Deep Stereo
Monocular, 2-view, N-view

Frank Dellaert, x476 Fall 2021

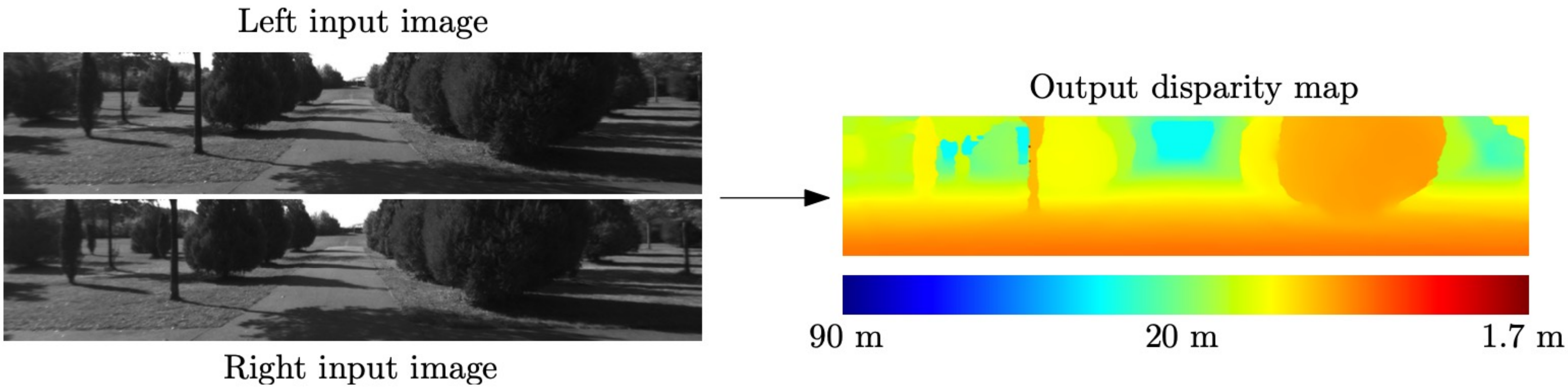


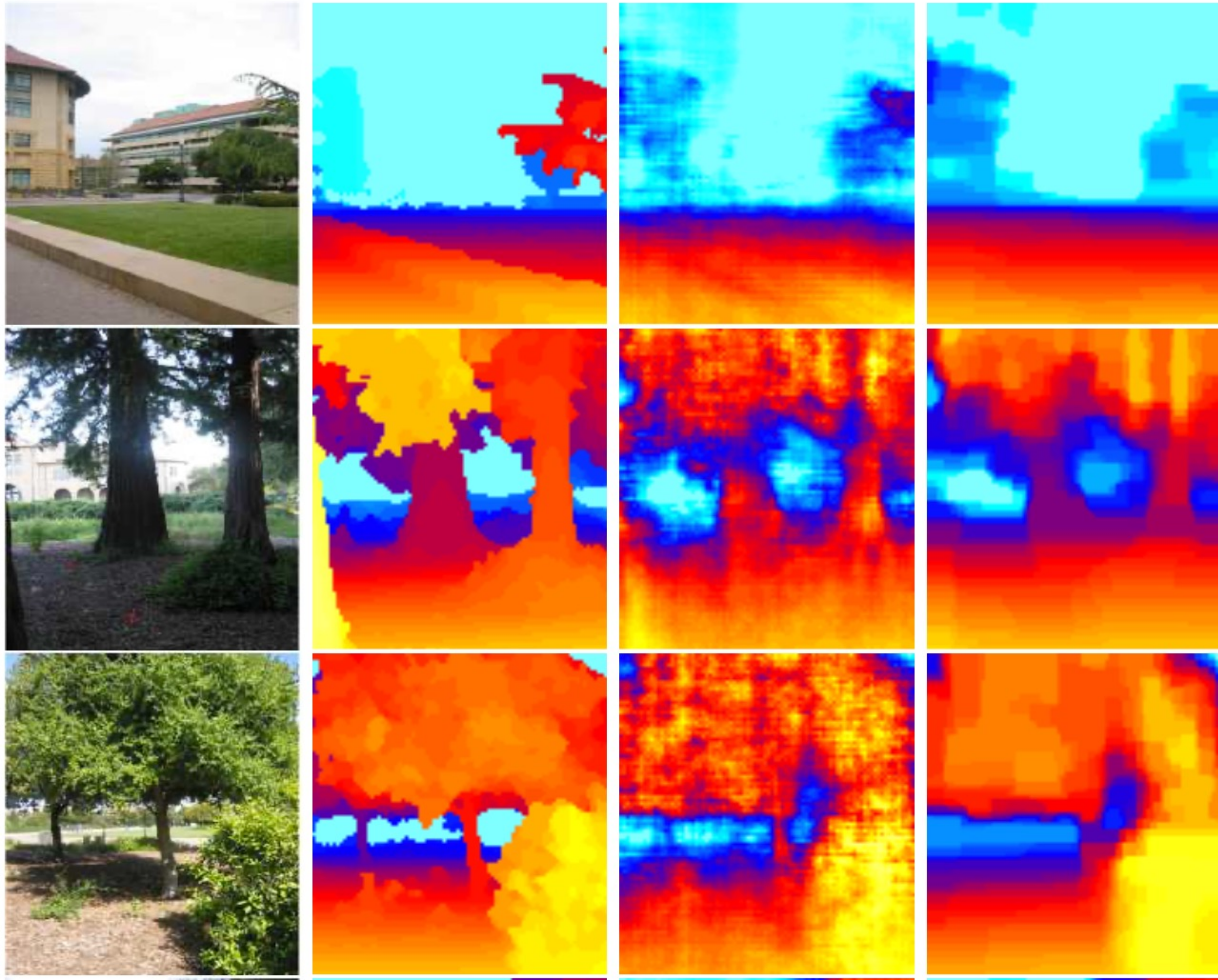
Image from Žbontar & LeCun, 2016

Learning Depth from Single Monocular Images

NIPS 2005 (!)

