

Adaptive Multi-Modal Cross-Entropy Loss for Stereo Matching

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Motivation

- Stereo matching networks poorly estimate clear edges due to the over-smoothing problem, causing **bleeding artifacts** in reconstructed point clouds.



- Existing methods model the disparity ground-truth as the uni-modal distribution, but fail to suppress the multi-modal outputs at the edge. Meanwhile, the single-modal disparity estimator (SME) suffers from severe **misalignment artifacts**.

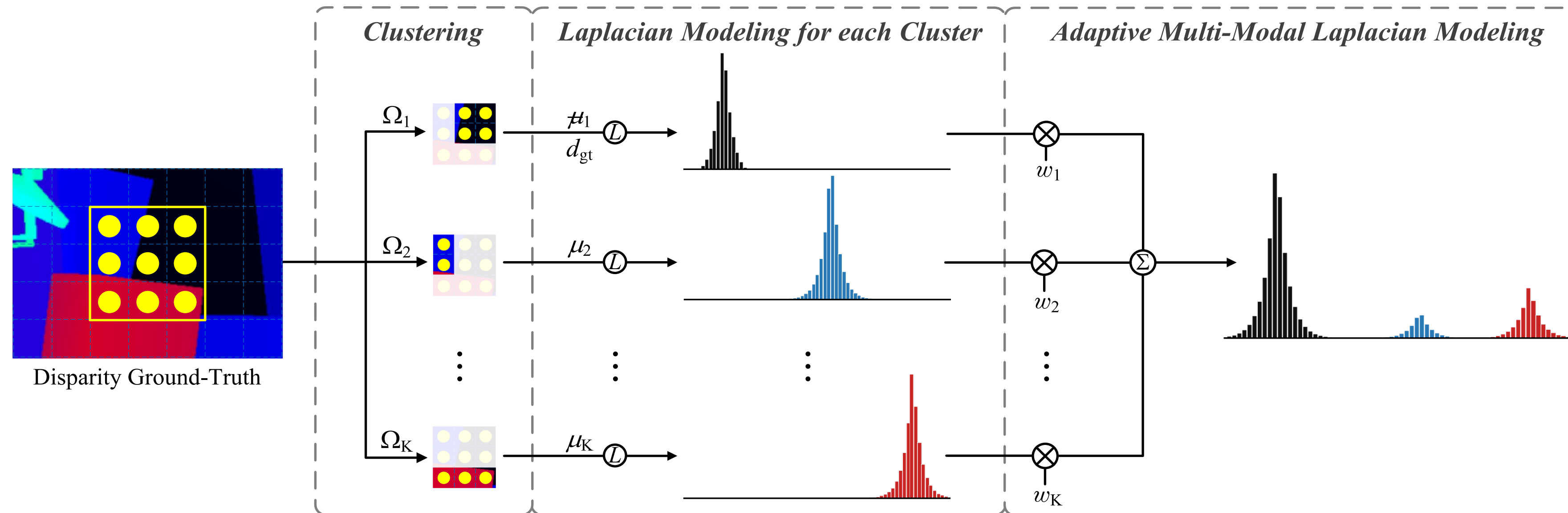


- Our work aims to explore a better modeling for the stereo ground-truth and improve the robustness of the disparity estimator.

