Recent Progress in Stereo Matching, Scene Flow and Object Pose Estimation

Sudipta Sinha

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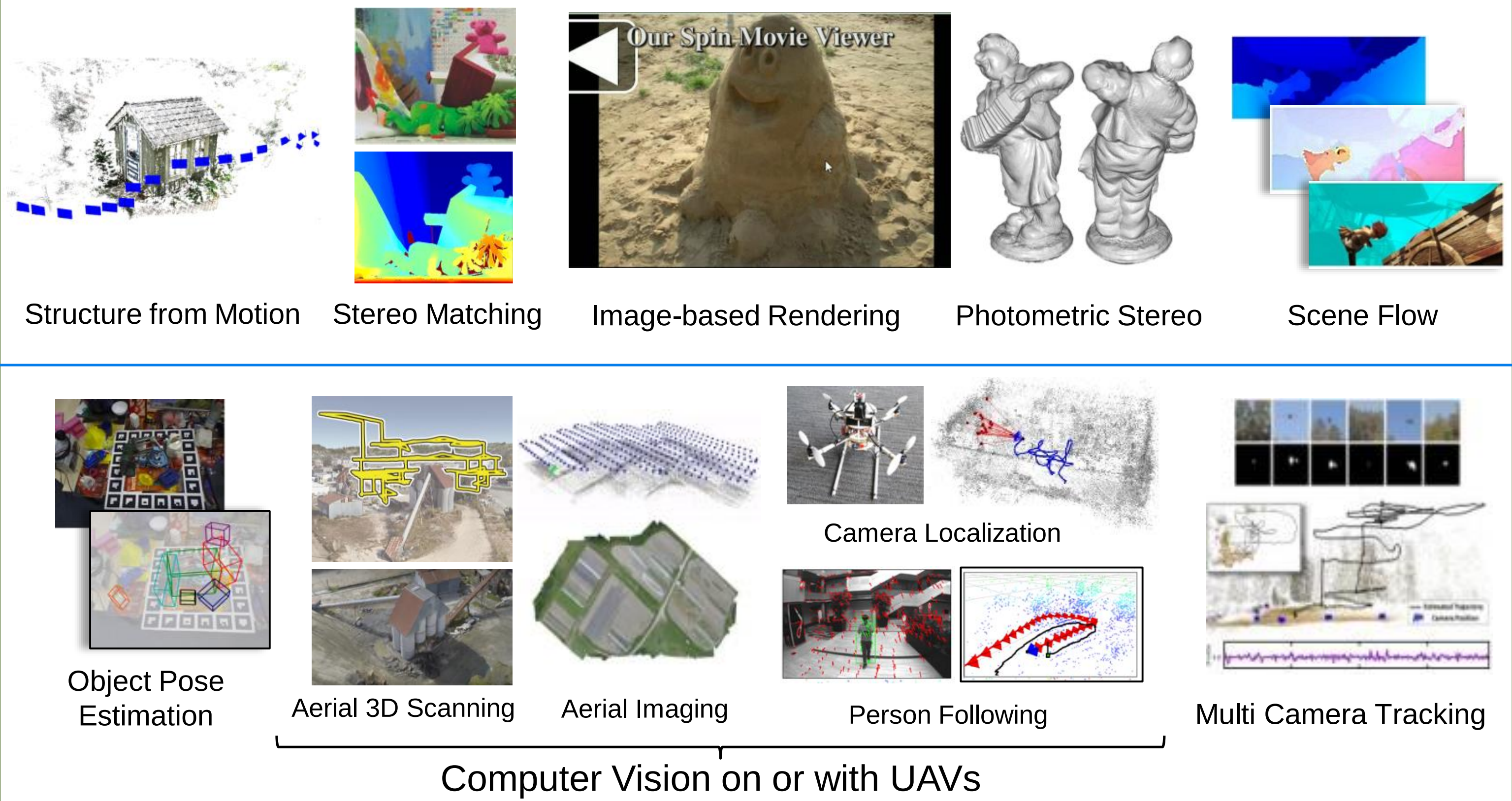
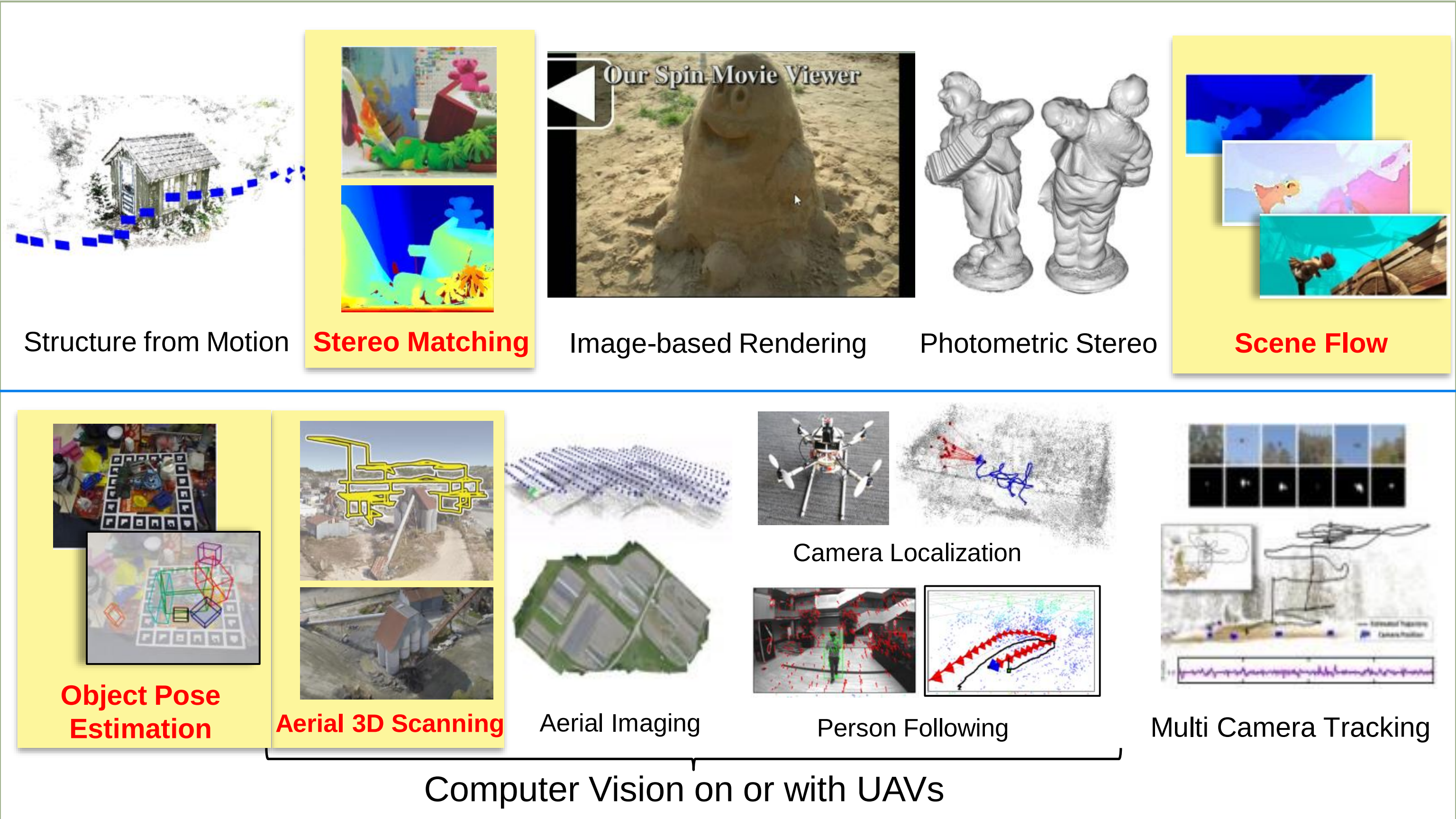
Talk at Georgia Tech, August 24, 2018