Ashutosh Saxena, Sung H. Chung, and Andrew Y. Ng

- A whole different beast: monocular depth
- Not deep: Markov random field (MRF)
- Learns a relatively small number of parameters

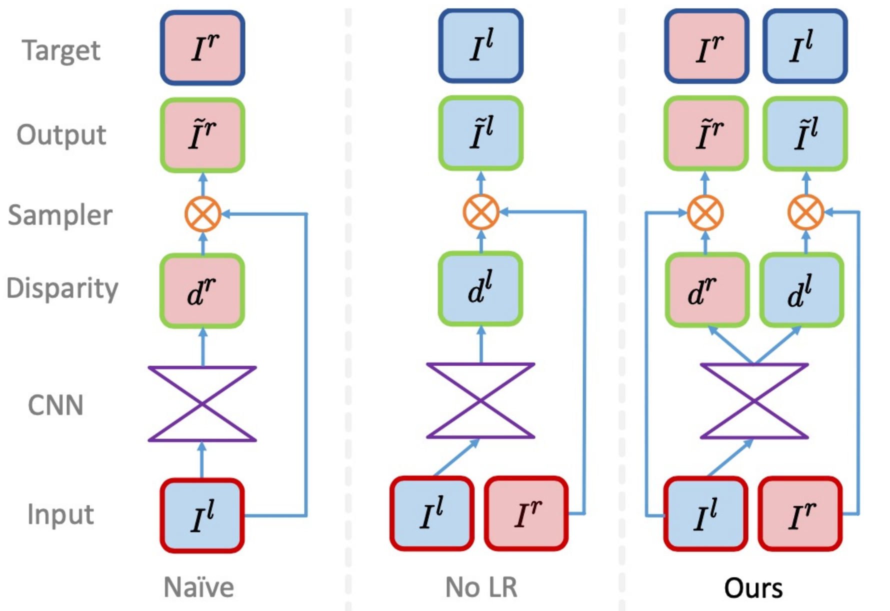


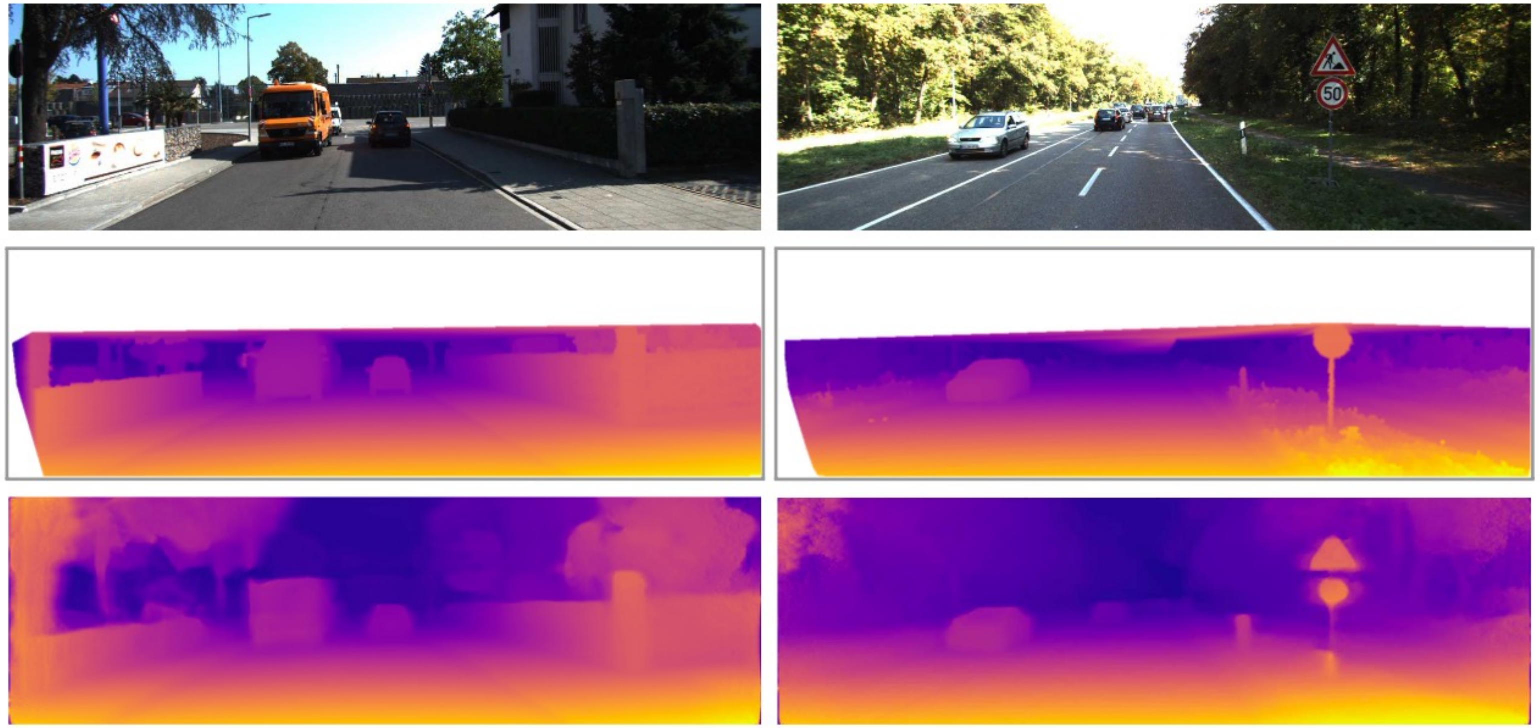
Unsupervised Monocular Depth Estimation with Left-Right Consistency

CVPR 2017

Clément Godard Oisin Mac Aodha Gabriel J. Brostow
University College London

http://visual.cs.ucl.ac.uk/pubs/monoDepth/





- LR- consistency
- Unsupervised monocular depth

Towards Robust Monocular Depth Estimation: Mixing Datasets for Zero-shot Cross-dataset Transfer

René Ranftl*, Katrin Lasinger*, David Hafner, Konrad Schindler, and Vladlen Koltun

