



KIDELTA
LEARNING

Scalable AI for Automated Driving

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A Benchmark and a Baseline for Robust Multi-view Depth Estimation

Philipp Schröppel

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2. Robust Multi-view Depth Benchmark

objective, test sets, evaluation settings, results

3. Robust MVD Baseline Model

overview, qualitative results

4. robustmvd Framework

5. Summary



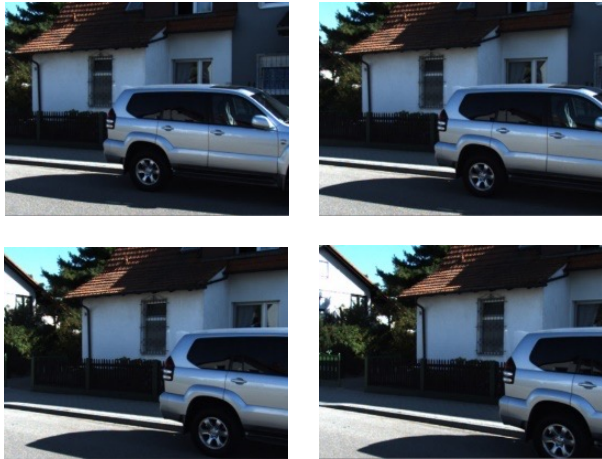
Introduction

Multi-view Depth Estimation

Keyview V_0



Source
views
 V_1, \dots, V_k





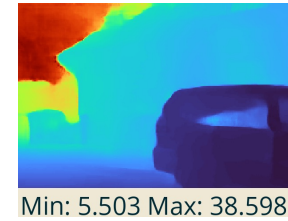
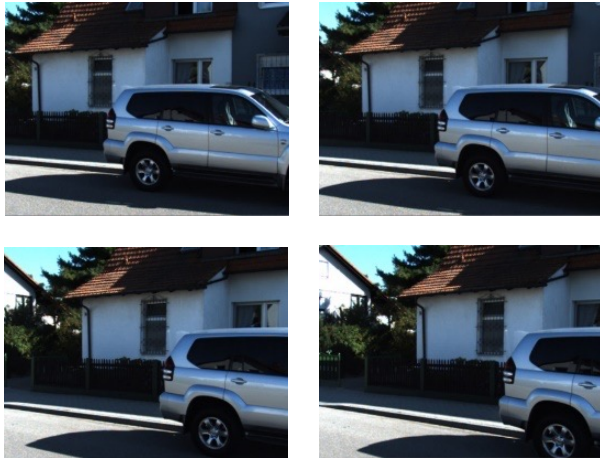
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Depth map
for the keyview



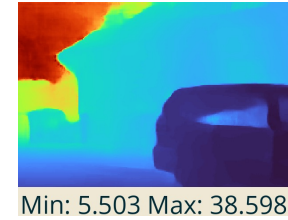
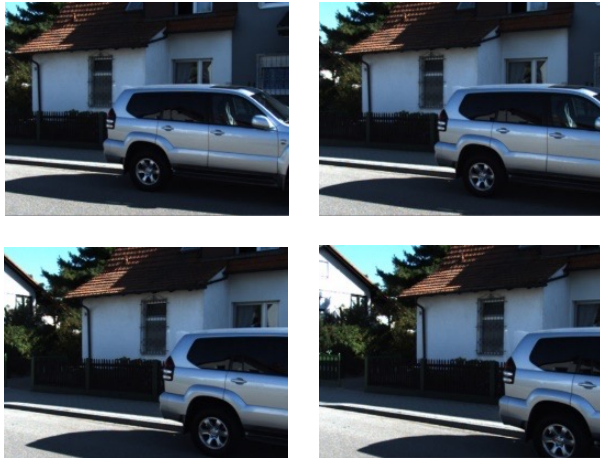
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Multi-view Depth Estimation

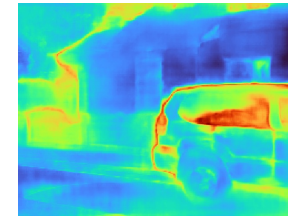
Keyview V_0



Source
views
 V_1, \dots, V_k



Depth map
for the keyview



Depth
Uncertainty

Introduction

Depth-from-video and Multi-view Stereo



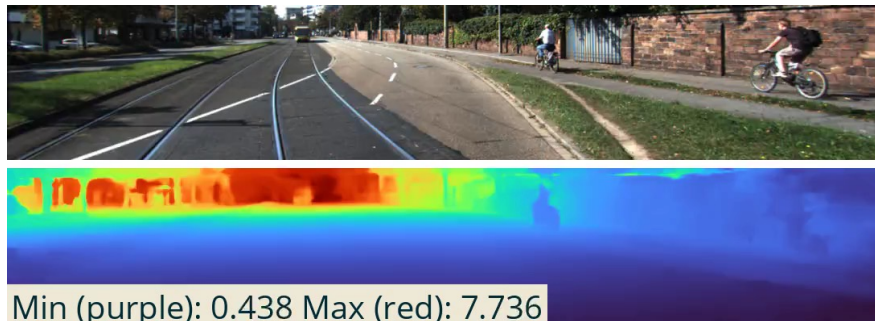


Introduction

Depth-from-video and Multi-view Stereo

Depth-from-video:

- sequential input views
- **inputs:** images, intrinsics
- **evaluation:** align and compare predicted and ground truth depth maps



[DeepV2D, Teed and Deng]

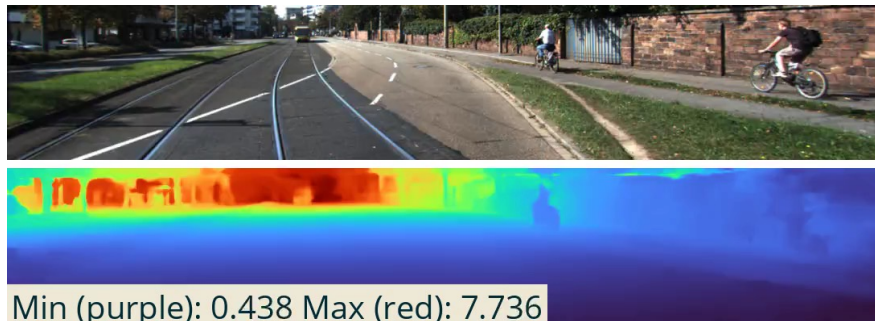


Introduction

Depth-from-video and Multi-view Stereo

Depth-from-video:

- sequential input views
- **inputs:** images, intrinsics
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[DeepV2D, Teed and Deng]

Multi-view Stereo:

- unstructured input views
- **inputs:** images, intrinsics, poses, depth range
- **evaluation:** fuse depth maps and compare predicted and ground truth pointclouds



[Vis-MVSNet, Zhang et al.]