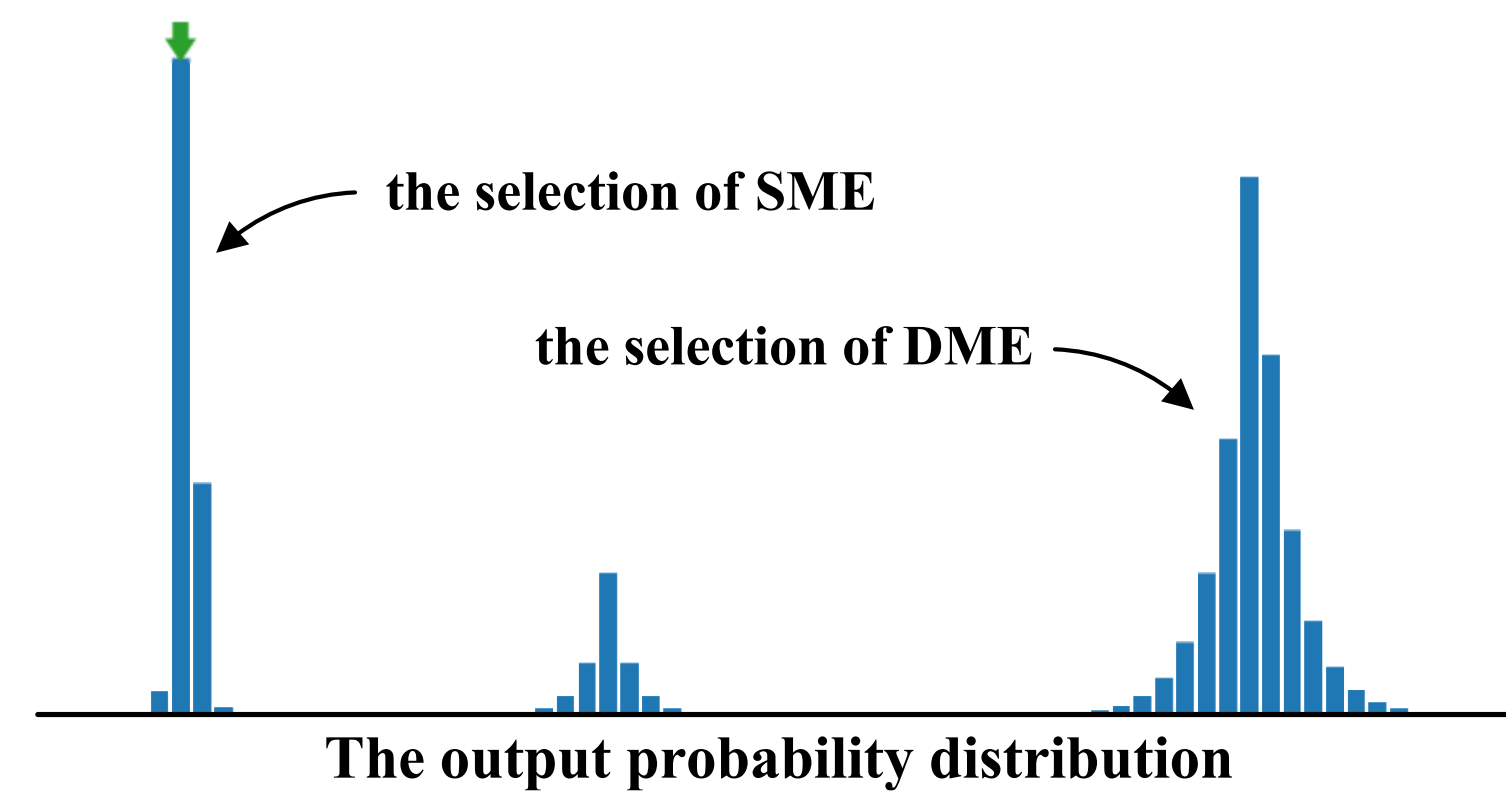
Contributions

- An **adaptive multi-modal probability modeling** for supervising stereo networks training, effectively guiding the networks to learn clear distribution patterns.
- A **dominant-modal disparity estimator (DME)** that can obtain accurate results upon multi-modal outputs.
- State-of-the-art performance** on both the KITTI 2015 and KITTI 2012 benchmarks.
- Excellent cross-domain generalization performance.**