Our Spin Movie Viewer
Structure from Motion
Stereo Matching
Image-based Rendering
Photometric Stereo
Scene Flow
Camera Localization
Object Pose Estimation
Aerial 3D Scanning
Aerial Imaging
Person Following
Multi Camera Tracking
Computer Vision on or with UAVs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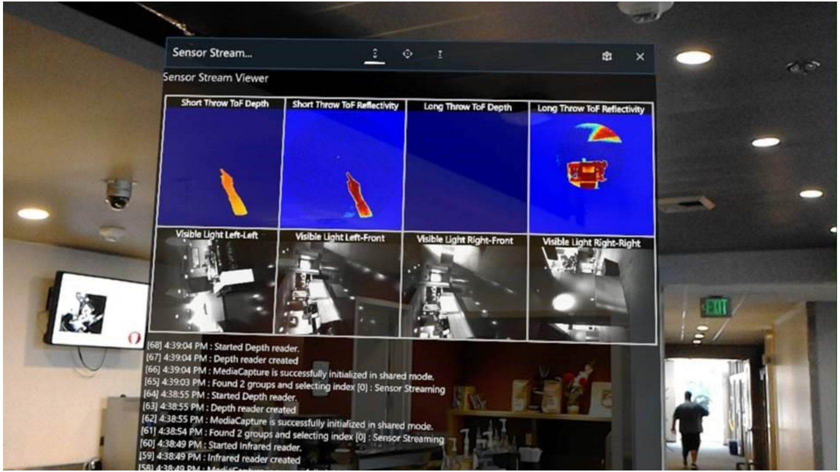
HoloLens *Research Mode*