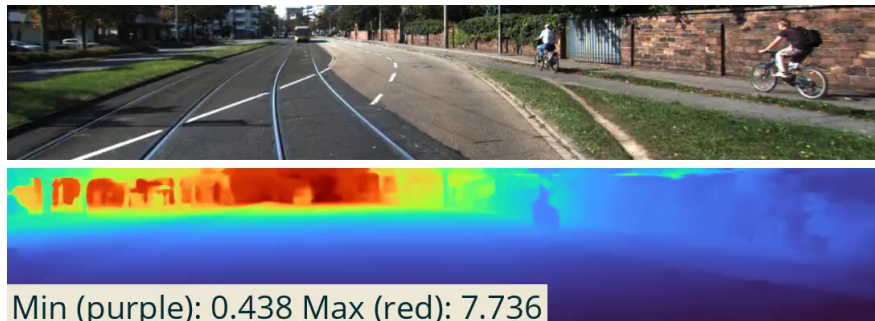


Introduction

Depth-from-video and Multi-view Stereo

Depth-from-video:

- sequential input views
- **inputs:** images, intrinsics
- **evaluation:** align and compare predicted and ground truth depth maps



[DeepV2D, Teed and Deng]

Multi-view Stereo:

- unstructured input views
- **inputs:** images, intrinsics, poses, depth range
- **evaluation:** fuse depth maps and compare predicted and ground truth pointclouds



[Vis-MVSNet, Zhang et al.]

→ depth is estimated from multiple input views



Introduction

Motivation for the Benchmark

Depth estimation is useful for many practical applications: autonomous driving, augmented reality, robotics, ...

- failures can be fatal
- depth estimation should function robustly in an **open-world setting** with potentially unseen objects
- multi-view depth estimation can derive depth from the **motion parallax** → generic principle that **should enable generalization**
- however: training and testing is often done on similar data

Objective: evaluate multi-view depth estimation in an open-world setting

Robust Multi-view Depth Benchmark



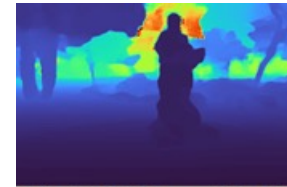
Benchmark multi-view depth estimation models regarding **robust application on arbitrary real-world data.**

Robust Multi-view Depth Benchmark



Benchmark multi-view depth estimation models regarding robust application on arbitrary real-world data.

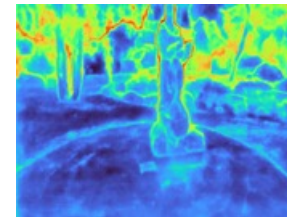
Keyview V_0



Min: 2.255 Max: 100.000

Depth map
for the keyview

Source
views
 V_1, \dots, V_k








Depth
Uncertainty



Robust Multi-view Depth Benchmark

Test Sets

Comprises test sets based on diverse existing datasets:

	KITTI	ScanNet	ETH3D	DTU	T & T
					
Domain	Driving	Indoor	In- & outdoor	Tabletop	In- & outdoor
Structure	Video	Video	None	None	None
Scene scale	2 - 85m	0.2 - 0.9m	0.3 - 60m	0.4 - 1.2m	1.1 - 42m
# samples	93	200	104	110	69

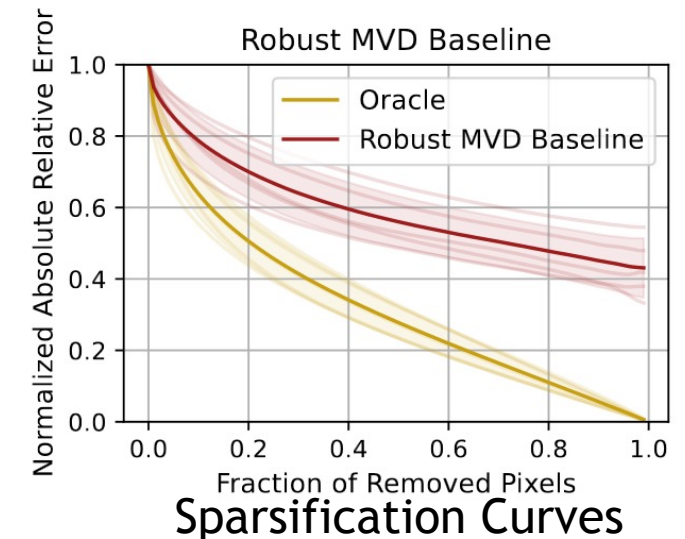
→ training data intentionally left undefined

→ evaluation in a zero-shot cross-dataset fashion



Robust Multi-view Depth Benchmark Settings and Metrics

- Features different evaluation settings:
 - input modalities: images, intrinsics, poses, depth range
 - optional alignment between predicted and GT depth maps
- Depth estimation metrics:
 - Absolute Relative Error (rel)
 - Inlier Ratio with a Threshold of 1.03 (τ)
- Uncertainty metrics:
 - Sparsification Error Curves
 - Area Under Sparsification Error (AUSE)



Robust Multi-view Depth Benchmark Results



Approach	GT Poses	GT Range	Align	KITTI		ScanNet		ETH3D		DTU		T&T		Average		
				rel ↓	τ ↑	rel ↓	τ ↑	rel ↓	τ ↑	rel ↓	τ ↑	rel ↓	τ ↑	rel ↓	τ ↑	time [s] ↓
COLMAP	✓	✗	✗	12.0	58.2	14.6	34.2	16.4	55.1	0.7	96.5	2.7	95.0	9.3	67.8	≈ 3 min
COLMAP Dense	✓	✗	✗	26.9	52.7	38.0	22.5	89.8	23.2	20.8	69.3	25.7	76.4	40.2	48.8	≈ 3 min
DeMoN	✗	✗	t	15.5	15.2	12.0	21.0	17.4	15.4	21.8	16.6	13.0	23.2	16.0	18.3	0.08
DeepV2D KITTI	✗	✗	med	(3.1)	(74.9)	23.7	11.1	27.1	10.1	24.8	8.1	34.1	9.1	22.6	22.7	2.07
DeepV2D ScanNet	✗	✗	med	10.0	36.2	(4.4)	(54.8)	11.8	29.3	7.7	33.0	8.9	46.4	8.6	39.9	3.57
MVSNet	✓	✓	✗	22.7	36.1	24.6	20.4	35.4	31.4	(1.8)	(86.0)	8.3	73.0	18.6	49.4	0.07
MVSNet Inv. Depth	✓	✓	✗	18.6	30.7	22.7	20.9	21.6	35.6	(1.8)	(86.7)	6.5	74.6	14.2	49.7	0.32
CVP-MVSNet	✓	✓	✗	156.7	2.2	137.1	15.9	156.4	13.6	(4.0)	(68.4)	24.7	52.9	95.8	30.6	0.49
Vis-MVSNet	✓	✓	✗	9.5	55.4	8.9	33.5	10.8	43.3	(1.8)	(87.4)	4.1	87.2	7.0	61.4	0.70
PatchmatchNet	✓	✓	✗	10.8	45.8	8.5	35.3	19.1	34.8	(2.1)	(82.8)	4.8	82.9	9.1	56.3	0.28
Fast-MVSNet	✓	✓	✗	14.4	37.1	17.0	24.6	25.2	32.0	(2.5)	(81.8)	8.3	68.6	13.5	48.8	0.30
MVS2D ScanNet	✓	✓	✗	21.2	8.7	(27.2)	(5.3)	27.4	4.8	17.2	9.8	29.2	4.4	24.4	6.6	0.04
MVS2D DTU	✓	✓	✗	226.6	0.7	32.3	11.1	99.0	11.6	(3.6)	(64.2)	25.8	28.0	77.5	23.1	0.05

