DPS-Net: Deep Polarimetric Stereo Depth Estimation

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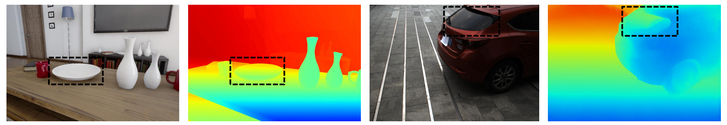
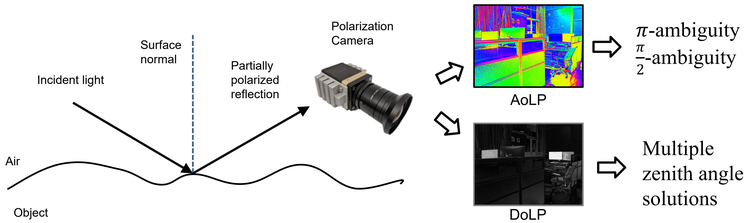
Motivation

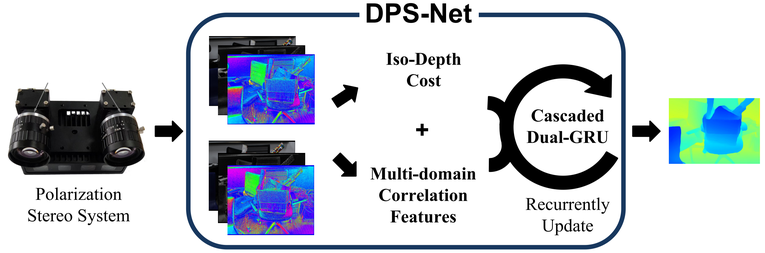
- RGB-based stereo matching struggles with textureless areas.



- Shape from polarization struggles with ambiguities.



Our Solution

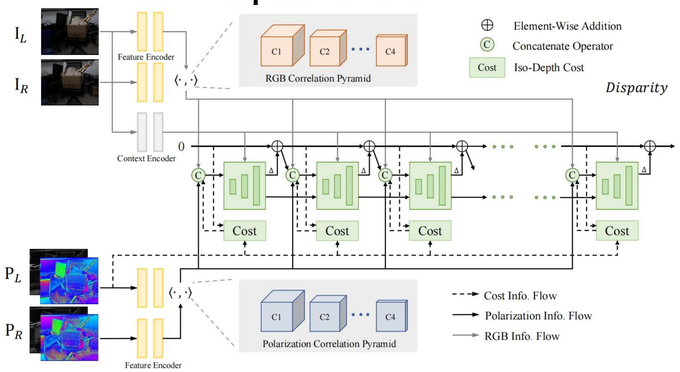


Reference

[1] Liu et al. Local similarity pattern and cost self-reassembling for deep stereo matching networks. AAAI 2022.
[2] Cheng et al. Hierarchical neural architecture search for deep stereo matching. NeurIPS 2020.
[3] Lipson et al. Raft-stereo: Multilevel recurrent field transforms for stereo matching. 3DV 2021.
[4] Zhu et al. Depth from a polarisation+ rgb stereo pair. CVPR 2019.
[5] Lei et al. Shape from polarization for complex scenes in the wild. CVPR 2022.
[6] Ba et al. Deep shape from polarization. ECCV 2020.

Method

Pipeline Overview



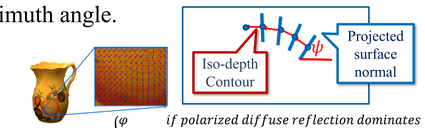
- Extract the multi-domain features.
- Integrate the iso-depth cost.
- Construct the multi-domain correlation pyramids.
- Update the disparity recurrently by the GRU.

Iso-Depth Cost

We construct the unified iso-depth cost.