Our Method

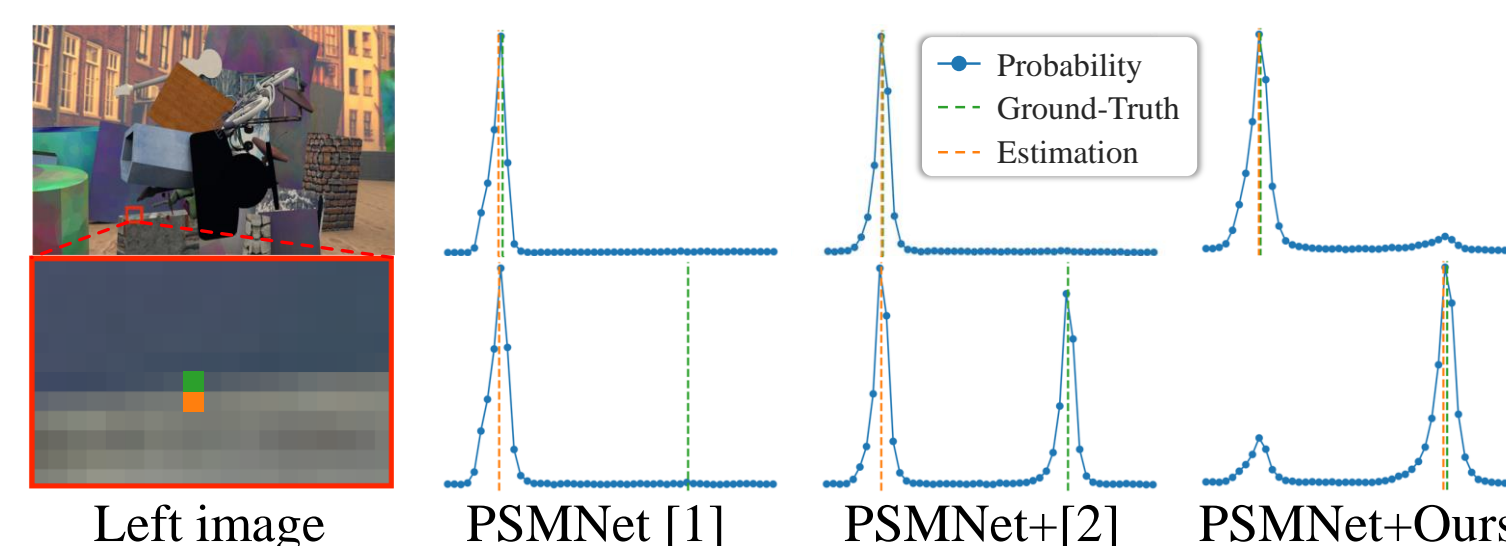


- Clustering is applied within the local window to separate different modals.
- Laplacian distribution is then employed for modeling each cluster.
- Local structural information is used to fuse the generated uni-modal distributions.