bold: best | (parentheses): trained on same domain

Robust Multi-view Depth Benchmark Results



Approach	GT	GT	Align	KITTI		ScanNet		ETH3D		DTU		T&T		Average		
	Poses	Range		rel ↓	τ ↑	rel ↓	τ ↑	rel ↓	τ ↑	rel ↓	τ ↑	rel ↓	τ ↑	rel ↓	τ ↑	time [s] ↓
COLMAP	✓	✗	✗	12.0	58.2	14.6	34.2	16.4	55.1	0.7	96.5	2.7	95.0	9.3	67.8	≈ 3 min
COLMAP Dense	✓	✗	✗	26.9	52.7	38.0	22.5	89.8	23.2	20.8	69.3	25.7	76.4	40.2	48.8	≈ 3 min
DeMoN	✗	✗	t	15.5	15.2	12.0	21.0	17.4	15.4	21.8	16.6	13.0	23.2	16.0	18.3	0.08
DeepV2D KITTI	✗	✗	med	(3.1)	(74.9)	23.7	11.1	27.1	10.1	24.8	8.1	34.1	9.1	22.6	22.7	2.07
DeepV2D ScanNet	✗	✗	med	10.0	36.2	(4.4)	(54.8)	11.8	29.3	7.7	33.0	8.9	46.4	8.6	39.9	3.57
MVSNet	✓	✓	✗	22.7	36.1	24.6	20.4	35.4	31.4	(1.8)	(86.0)	8.3	73.0	18.6	49.4	0.07
MVSNet Inv. Depth	✓	✓	✗	18.6	30.7	22.7	20.9	21.6	35.6	(1.8)	(86.7)	6.5	74.6	14.2	49.7	0.32
CVP-MVSNet	✓	✓	✗	156.7	2.2	137.1	15.9	156.4	13.6	(4.0)	(68.4)	24.7	52.9	95.8	30.6	0.49
Vis-MVSNet	✓	✓	✗	9.5	55.4	8.9	33.5	10.8	43.3	(1.8)	(87.4)	4.1	87.2	7.0	61.4	0.70
PatchmatchNet	✓	✓	✗	10.8	45.8	8.5	35.3	19.1	34.8	(2.1)	(82.8)	4.8	82.9	9.1	56.3	0.28
Fast-MVSNet	✓	✓	✗	14.4	37.1	17.0	24.6	25.2	32.0	(2.5)	(81.8)	8.3	68.6	13.5	48.8	0.30
MVS2D ScanNet	✓	✓	✗	21.2	8.7	(27.2)	(5.3)	27.4	4.8	17.2	9.8	29.2	4.4	24.4	6.6	0.04
MVS2D DTU	✓	✓	✗	226.6	0.7	32.3	11.1	99.0	11.6	(3.6)	(64.2)	25.8	28.0	77.5	23.1	0.05

bold: best | (parentheses): trained on same domain

Robust Multi-view Depth Benchmark Results



Approach	GT	GT	Align	KITTI		ScanNet		ETH3D		DTU		T&T		Average		
	Poses	Range		rel ↓	τ ↑	rel ↓	τ ↑	rel ↓	τ ↑	rel ↓	τ ↑	rel ↓	τ ↑	rel ↓	τ ↑	time [s] ↓
COLMAP	✓	✗	✗	12.0	58.2	14.6	34.2	16.4	55.1	0.7	96.5	2.7	95.0	9.3	67.8	≈ 3 min
COLMAP Dense	✓	✗	✗	26.9	52.7	38.0	22.5	89.8	23.2	20.8	69.3	25.7	76.4	40.2	48.8	≈ 3 min
DeMoN	✗	✗	t	15.5	15.2	12.0	21.0	17.4	15.4	21.8	16.6	13.0	23.2	16.0	18.3	0.08
DeepV2D KITTI	✗	✗	med	(3.1)	(74.9)	23.7	11.1	27.1	10.1	24.8	8.1	34.1	9.1	22.6	22.7	2.07
DeepV2D ScanNet	✗	✗	med	10.0	36.2	(4.4)	(54.8)	11.8	29.3	7.7	33.0	8.9	46.4	8.6	39.9	3.57
MVSNet	✓	✓	✗	22.7	36.1	24.6	20.4	35.4	31.4	(1.8)	(86.0)	8.3	73.0	18.6	49.4	0.07
MVSNet Inv. Depth	✓	✓	✗	18.6	30.7	22.7	20.9	21.6	35.6	(1.8)	(86.7)	6.5	74.6	14.2	49.7	0.32
CVP-MVSNet	✓	✓	✗	156.7	2.2	137.1	15.9	156.4	13.6	(4.0)	(68.4)	24.7	52.9	95.8	30.6	0.49
Vis-MVSNet	✓	✓	✗	9.5	55.4	8.9	33.5	10.8	43.3	(1.8)	(87.4)	4.1	87.2	7.0	61.4	0.70
PatchmatchNet	✓	✓	✗	10.8	45.8	8.5	35.3	19.1	34.8	(2.1)	(82.8)	4.8	82.9	9.1	56.3	0.28
Fast-MVSNet	✓	✓	✗	14.4	37.1	17.0	24.6	25.2	32.0	(2.5)	(81.8)	8.3	68.6	13.5	48.8	0.30
MVS2D ScanNet	✓	✓	✗	21.2	8.7	(27.2)	(5.3)	27.4	4.8	17.2	9.8	29.2	4.4	24.4	6.6	0.04
MVS2D DTU	✓	✓	✗	226.6	0.7	32.3	11.1	99.0	11.6	(3.6)	(64.2)	25.8	28.0	77.5	23.1	0.05