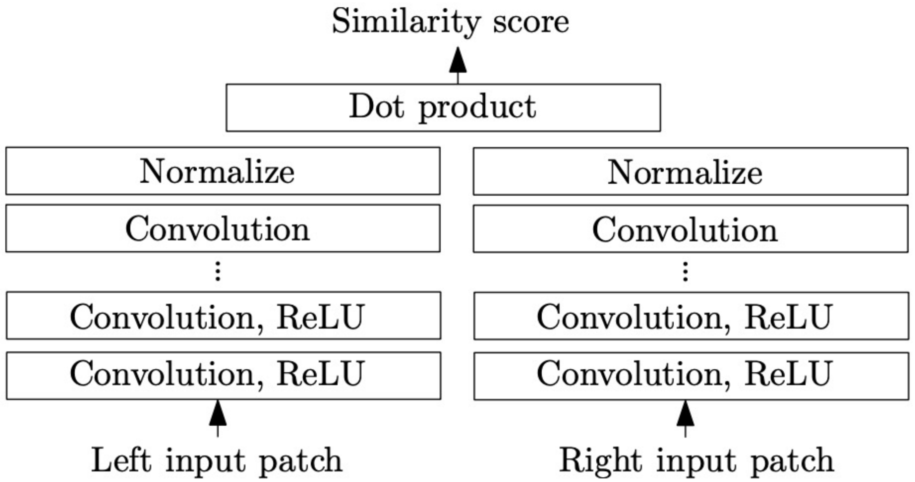
PAMI 2020

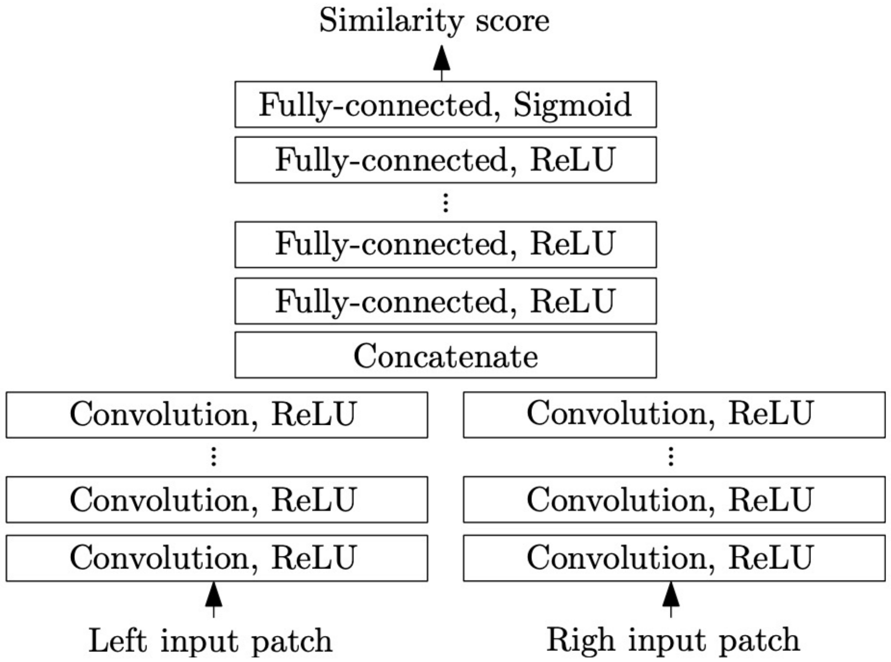
First Idea: matching costs

Stereo Matching by Training a Convolutional Neural Network to Compare Image Patches

Jure Žbontar*

Yann LeCun†





- Two versions: fast, and accurate
- Tries to make distance between positive examples (matched patches) and negative (incorrectly matched patches) large

Results

- On KITTI (2012) dataset, in October 2015
- percentage of misclassified pixels

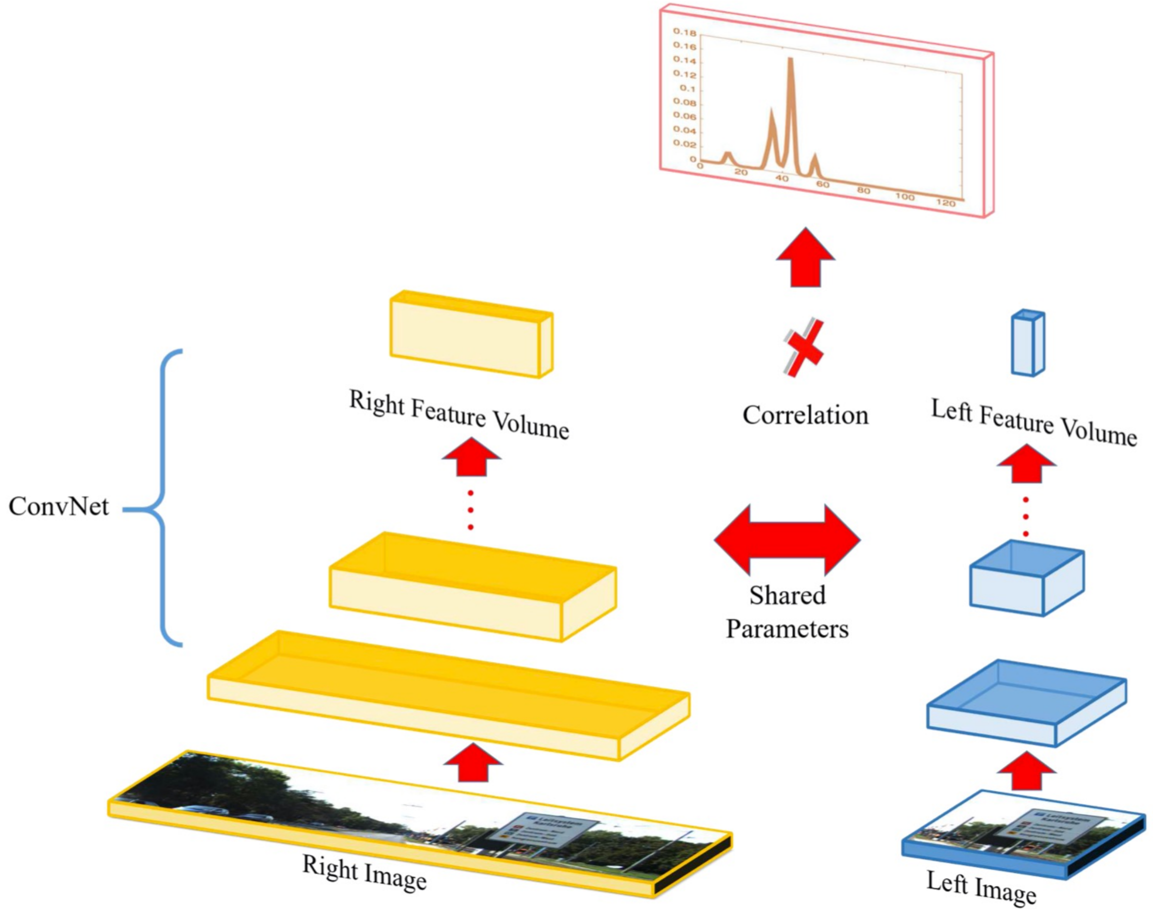
Rank	Method		Setting	Error	Runtime
1	**MC-CNN-acrt**	**Accurate architecture**		2.43	67
2	Displets	Güney and Geiger (2015)		2.47	265
3	MC-CNN	Žbontar and LeCun (2015)		2.61	100
4	PRSM	Vogel et al. (2015)	F, MV	2.78	300
	MC-CNN-fst	**Fast architecture**		2.82	0.8
5	SPS-StFl	Yamaguchi et al. (2014)	F, MS	2.83	35
6	VC-SF	Vogel et al. (2014)	F, MV	3.05	300
7	Deep Embed	Chen et al. (2015)		3.10	3
8	JSOSM	Unpublished work		3.15	105
9	OSF	Menze and Geiger (2015)	F	3.28	3000
10	CoR	Chakrabarti et al. (2015)		3.30	6