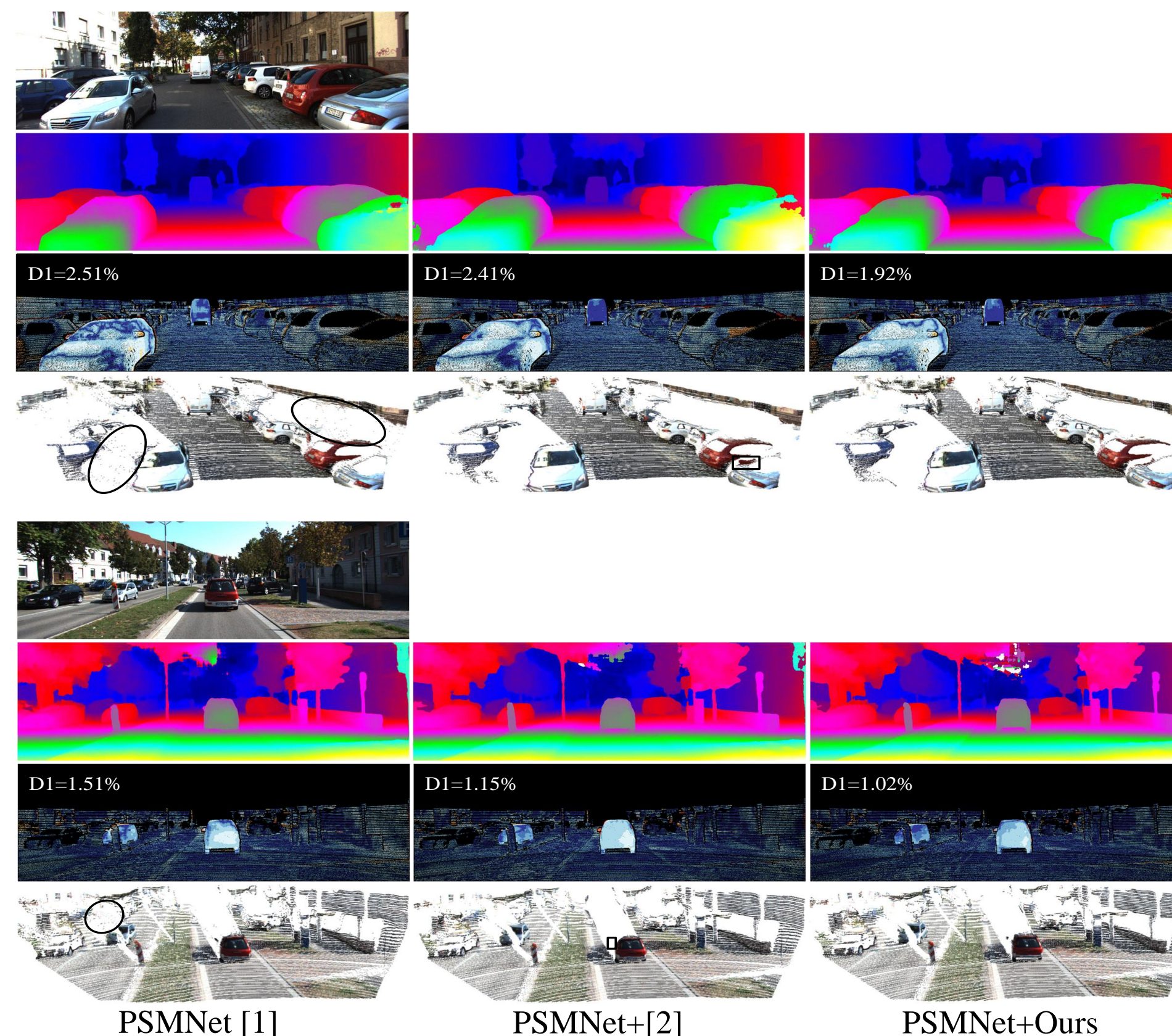
- we propose a dominant-modal disparity estimator (DME) to better tackle the difficulties brought by the multi-modal outputs from the network.