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Robust Multi-view Depth Benchmark Results



Approach	GT	GT	Align	KITTI		ScanNet		ETH3D		DTU		T&T		Average		
	Poses	Range		rel ↓	τ ↑	rel ↓	τ ↑	rel ↓	τ ↑	rel ↓	τ ↑	rel ↓	τ ↑	rel ↓	τ ↑	time [s] ↓
DeMoN	✓	✗	✗	16.7	13.4	75.0	0.0	19.0	16.2	23.7	11.5	17.6	18.3	30.4	11.9	0.08
DeepTAM	✓	✗	✗	68.7	0.4	(6.7)	(39.7)	20.4	19.8	58.0	9.1	40.0	12.9	38.8	16.4	0.85
DeepV2D KITTI	✓	✗	✗	(20.4)	(16.3)	25.8	8.1	30.1	9.4	24.6	8.2	38.5	9.6	27.9	10.3	1.43
DeepV2D ScanNet	✓	✗	✗	61.9	5.2	(3.8)	(60.2)	18.7	28.7	9.2	27.4	33.5	38.0	25.4	31.9	2.15
MVSNet	✓	✗	✗	14.0	35.8	1568.0	5.7	507.7	8.3	(4429.1)	(0.1)	118.2	50.7	1327.4	20.1	0.15
MVSNet Inv. Depth	✓	✗	✗	29.6	8.1	65.2	28.5	60.3	5.8	(28.7)	(48.9)	51.4	14.6	47.0	21.2	0.28
CVP-MVSNet	✓	✗	✗	158.2	1.2	2289.0	0.1	1735.3	1.2	(8314.0)	(0.0)	415.9	9.5	2582.5	2.4	0.50
Vis-MVSNet	✓	✗	✗	10.3	54.4	84.9	15.6	51.5	17.4	(374.2)	(1.7)	21.1	65.6	108.4	31.0	0.82
PatchmatchNet	✓	✗	✗	29.0	16.3	70.1	16.7	99.4	3.5	(82.6)	(5.6)	39.4	19.3	64.1	12.3	0.18
Fast-MVSNet	✓	✗	✗	12.1	37.4	287.1	9.4	131.2	9.6	(540.4)	(1.9)	33.9	47.2	200.9	21.1	0.35
MVS2D ScanNet	✓	✗	✗	73.4	0.0	(4.5)	(54.1)	30.7	14.4	5.0	57.9	56.4	11.1	34.0	27.5	0.05
MVS2D DTU	✓	✗	✗	93.3	0.0	51.5	1.6	78.0	0.0	(1.6)	(92.3)	87.5	0.0	62.4	18.8	0.06
Robust MVD Baseline	✓	✗	✗	7.1	41.9	7.4	38.4	9.0	42.6	2.7	82.0	5.0	75.1	6.3	56.0	0.06

bold: best | (parentheses): trained on same domain



Robust Multi-view Depth Benchmark Results

Approach	GT Poses	GT Range	Align	KITTI		ScanNet		ETH3D		DTU		T&T		Average		
				rel ↓	τ ↑	rel ↓	τ ↑	rel ↓	τ ↑	rel ↓	τ ↑	rel ↓	τ ↑	rel ↓	τ ↑	time [s] ↓
DeMoN	✓	✗	✗	16.7	13.4	75.0	0.0	19.0	16.2	23.7	11.5	17.6	18.3	30.4	11.9	0.08
DeepTAM	✓	✗	✗	68.7	0.4	(6.7)	(39.7)	20.4	19.8	58.0	9.1	40.0	12.9	38.8	16.4	0.85
DeepV2D KITTI	✓	✗	✗	(20.4)	(16.3)	25.8	8.1	30.1	9.4	24.6	8.2	38.5	9.6	27.9	10.3	1.43
DeepV2D ScanNet	✓	✗	✗	61.9	5.2	(3.8)	(60.2)	18.7	28.7	9.2	27.4	33.5	38.0	25.4	31.9	2.15
MVSNet	✓	✗	✗	14.0	35.8	1568.0	5.7	507.7	8.3	(4429.1)	(0.1)	118.2	50.7	1327.4	20.1	0.15
MVSNet Inv. Depth	✓	✗	✗	29.6	8.1	65.2	28.5	60.3	5.8	(28.7)	(48.9)	51.4	14.6	47.0	21.2	0.28
CVP-MVSNet	✓	✗	✗	158.2	1.2	2289.0	0.1	1735.3	1.2	(8314.0)	(0.0)	415.9	9.5	2582.5	2.4	0.50
Vis-MVSNet	✓	✗	✗	10.3	54.4	84.9	15.6	51.5	17.4	(374.2)	(1.7)	21.1	65.6	108.4	31.0	0.82
PatchmatchNet	✓	✗	✗	29.0	16.3	70.1	16.7	99.4	3.5	(82.6)	(5.6)	39.4	19.3	64.1	12.3	0.18
Fast-MVSNet	✓	✗	✗	12.1	37.4	287.1	9.4	131.2	9.6	(540.4)	(1.9)	33.9	47.2	200.9	21.1	0.35
MVS2D ScanNet	✓	✗	✗	73.4	0.0	(4.5)	(54.1)	30.7	14.4	5.0	57.9	56.4	11.1	34.0	27.5	0.05
MVS2D DTU	✓	✗	✗	93.3	0.0	51.5	1.6	78.0	0.0	(1.6)	(92.3)	87.5	0.0	62.4	18.8	0.06
Robust MVD Baseline	✓	✗	✗	7.1	41.9	7.4	38.4	9.0	42.6	2.7	82.0	5.0	75.1	6.3	56.0	0.06