Similar idea:

Efficient Deep Learning for Stereo Matching

CVPR 2016

Wenjie Luo Alexander G. Schwing Raquel Urtasun
Department of Computer Science, University of Toronto

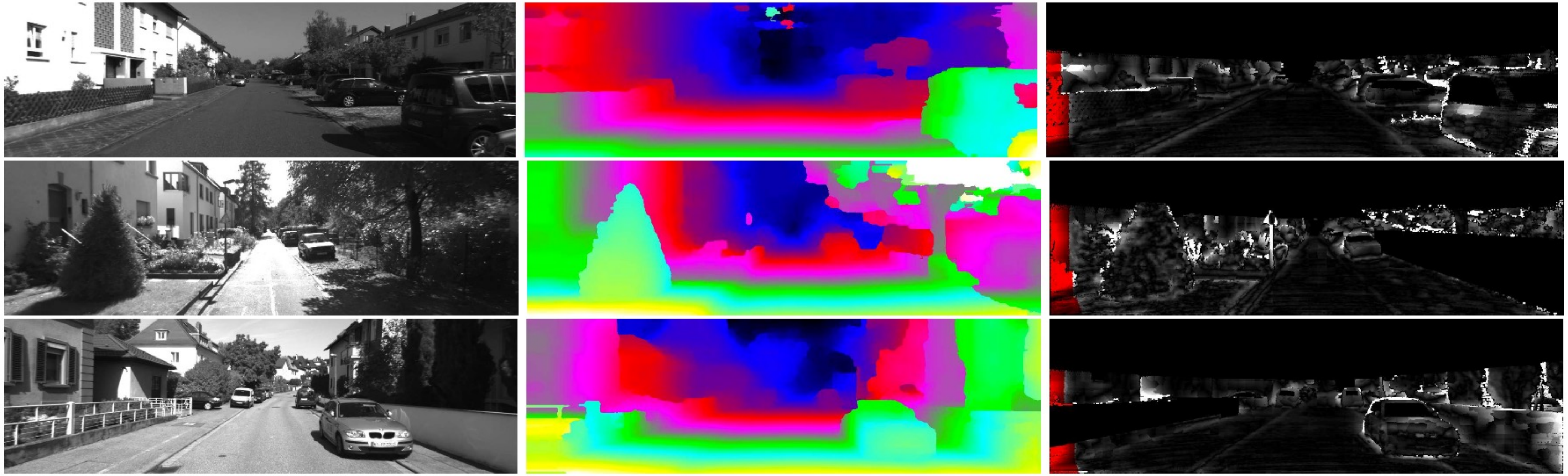


- CNN for feature representation, shared parameters
- Probability density over disparities

Results (percentage over threshold)

	> 2 pixels		> 3 pixels		> 4 pixels		> 5 pixels		End-Point		Runtime
	Non-Occ	**All**	**Non-Occ**	**All**	**Non-Occ**	**All**	**Non-Occ**	**All**	**Non-Occ**	**All**	(s)
StereoSLIC [26]	5.76	7.20	3.92	5.11	3.04	4.04	2.49	3.33	0.9 px	1.0 px	2.3
PCBP-SS [26]	5.19	6.75	3.40	4.72	2.62	3.75	2.18	3.15	0.8 px	1.0 px	300
SPS-st [27]	4.98	6.28	3.39	4.41	2.72	3.52	2.33	3.00	0.9 px	1.0 px	2
Deep Embed [7]	5.05	6.47	3.10	4.24	2.32	3.25	1.92	2.68	0.9 px	1.1 px	3
MC-CNN-acrt [30]	3.90	5.45	2.43	3.63	1.90	2.85	1.64	2.39	0.7 px	0.9 px	67
Displets v2 [12]	3.43	4.46	2.37	3.09	1.97	2.52	1.72	2.17	0.7 px	0.8 px	265
Ours(19)	4.98	6.51	3.07	4.29	2.39	3.36	2.03	2.82	0.8 px	1.0 px	0.7

Table 3: Comparison to stereo state-of-the-art on the test set of the KITTI 2012 benchmark.