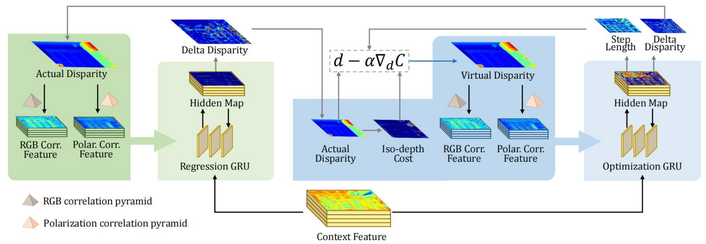
- Bypass both the zenith angle ambiguity and π-ambiguity of azimuth angle.
- Handle the π/2-ambiguity of azimuth angle.

$$\mathbf{C}_s(\varphi) = [sin(\phi)\,sin(\varphi) + cos(\phi)\,cos(\varphi)]^2,$$
$$\mathbf{C}_d(\varphi) = [sin(\phi)\,cos(\varphi) - cos(\phi)\,sin(\varphi)]^2,$$
$$\mathbf{C}(\varphi) = \min\{\mathbf{C}_s(\varphi), \mathbf{C}_d(\varphi)\},$$
$$\mathbf{R}(\varphi) = \arg\min\{\mathbf{C}_s(\varphi), \mathbf{C}_d(\varphi)\}.$$



$$\psi = \begin{cases} \varphi & \text{if polarized diffuse reflection dominates} \\ \varphi - \frac{\pi}{2} & \text{otherwise} \end{cases}$$

Cascaded Dual-GRU Architecture



- In the regression GRU, the increment is regressed directly from the multi-domain correlation feature.
- In the optimization GRU, the disparity is further optimized based on the iso-depth cost.

Experiments

Quantitative Result

Comparison Results on the IPS dataset.

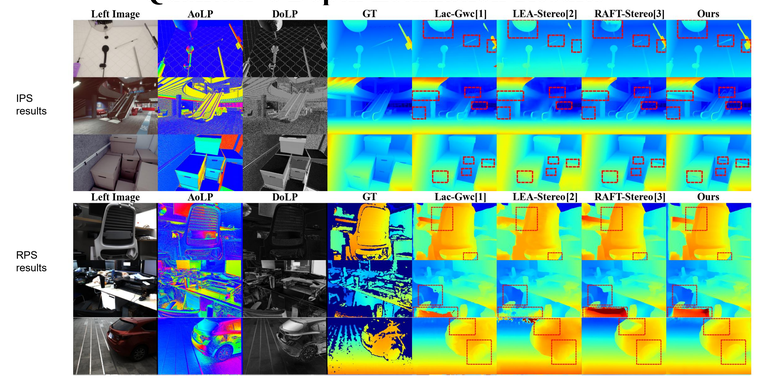
Method	AvgErr	RMSE	bad 2.0
Lac-Gwc [1]	1.2135	3.4503	8.2061
LEA-Stereo [2]	1.6094	3.5475	11.247
RAFT-Stereo [3]	0.9266	2.6755	6.9791
Ours	**0.5790**	**1.8616**	**3.9705**

AvgErr : Average endpoint error.
RMSE : RMS of the endpoint error
bad 2.0 : The bad pixel ratio with the 2-pixel threshold.

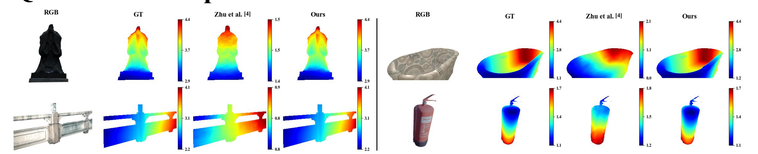
Comparison Results on the RPS dataset.

Method	AvgErr	bad 2.0	Runtime(s)
Lac-Gwc [1]	0.6919	3.6735	0.702
LEA-Stereo [2]	0.7518	5.0487	0.359
RAFT-Stereo [3]	0.6807	3.8864	0.352
Lac-Gwc-RBGP	0.6674	3.4693	0.798
LEA-Stereo-RGBP	0.7517	5.1257	0.577
RAFT-Stereo-RGBP	0.6244	3.4306	0.958
Ours	**0.6187**	**3.3541**	**0.255**

Qualitative Depth Estimation Results



Qualitative Comparison with Traditional Polarimetric Method



Qualitative Normal Estimation Results