bold: best | (parentheses): trained on same domain

Robust Multi-view Depth Benchmark Results

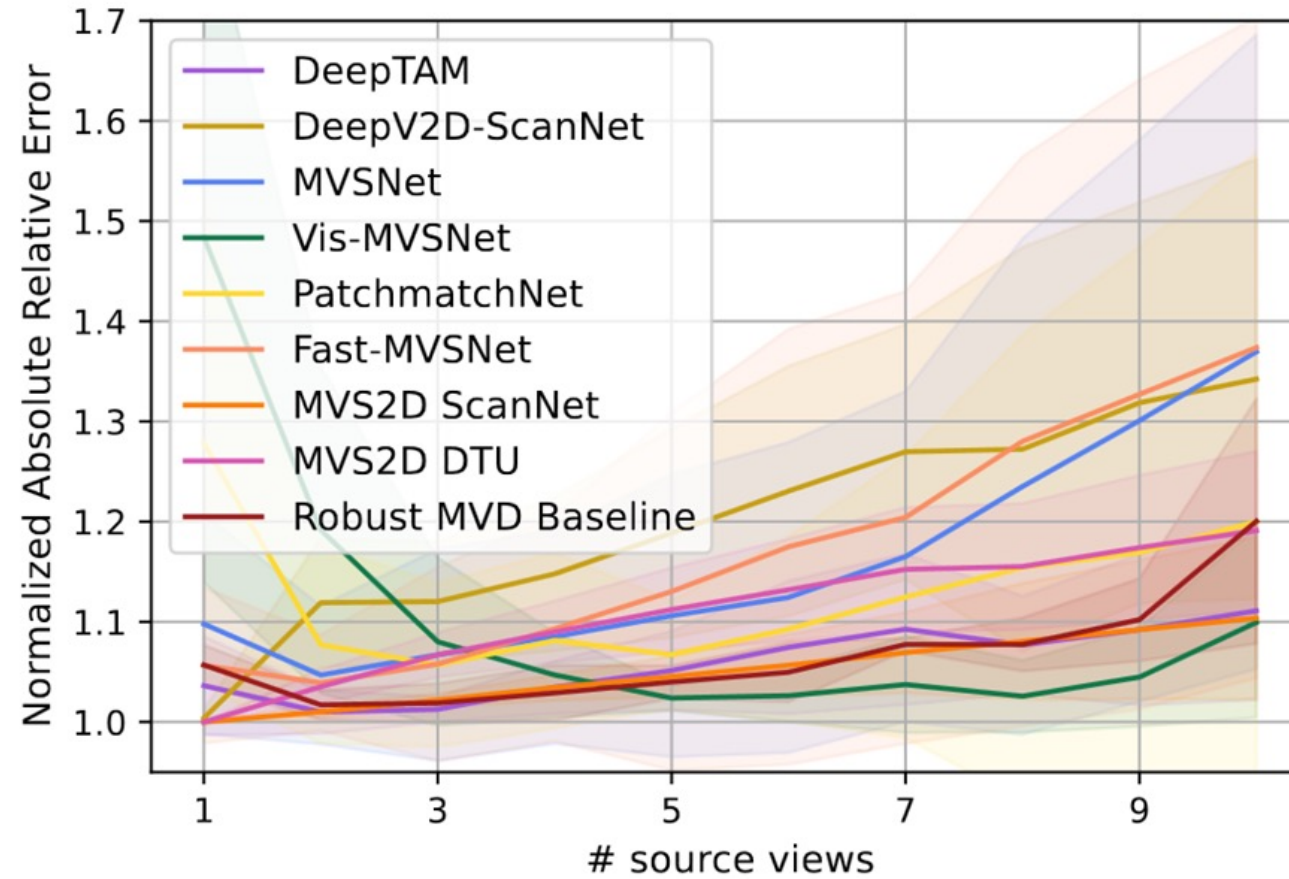


Approach	GT Poses	GT Range	Align	KITTI		ScanNet		ETH3D		DTU		T&T		Average		
				rel ↓	τ ↑	rel ↓	τ ↑	rel ↓	τ ↑	rel ↓	τ ↑	rel ↓	τ ↑	rel ↓	τ ↑	time [s] ↓
DeMoN	✓	✗	✗	16.7	13.4	75.0	0.0	19.0	16.2	23.7	11.5	17.6	18.3	30.4	11.9	0.08
DeepTAM	✓	✗	✗	68.7	0.4	(6.7)	(39.7)	20.4	19.8	58.0	9.1	40.0	12.9	38.8	16.4	0.85
DeepV2D KITTI	✓	✗	✗	(20.4)	(16.3)	25.8	8.1	30.1	9.4	24.6	8.2	38.5	9.6	27.9	10.3	1.43
DeepV2D ScanNet	✓	✗	✗	61.9	5.2	(3.8)	(60.2)	18.7	28.7	9.2	27.4	33.5	38.0	25.4	31.9	2.15
MVSNet	✓	✗	✗	14.0	35.8	1568.0	5.7	507.7	8.3	(4429.1)	(0.1)	118.2	50.7	1327.4	20.1	0.15
MVSNet Inv. Depth	✓	✗	✗	29.6	8.1	65.2	28.5	60.3	5.8	(28.7)	(48.9)	51.4	14.6	47.0	21.2	0.28
CVP-MVSNet	✓	✗	✗	158.2	1.2	2289.0	0.1	1735.3	1.2	(8314.0)	(0.0)	415.9	9.5	2582.5	2.4	0.50
Vis-MVSNet	✓	✗	✗	10.3	54.4	84.9	15.6	51.5	17.4	(374.2)	(1.7)	21.1	65.6	108.4	31.0	0.82
PatchmatchNet	✓	✗	✗	29.0	16.3	70.1	16.7	99.4	3.5	(82.6)	(5.6)	39.4	19.3	64.1	12.3	0.18
Fast-MVSNet	✓	✗	✗	12.1	37.4	287.1	9.4	131.2	9.6	(540.4)	(1.9)	33.9	47.2	200.9	21.1	0.35
MVS2D ScanNet	✓	✗	✗	73.4	0.0	(4.5)	(54.1)	30.7	14.4	5.0	57.9	56.4	11.1	34.0	27.5	0.05
MVS2D DTU	✓	✗	✗	93.3	0.0	51.5	1.6	78.0	0.0	(1.6)	(92.3)	87.5	0.0	62.4	18.8	0.06
Robust MVD Baseline	✓	✗	✗	7.1	41.9	7.4	38.4	9.0	42.6	2.7	82.0	5.0	75.1	6.3	56.0	0.06