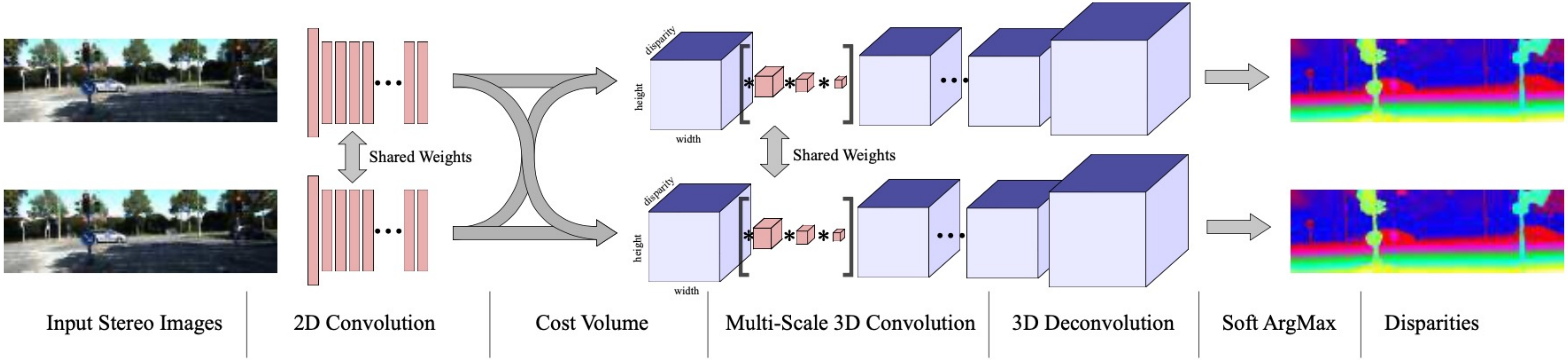
Cost Volume Aggregation

End-to-End Learning of Geometry and Context for Deep Stereo Regression

ICCV 2017

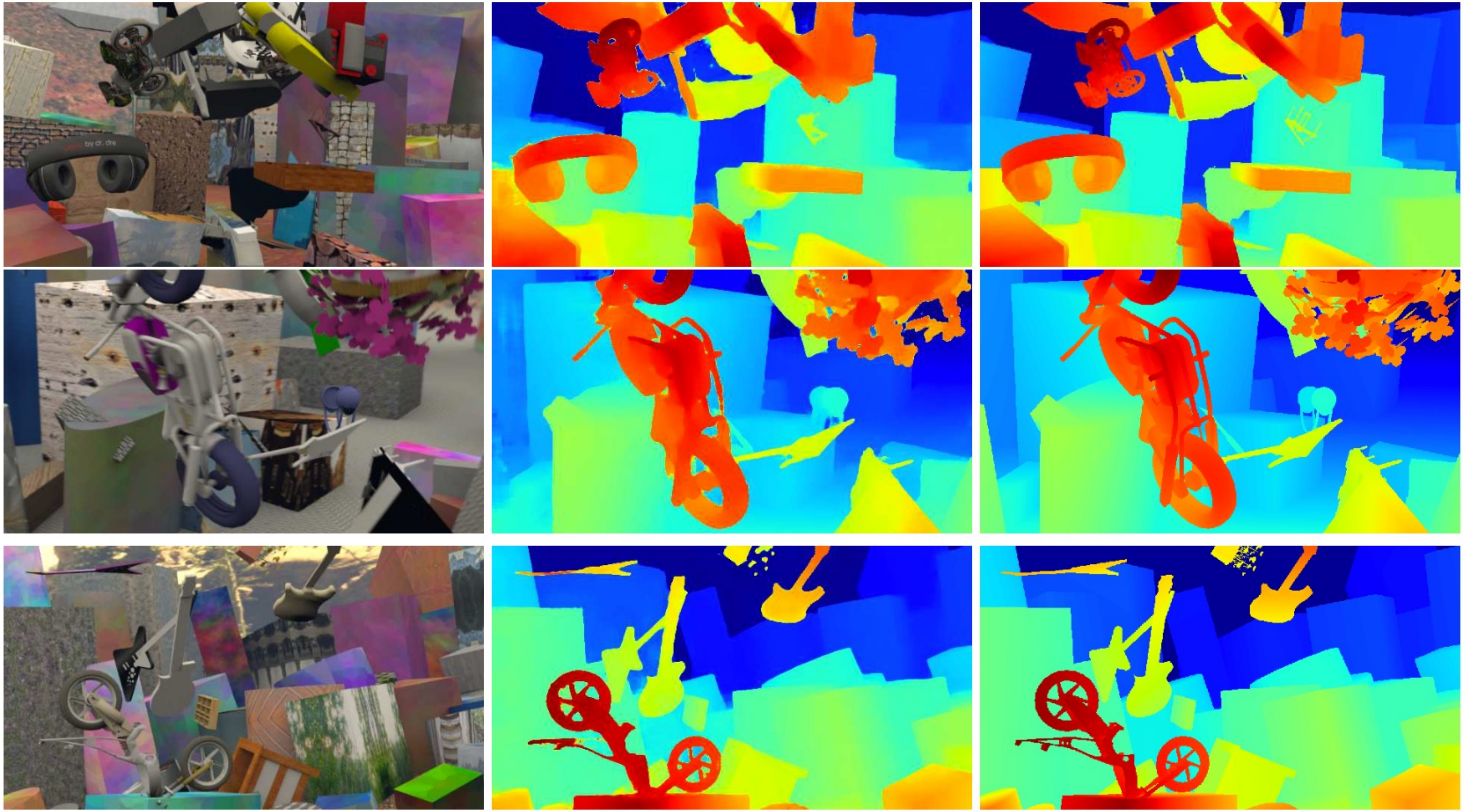
Alex Kendall Hayk Martirosyan Saumitro Dasgupta Peter Henry
Ryan Kennedy Abraham Bachrach Adam Bry

Skydio Research



- CNN for features, shared weights, then 3D convolutions

Results on Scene Flow Dataset (from CVPR 2016)



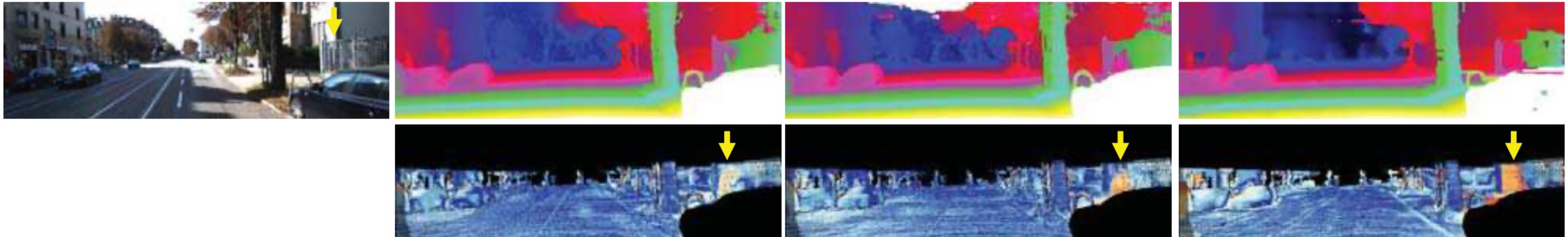
Pyramid Stereo Matching Network

CVPR 2018

Jia-Ren Chang Yong-Sheng Chen
Department of Computer Science, National Chiao Tung University, Taiwan

- Architectural improvements: spatial pyramid pooling
- Results on KITTI 2015, March 2018 leaderboard:

Rank	Method	All (%)			Noc (%)			Runtime (s)
		D1-bg	D1-fg	D1-all	D1-bg	D1-fg	D1-all	
1	PSMNet (ours)	**1.86**	4.62	**2.32**	**1.71**	4.31	**2.14**	0.41
3	iResNet-i2e2 [14]	2.14	3.45	2.36	1.94	3.20	2.15	0.22
6	iResNet [14]	2.35	**3.23**	2.50	2.15	**2.55**	2.22	**0.12**
8	CRL [21]	2.48	3.59	2.67	2.32	3.12	2.45	0.47
11	GC-Net [13]	2.21	6.16	2.87	2.02	5.58	2.61	0.90