https://docs.microsoft.com/en-us/windows/mixed-reality/cvpr-2018

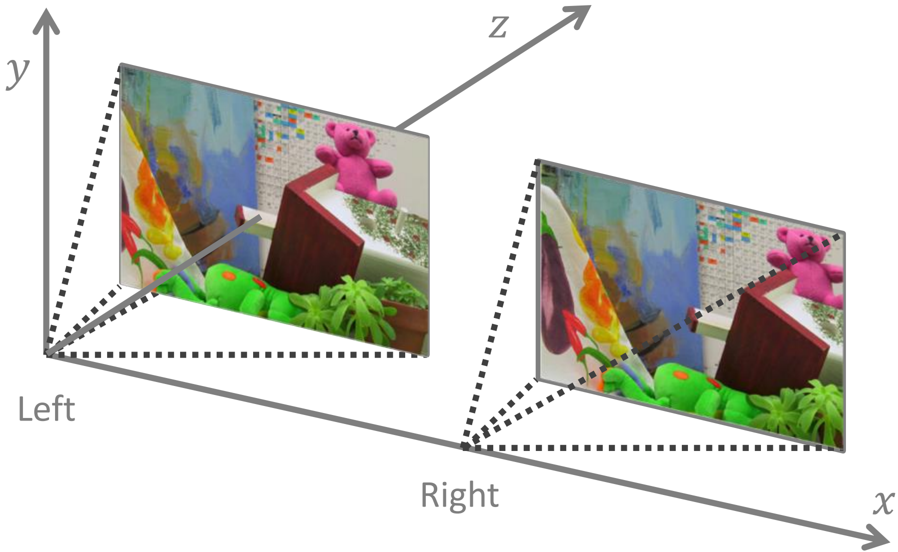
- On-device API
- Gives access to
  - audio
  - 6-dof pose
  - surface mesh
  - raw video streams
    - 4x greyscale cameras
    - Color camera
    - ToF Depth & IR Reflectivity (near, far)