bold: best | (parentheses): trained on same domain

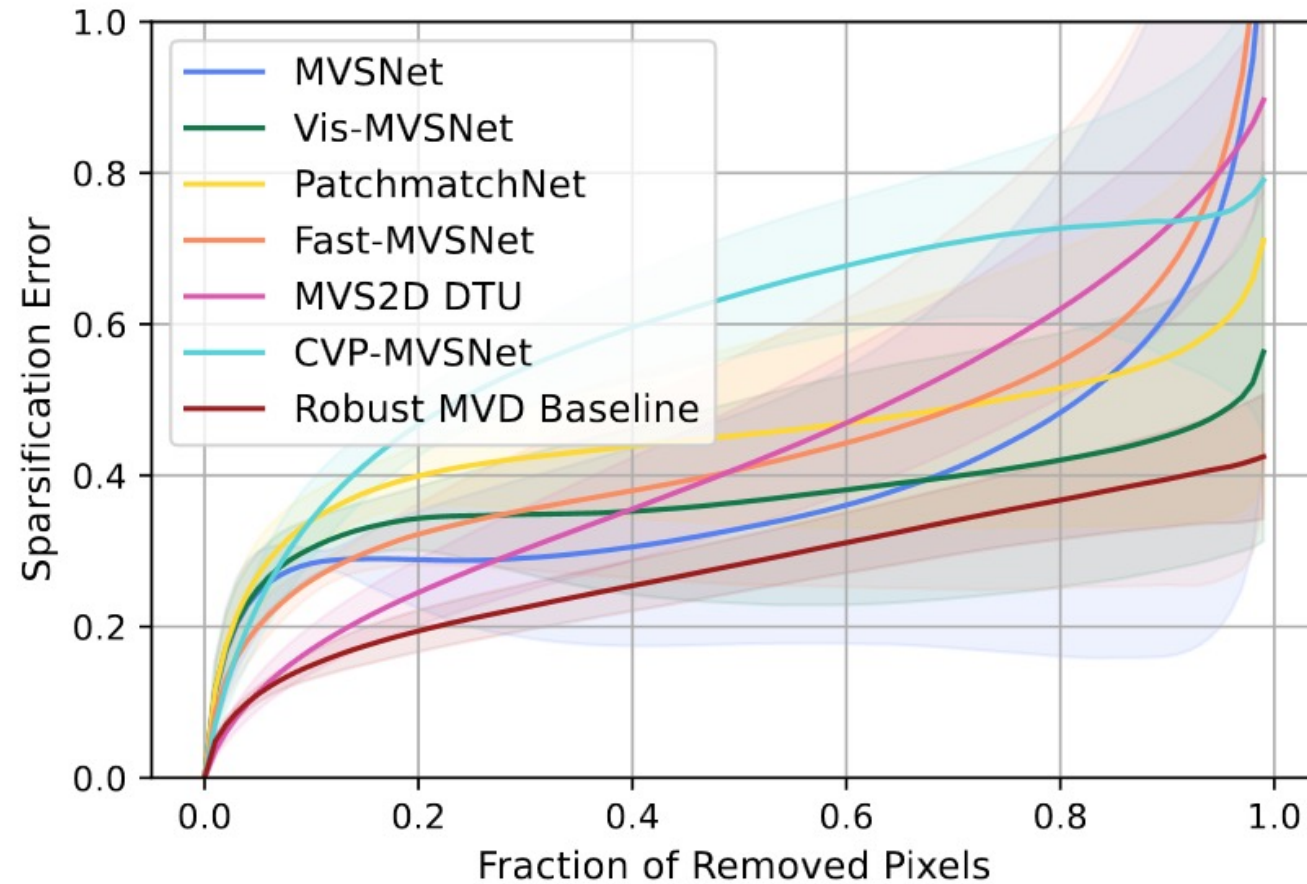
Robust Multi-view Depth Benchmark

Multi-view Fusion Results



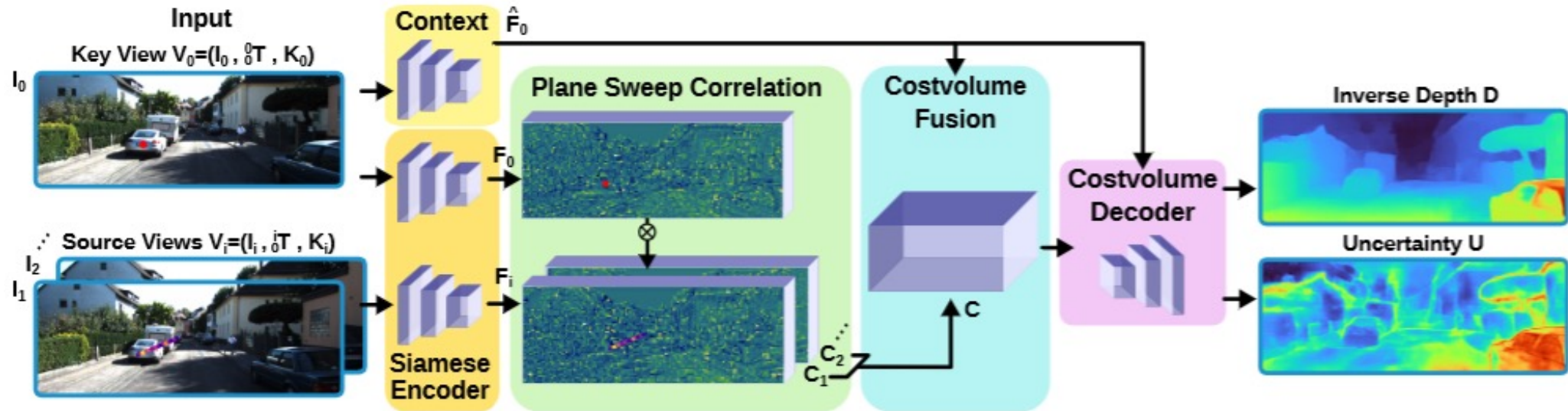
Robust Multi-view Depth Benchmark

Uncertainty Estimation Results

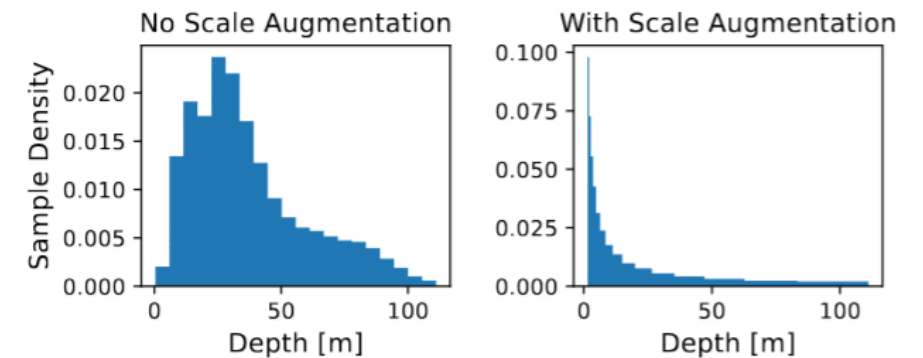




Robust MVD Baseline Model Overview



- **Architecture:** based on DispNet
- **Training data:** BlendedMVS + StaticThings3D
- **Data augmentation:** Scale augmentation