Hierarchical Deep Stereo Matching on High-resolution Images

CVPR 2019

Gengshan Yang[1*], Joshua Manela[2], Michael Happold[2], Deva Ramanan[1,2]
[1]Carnegie Mellon University, [2]Argo AI

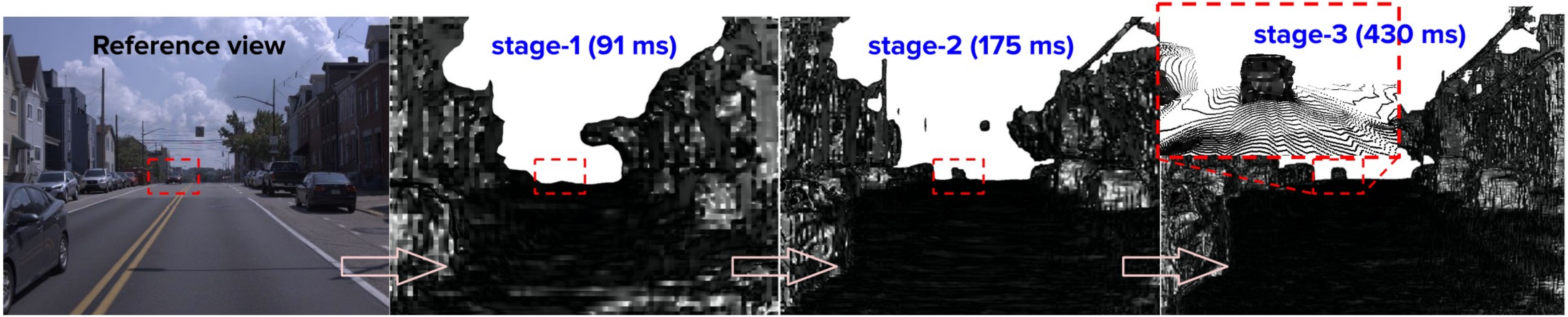
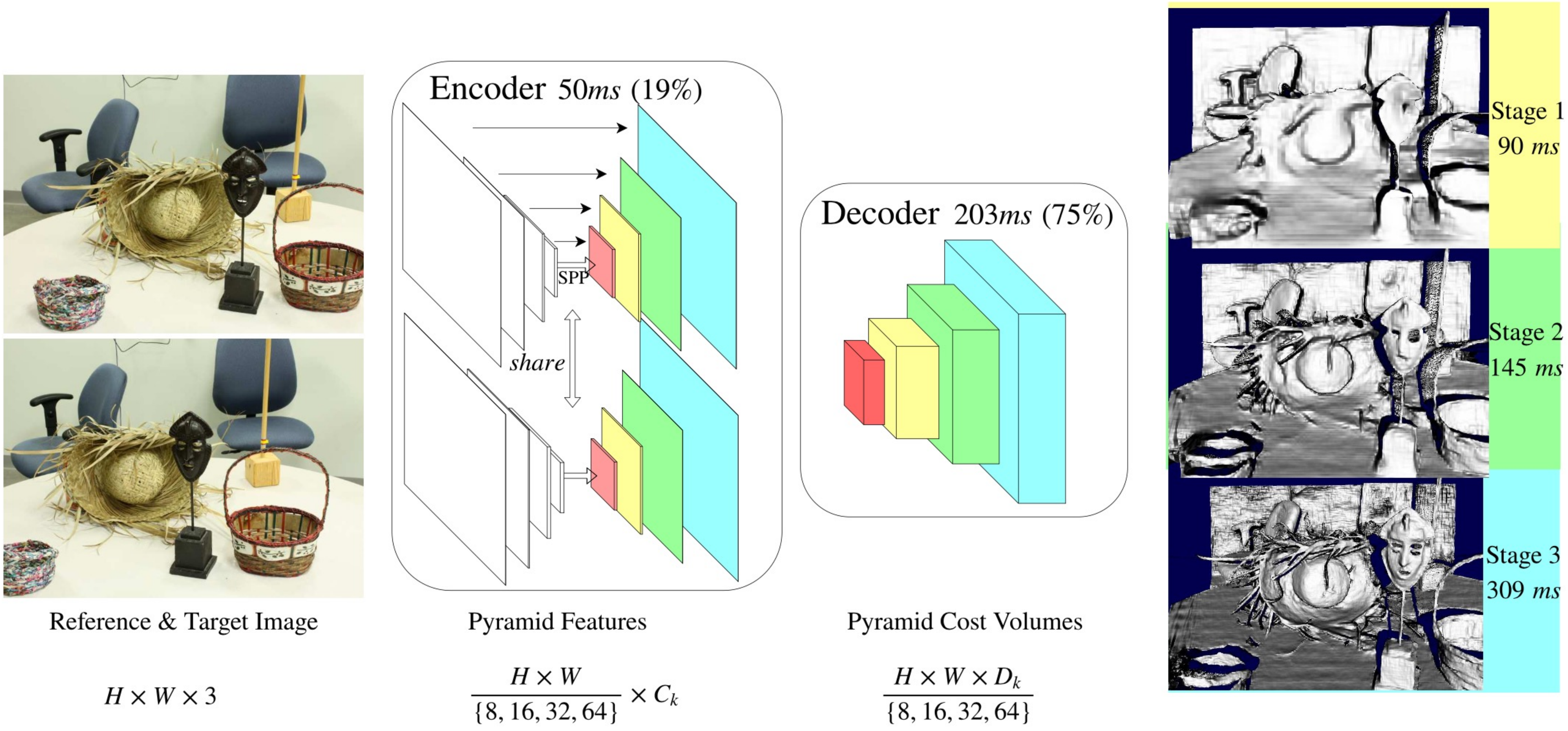


Figure 1: Illustration of on-demand depth sensing with a coarse-to-fine hierarchy on the proposed dataset. Our method (HSM) captures the coarse layout of the scene in 91 milliseconds, finds the far-away car (shown in the red box) in 175 ms, and recovers the details of the car given extra 255 ms.

- High-resolution for self-driving: Z=f B/Z, increase f !