Vis. of Output Distributions



- Top row: **background** pixel
- Bottom row: **foreground** pixel

Qualitative Results



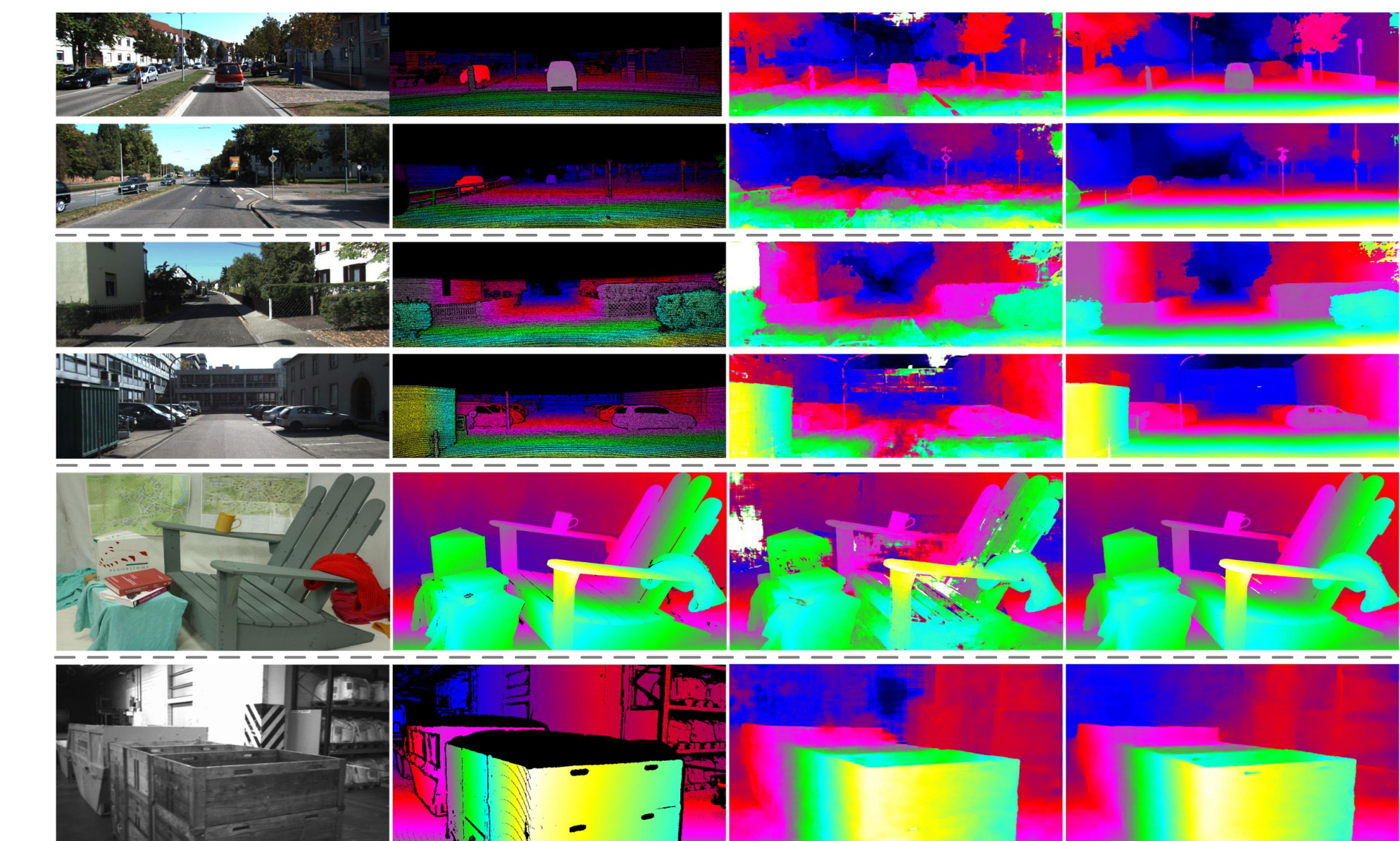
- From top to bottom: left images, disparity maps, error maps, and reconstructed point clouds.