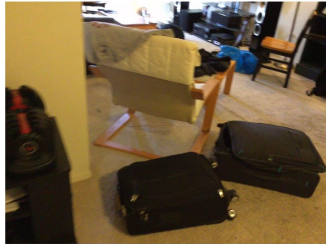
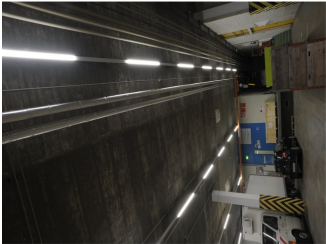


Robust MVD Baseline Model

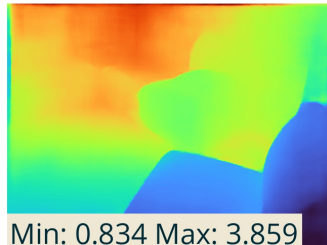
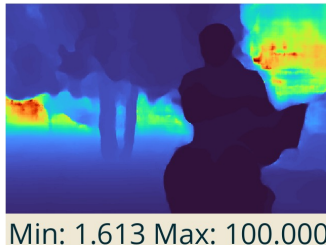
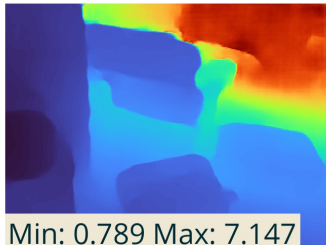
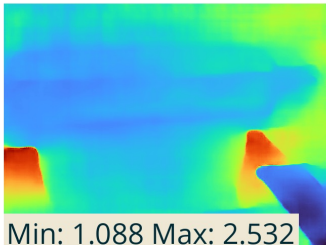
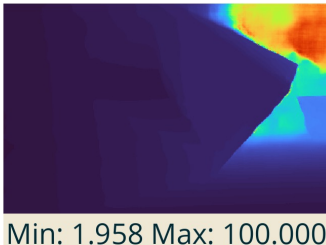
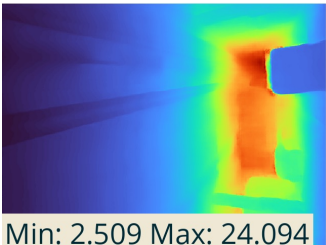
Qualitative Results



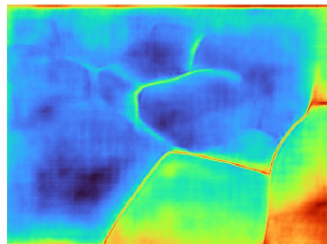
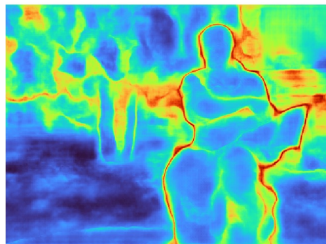
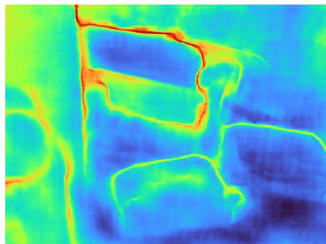
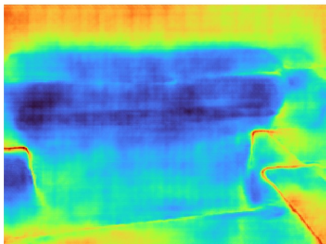
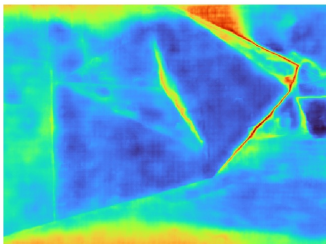
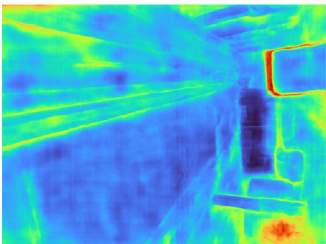
Keyimage



Depth



Uncertainty



robustmvd Framework



<https://github.com/lmb-freiburg/robustmvd>

- **data:** provides scripts and dataloaders to setup and use multiple datasets with a common interface
- **model zoo:** of pre-trained depth estimation models with a common interface
- **evaluation:** provides code to evaluate models on the rmvd benchmark



Code

robustmvd Framework



<https://github.com/lmb-freiburg/robustmvd>

- **inference**: provides scripts to run multi-view depth estimation on custom data with any of the available models
- **data viewer**: provides a data viewer to visualize input data and model predictions
- **current student project**: add training code and conduct analysis



Code

Summary



- We show **problems of current multi-view depth models**: cross-domain generalization, uncertainty estimation, multi-view fusion
- We introduce a **benchmark to improve upon these problems**
- **Robust MVD Baseline model** can be used as baseline on the benchmark and for robust multi-view depth estimation in applications where camera poses are known
- **robustmvd Framework** unifies datasets and models with a common interface



Thanks!

Questions?



Code:

<https://github.com/lmb-freiburg/robustmvd>



KIDELTA
LEARNING

Scalable AI for Automated Driving

Philipp Schröppel | Uni Freiburg

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KI Delta Learning is a project of the KI Familie. It was initiated and developed by the VDA Leitinitiative autonomous and connected driving and is funded by the Federal Ministry for Economic Affairs and Climate Action.



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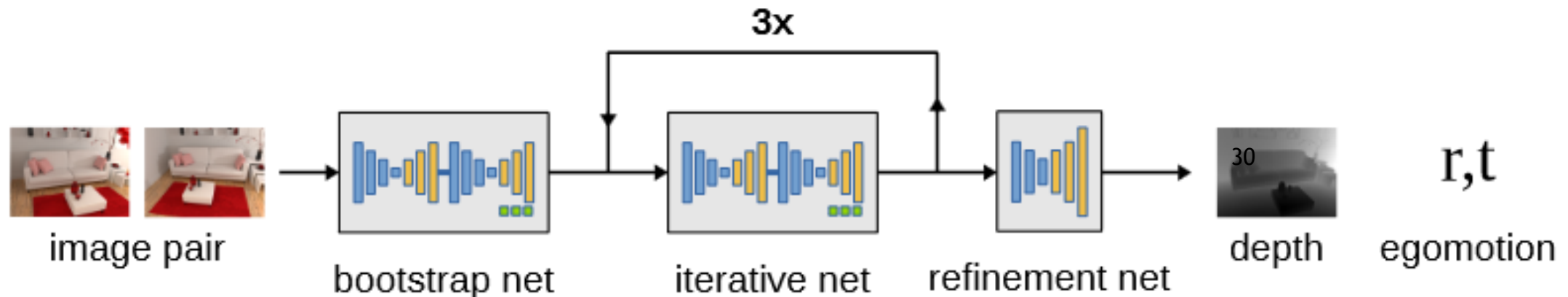
on the basis of a decision
by the German Bundestag



Related Work

DeMoN (first depth-from-“video”)

