Supplementary Material
Gradient-based Uncertainty for Monocular Depth Estimation

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1 Further Visual Results

In Fig. 1 to Fig. 4, further visual results are provided. The examples show the RGB images, the depth prediction, the true error in terms of RMSE as well as the uncertainty obtained from the base model, inference dropout (\textit{In-Drop}) and the gradients extracted from the neural network (Ours).

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{uncertainty_estimation}
\caption{Uncertainty estimation example from Monodepth2 [2] trained on NYU Depth V2 [3]. In (a), the input image is shown, while (b) and (c) display the depth prediction and the true error in terms of RMSE, respectively. The second row demonstrates the uncertainty estimated by post-processing (\textit{Post}) (d), inference dropout (\textit{In-Drop}) (e) and gradients (Ours) (f).}
\end{figure}

\textsuperscript{*} Most of this work was done while Vasileios Belagiannis was with Ulm University.
Fig. 2. Uncertainty estimation example from Monodepth2 [2] trained on NYU Depth V2 [3] with log-likelihood maximization (Log). In (a), the input image is shown, while (b) and (c) display the depth prediction and the true error in terms of RMSE, respectively. The second row demonstrates the uncertainty estimated by log-likelihood maximization (Log) (d), inference dropout (In-Drop) (e) and gradients (Ours) (f).

Fig. 3. Uncertainty estimation example from Monodepth2 [2] trained on KITTI [1] with stereo pair supervision. In (a), the input image is shown, while (b) and (c) display the depth prediction and the true error in terms of RMSE, respectively. Note that ground truth depth is not available for all pixels. In (d), (e) and (f), the uncertainty estimated by gradients (Ours), inference dropout (In-Drop) and post-processing (Post) is demonstrated, respectively.
Fig. 4. Uncertainty estimation example from Monodepth2 [2] trained on KITTI [1] with stereo pair supervision and self-teaching. In (a), the input image is shown, while (b) and (c) display the depth prediction and the true error in terms of RMSE, respectively. Note that ground truth depth is not available for all pixels. In (d), (e) and (f), the uncertainty estimated by gradients (Ours), inference dropout (In-Drop) and self-teaching (Self) is demonstrated, respectively.
2 Additional Sparsification Error Plots

In Fig. 5 and Fig. 6, the sparsification error plots in terms of Abs Rel and $\delta \geq 1.25$ are displayed for Monodepth2 [2] trained on KITTI [1] with monocular sequences and stereo pairs, respectively. In Fig. 7, the sparsification error curves in terms of Abs Rel, $\delta \geq 1.25$ and RMSE for Monodepth2 [2] trained on NYU Depth V2 [3] are shown. The curves are averaged over the respective test sets.

![Fig. 5](image1.png)

**Fig. 5.** The sparsification error in terms of Abs Rel (a) and $\delta \geq 1.25$ (b) over the fraction of removed pixels is illustrated for Monodepth2 [2] trained on KITTI [1] with monocular sequences.

![Fig. 6](image2.png)

**Fig. 6.** The sparsification error in terms of Abs Rel (a) and $\delta \geq 1.25$ (b) over the fraction of removed pixels is illustrated for Monodepth2 [2] trained on KITTI [1] with stereo pairs.
3 Additional Ablation Studies

**Importance Loss Components** In Tab. 1, we evaluate the importance of the individual components of the loss function for the Bayesian models. Therefore, we compare the use of the entire loss function $L_b$, the loss $L_r$ without the variance and solely the variance $\sigma^2$ for the gradient generation. We conduct the experiments on the Log models.

**Layer Selection** In Tab. 2, we demonstrate the performance of our gradient-based uncertainty estimation for the Monodepth2 [2] Post model trained on NYU Depth V2 [3] with gradients extracted at different decoder layers. We consider gradients extracted from the 6th to the 9th decoder layer. The layers are counted starting from the first to the last decoder layer.

**Variance over Augmentations as Gradient Extraction Loss** In Tab. 3, we evaluate the usage of the variance over test-time augmentations as loss func-
Table 1. Uncertainty estimation results for Monodepth2 [2] trained on NYU Depth V2 [3] or KITTI [1] with monocular (Mono) or stereo pair (Stereo) supervision comparing the importance of the single loss terms using the Log models. The estimated uncertainty is evaluated with the Area Under the Sparsification Error (AUSE) and the Area Under the Random Gain (AURG) in terms of absolute relative error (Abs Rel), root mean squared error (RMSE) and accuracy $\delta \geq 1.25$.