Quantitative Results

| Method | KITTI 2015 | | | | | | KITTI 2012 | | | |
|---------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|
| | All | | | Noc | | | >2px | | >3px | |
| | D1-bg | D1-fg | D1-all | D1-bg | D1-fg | D1-all | Out-Noc | Out-All | Out-Noc | Out-All |
| PDSNet | 2.29 | 4.05 | 2.58 | 2.09 | 3.68 | 2.36 | 3.82 | 4.65 | 1.92 | 2.53 |
| PSMNet | 1.86 | 4.62 | 2.32 | 1.71 | 4.31 | 2.14 | 2.44 | 3.01 | 1.49 | 1.89 |
| PSMNet + [2] | 1.54 | 4.33 | 2.14 | 1.70 | 3.90 | 1.93 | 2.17 | 2.81 | 1.35 | 1.81 |
| GwcNet | 1.74 | 3.93 | 2.11 | 1.61 | 3.49 | 1.92 | 2.16 | 2.71 | 1.32 | 1.70 |
| PSMNet+SMDNet | 1.69 | 4.01 | 2.08 | 1.54 | 3.70 | 1.89 | — | — | — | — |
| CDN | 1.66 | 3.20 | 1.92 | 1.50 | 2.79 | 1.72 | — | — | — | — |
| AcfNet | 1.51 | 3.80 | 1.89 | 1.43 | 3.25 | 1.73 | 1.83 | 2.35 | 1.17 | 1.54 |
| GANet | 1.48 | 3.46 | 1.81 | 1.34 | 3.11 | 1.63 | 1.89 | 2.50 | 1.19 | 1.60 |
| GANet + LaC | 1.44 | 2.83 | 1.67 | 1.26 | 2.64 | 1.49 | 1.72 | 2.26 | 1.05 | 1.42 |
| ACVNet | 1.37 | 3.07 | 1.65 | 1.26 | 2.84 | 1.52 | 1.83 | 2.34 | 1.13 | 1.47 |
| LEAStereo | 1.40 | 2.91 | 1.65 | 1.29 | 2.65 | 1.51 | 1.90 | 2.39 | 1.13 | 1.45 |
| IGEVStereo | 1.38 | 2.67 | 1.59 | 1.27 | 2.62 | 1.49 | 1.71 | 2.17 | 1.12 | 1.44 |
| CroCoStereo | 1.38 | 2.65 | 1.59 | 1.30 | 2.56 | 1.51 | — | — | — | — |
| PSMNet + Ours | 1.44 | 3.25 | 1.74 | 1.30 | 3.04 | 1.59 | 1.80 | 2.32 | 1.14 | 1.50 |
| GwcNet + Ours | 1.42 | 3.01 | 1.68 | 1.30 | 2.76 | 1.54 | 1.65 | 2.17 | 1.05 | 1.42 |
| GANet + Ours | 1.38 | 2.38 | 1.55 | 1.24 | 2.18 | 1.40 | 1.52 | 2.01 | 0.98 | 1.29 |

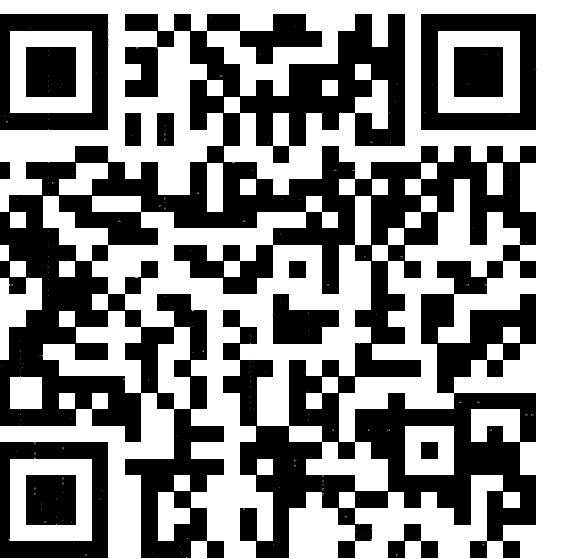
- All of the three baselines are lifted to a highly competitive level by our method.
- GANet with our method achieves new state-of-the-art results on both KITTI 2015 and KITTI 2012 benchmarks.

Generalization Performance



- From top to bottom: KITTI 2015, KITTI 2012, Middlebury, and ETH3D.

Links



paper



demo

References

- [1] Chang and Chen. Pyramid stereo matching network. CVPR 2018.
- [2] Chen, Chen, and Cheng. On the over-smoothing problem of cnn based disparity estimation. ICCV 2019.