- estimates depths and poses from two views
- no explicit correlation layer within the network, but intermediate optical flow estimation
- trained on diverse data



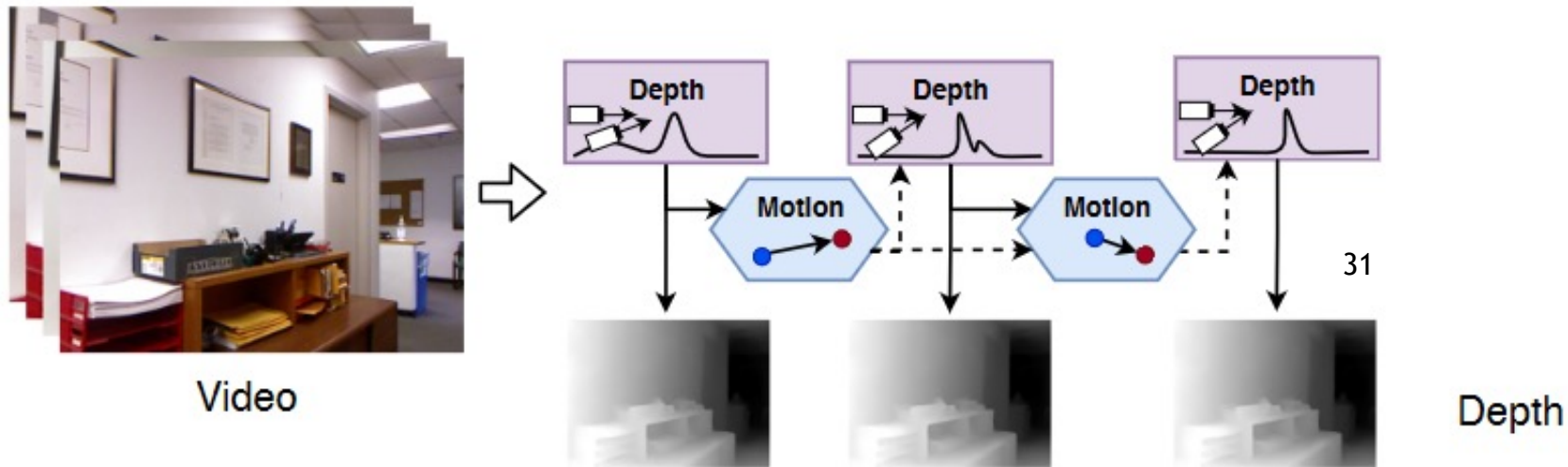
[Ummenhofer et al. *Demon: Depth and Motion Network for Learning Monocular Stereo*. CVPR 2017]



Related Work

DeepV2D (depth-from-video)

- separate mapping and tracking modules to estimate depths and poses alternatingly
- builds plane sweep stereo costvolume from learned features
- trained on multi-view depth estimation

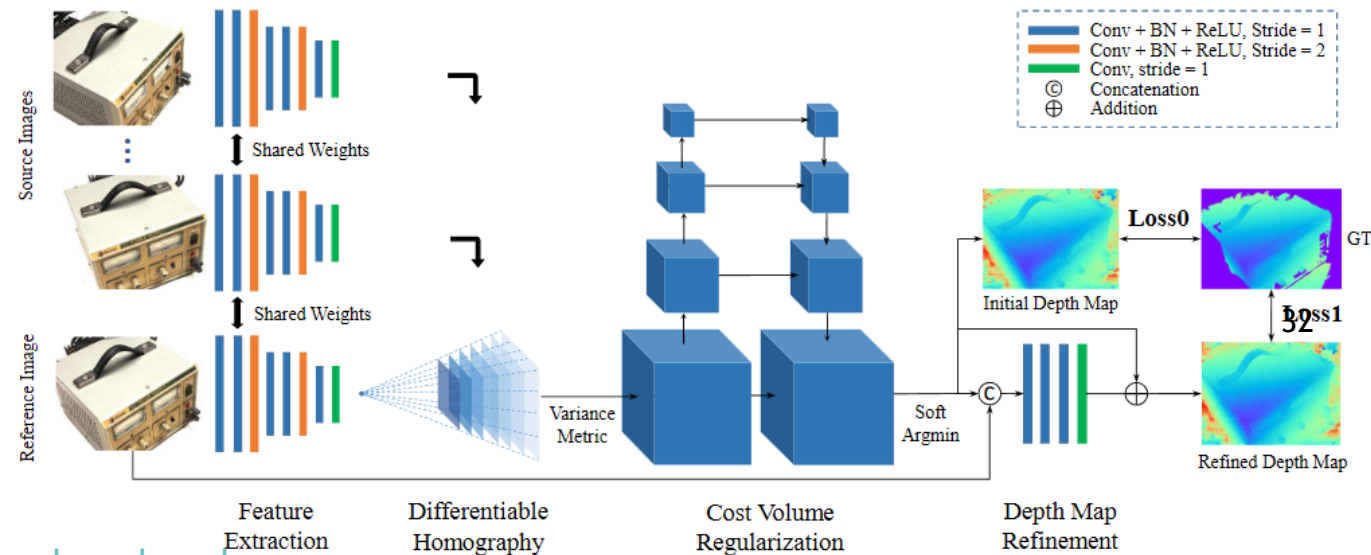




Related Work

MVSNet (multi-view stereo)

- builds costvolume in a plane sweep stereo fashion based on the variance between multi-view features + decodes costvolume with 3d convolutions
- trained on B



Robust Multi-view Depth Estimation

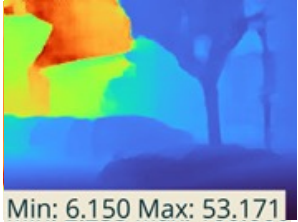


Input:

Keyview



Output:

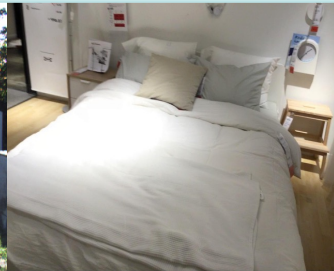





Depth map
for the keyview



Robust Multi-view Depth Estimation

We define a benchmark based on **diverse existing datasets**:

KITTI	ScanNet	ETH3D	DTU	T & T
				
Driving	Indoor	In- & outdoor	Tabletop	In- & outdoor

→ evaluation in a zero-shot cross-dataset fashion



Robust Multi-view Depth Estimation

- We show problems of current multi-view depth models: cross-domain generalization, uncertainty estimation, multi-view fusion
- The benchmark can be used to improve upon these problems
- Introduce **model** for robust multi-view depth estimation on data from different domains

