**0.979**
Godard (M2) [12]	0.107	0.849	4.764	0.201	0.874	0.953	0.977
M2 + panoptic	**0.103**	**0.840**	**4.761**	**0.200**	**0.879**	**0.958**	**0.980**

Table 6. Complete results for Table 2 of the main paper.

Method	Abs. Rel.	Sq. Rel.	RMSE	RMSE_{log}	$\delta < 1.25$	$\delta < 1.25^2$	$\delta < 1.25^3$
Monodepth [11]	0.148	2.104	6.439	0.224	0.839	0.936	0.972
Ramirez *et al*. [28]	0.144	1.973	6.199	0.217	**0.849**	**0.940**	0.975
Geometric baseline	0.147	1.998	6.312	0.221	0.835	0.936	0.973
$+\mathcal{L}_{\text{pgs}}$	0.142	1.989	6.306	0.219	0.848	**0.940**	0.976
$+\mathcal{L}_{\text{plr}}$	0.138	1.951	6.206	0.215	0.842	0.930	**0.977**
$+\mathcal{L}_{\text{pga}}$ (Final)	**0.135**	**1.949**	**6.203**	**0.214**	0.848	0.939	0.976

Table 7. Complete results for Table 3 of the main paper.

Segmentation	Abs. Rel.	Sq. Rel.	RMSE	RMSE_{log}	$\delta < 1.25$	$\delta < 1.25^2$	$\delta < 1.25^3$
Geometric	0.147	1.998	6.312	0.221	0.835	0.936	0.973
G+Semantic	0.141	1.963	6.284	0.216	0.840	0.939	0.975
G+Panoptic	**0.135**	**1.949**	**6.203**	**0.214**	**0.848**	**0.939**	**0.976**

Table 8. Complete results for Table 4 of the main paper.