Yang18cvpr architecture figure:

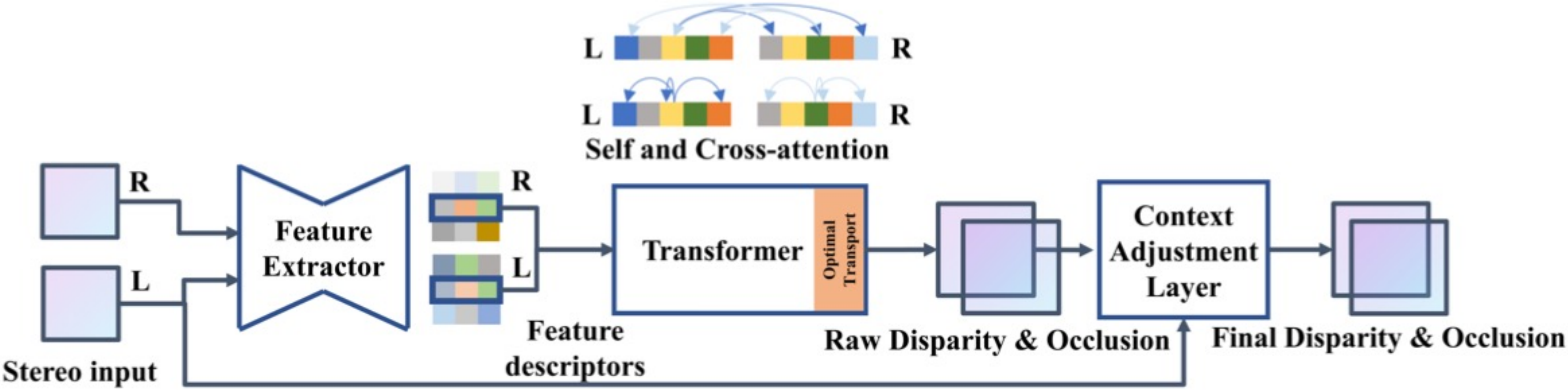


Revisiting Stereo Depth Estimation From a Sequence-to-Sequence Perspective with Transformers

ICCV 2021

Zhaoshuo Li, Xingtong Liu, Nathan Drenkow, Andy Ding, Francis X. Creighton, Russell H. Taylor, and Mathias Unberath

Johns Hopkins University

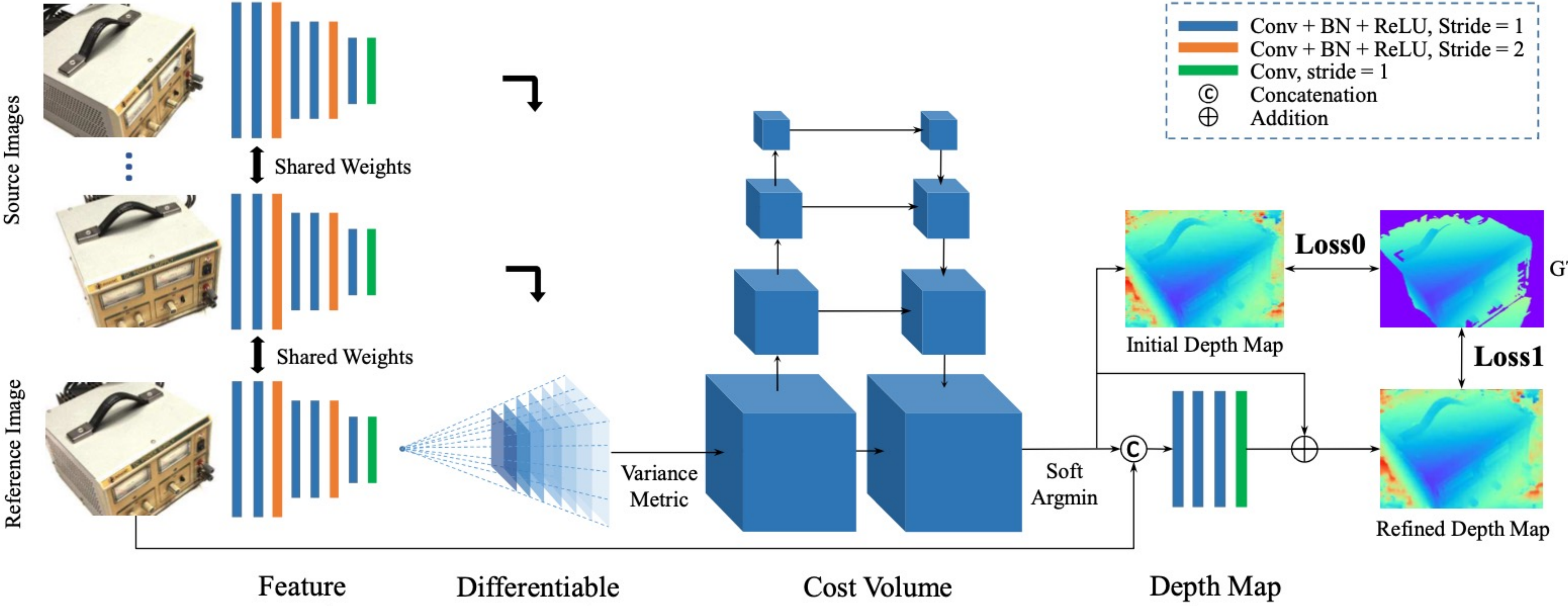


Results for STTR

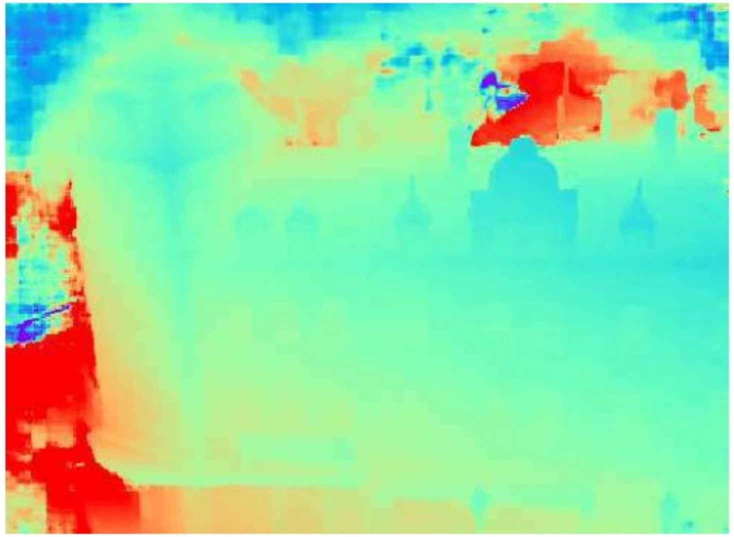
MVSNet: Depth Inference for Unstructured Multi-view Stereo