| Setup | Loss | Abs Rel | RMSE | $\delta \geq 1.25$ |
|-------|------|---------|------|------------------|
| NYU   | $\mathcal{L}_b$ | 0.053   | 0.032 | 0.176   | 0.193 | 0.086 | 0.069 |
|       | $\sigma^2$   | 0.054   | 0.031 | 0.163   | 0.205 | 0.085 | 0.070 |
|       | $\mathcal{L}_r$ | 0.059   | 0.026 | 0.236   | 0.133 | 0.100 | 0.055 |
| KITTI Mono | $\mathcal{L}_b$ | 0.026   | 0.033 | 0.819   | 2.658 | 0.024 | 0.059 |
|       | $\sigma^2$   | 0.036   | 0.023 | 2.399   | 1.079 | 0.042 | 0.041 |
|       | $\mathcal{L}_r$ | 0.028   | 0.031 | 0.577   | 2.900 | 0.027 | 0.056 |
| KITTI Stereo | $\mathcal{L}_b$ | 0.019   | 0.038 | 0.490   | 2.849 | 0.018 | 0.061 |
|       | $\sigma^2$   | 0.026   | 0.031 | 1.685   | 1.655 | 0.028 | 0.051 |
|       | $\mathcal{L}_r$ | 0.022   | 0.036 | 0.495   | 2.845 | 0.022 | 0.047 |

Table 2. Uncertainty estimation results for Monodepth2 [2] Post model trained on NYU Depth V2 [3] with gradients extracted from different decoder layers. The estimated uncertainty is evaluated with the Area Under the Sparsification Error (AUSE) and the Area Under the Random Gain (AURG) in terms of absolute relative error (Abs Rel), root mean squared error (RMSE) and accuracy $\delta \geq 1.25$.

| Layer | Abs Rel | RMSE | $\delta \geq 1.25$ |
|-------|---------|------|------------------|
|       | AUSE ↓ AURG ↑ | AUSE ↓ AURG ↑ | AUSE ↓ AURG ↑ |
| 5     | 0.063   | 0.023 | 0.237   | 0.135 | 0.111 | 0.044 |
| 6     | 0.061   | 0.025 | 0.252   | 0.120 | 0.106 | 0.048 |
| 7     | 0.063   | 0.023 | 0.259   | 0.113 | 0.110 | 0.045 |
| 8     | 0.064   | 0.022 | 0.284   | 0.088 | 0.114 | 0.041 |
| 9     | 0.066   | 0.021 | 0.298   | 0.073 | 0.118 | 0.037 |

Reference Depth Augmentation In Tab. 4, the uncertainty estimation results of our gradient-based approach on Monodepth2 [2] trained with NYU Depth V2 [3] are reported for the Log model. We demonstrate different configurations to define the loss for the gradient generation. We consider the squared difference of the prediction to the ground truth depth (GT) and to transformed images by image flipping (Flip), gray-scale conversion (Gray) and additive Gaussian noise (Noise).
Table 3. Uncertainty estimation results for Monodepth2 [2] Post model trained on NYU Depth V2 [3] where the gradients are extracted with the variance over different test-time augmentations. The estimated uncertainty is evaluated with the Area Under the Sparsification Error (AUSE) and the Area Under the Random Gain (AURG) in terms of absolute relative error (Abs Rel), root mean squared error (RMSE) and accuracy $\delta \geq 1.25$.

| Layer   | AUSE | AURG | AUSE | AURG | AUSE | AURG |
|---------|------|------|------|------|------|------|
| Var-Grad| 0.064| 0.023| 0.256| 0.116| 0.113| 0.042|
| Ours    | 0.061| 0.025| 0.252| 0.120| 0.106| 0.048|

Table 4. Uncertainty estimation results for Monodepth2 [2] Log trained on NYU Depth V2 [3] when using different loss functions for the gradient generation. We compare the error of the prediction to the ground truth depth (GT) and depth predictions obtained by different image transformations. We consider image flipping (Flip), grayscale conversion (Gray) and additive Gaussian noise (Noise). The estimated uncertainty is evaluated with the Area Under the Sparsification Error (AUSE) and the Area Under the Random Gain (AURG) in terms of absolute relative error (Abs Rel), root mean squared error (RMSE) and accuracy $\delta \geq 1.25$.

| Loss   | AUSE | AURG | AUSE | AURG | AUSE | AURG |
|--------|------|------|------|------|------|------|
| GT     | 0.014| 0.071| 0.072| 0.297| 0.018| 0.136|
| Flip   | 0.053| 0.032| 0.176| 0.193| 0.088| 0.069|
| Gray   | 0.054| 0.031| 0.177| 0.192| 0.086| 0.068|
| Noise  | 0.054| 0.031| 0.165| 0.203| 0.085| 0.069|

References

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