ECCV 2018

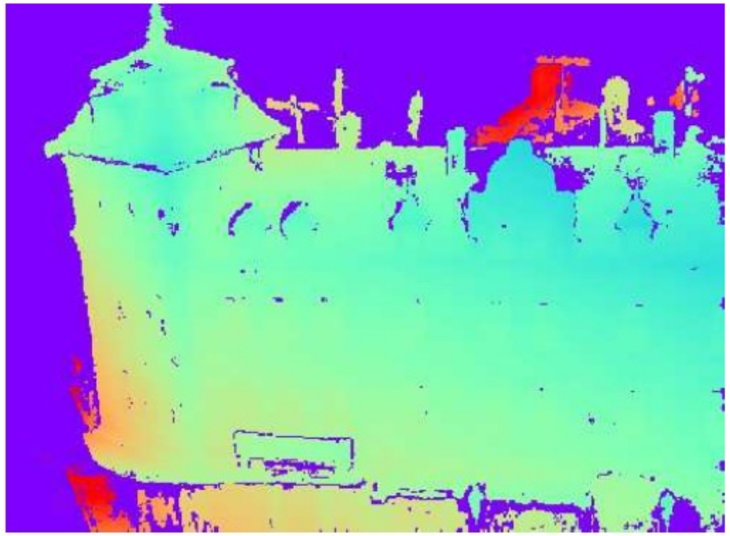
Yao Yao[1], Zixin Luo[1], Shiwei Li[1], Tian Fang[2], and Long Quan[1]



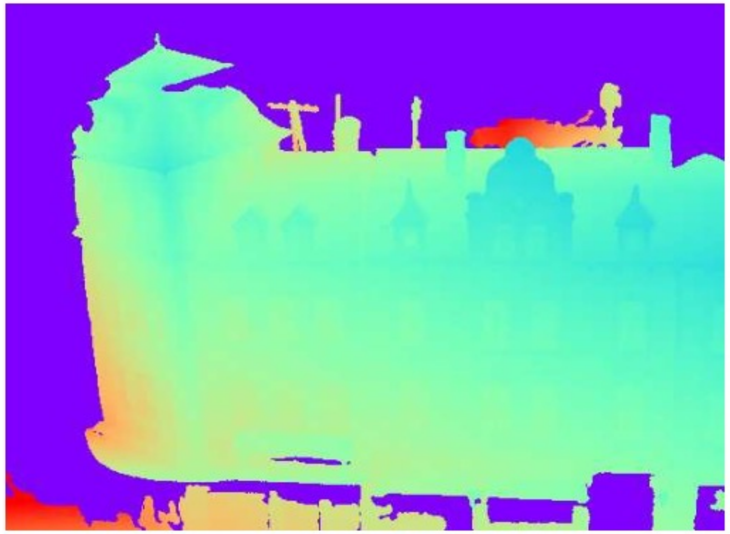
MVSNet results



(a) Inferred depth map



(b) Filtered depth map



(c) GT depth map

(d) Reference image

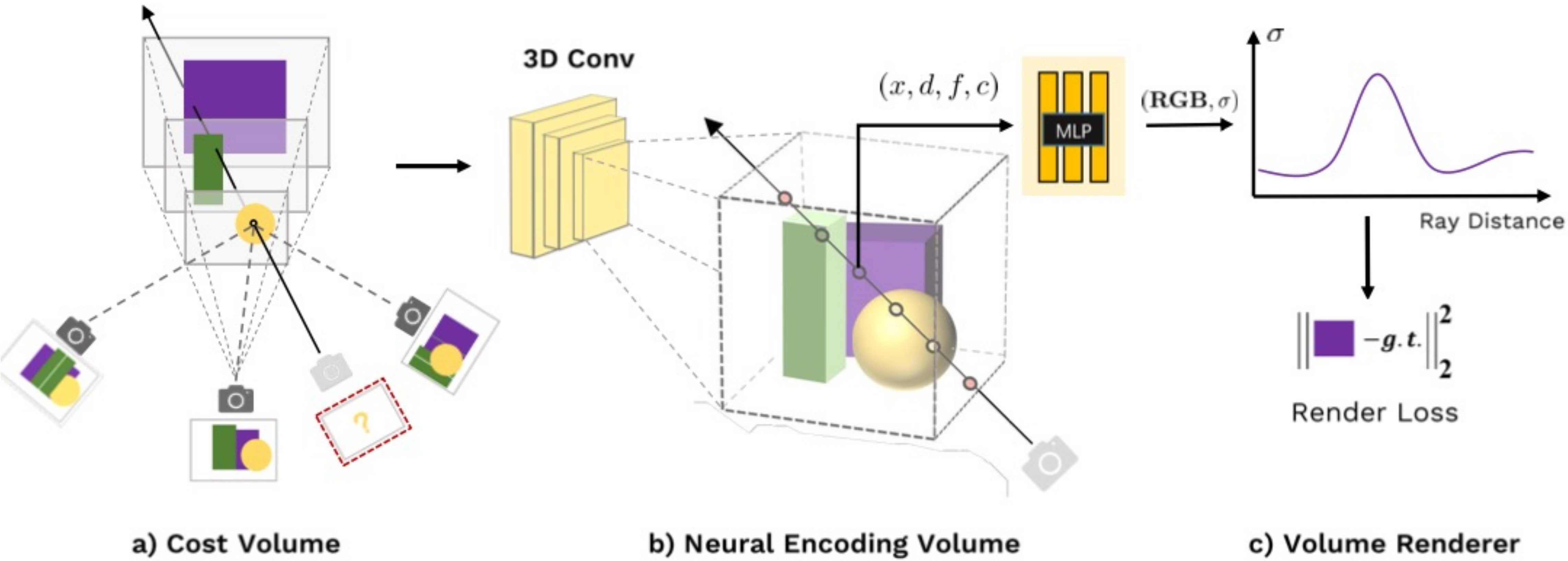
(e) Fused point cloud

(f) GT point cloud

MVSNeRF: Fast Generalizable Radiance Field Reconstruction from Multi-View Stereo

ICCV 2021

Anpei Chen*[1] Zexiang Xu*[2] Fuqiang Zhao[1] Xiaoshuai Zhang[3] Fanbo Xiang[3]
Jingyi Yu[1] Hao Su[3]
[1] ShanghaiTech University [2] Adobe Research [3] University of California, San Diego



MVSNeRF Results

a) Source views b) MVS-NeRF no fine-tuning c) MVS-NeRF 6 min fine-tuning d) NeRF 5.1h optimization

https://apchenstu.github.io/mvsnerf/