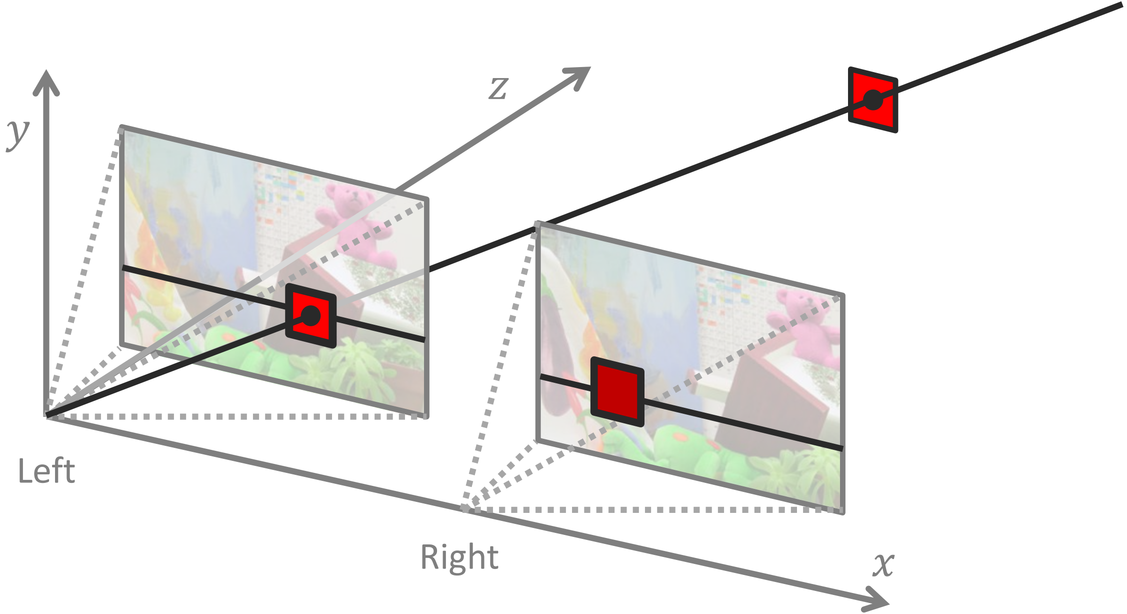
Outline

- Stereo Matching: New Trends
- Semi-Global Stereo Matching (SGM)
  - SGM with Surface Orientation Priors
  - Learning to Fuse Proposals
- Stereo Scene Flow with Motion Segmentation
- Camera Trajectory Planning for Aerial 3D Scanning
- Deep 6-DoF Object Pose Prediction

Stereo Matching



Stereo Matching



Solved Problem?

Still difficult …

Fore-shortening

Specular surfaces

Transparency, reflections

Different lighting

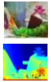
High Dynamic range

Untextured slanted surfaces

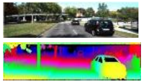
- Top methods still inaccurate in corner cases and infeasible for real-time, low power systems

Stereo benchmarks

Middlebury (2005)



KITTI (2012—15)



Middlebury (2014)

(5 — 6 MPixels)

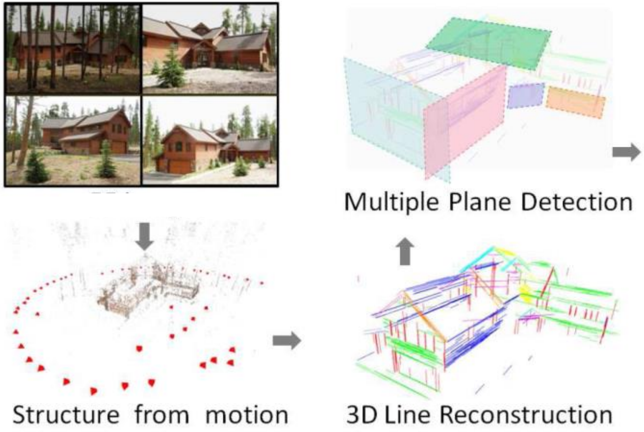
Disney Research (2013)

(10—20 Mpixels)

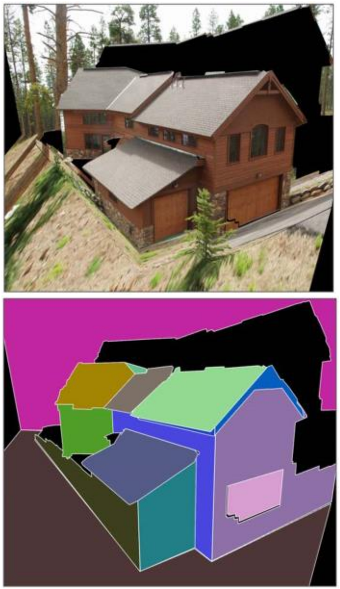
ETH3D (2017)

Piecewise Planar Stereo

[Sinha, Steedly, Szeliski 2009]



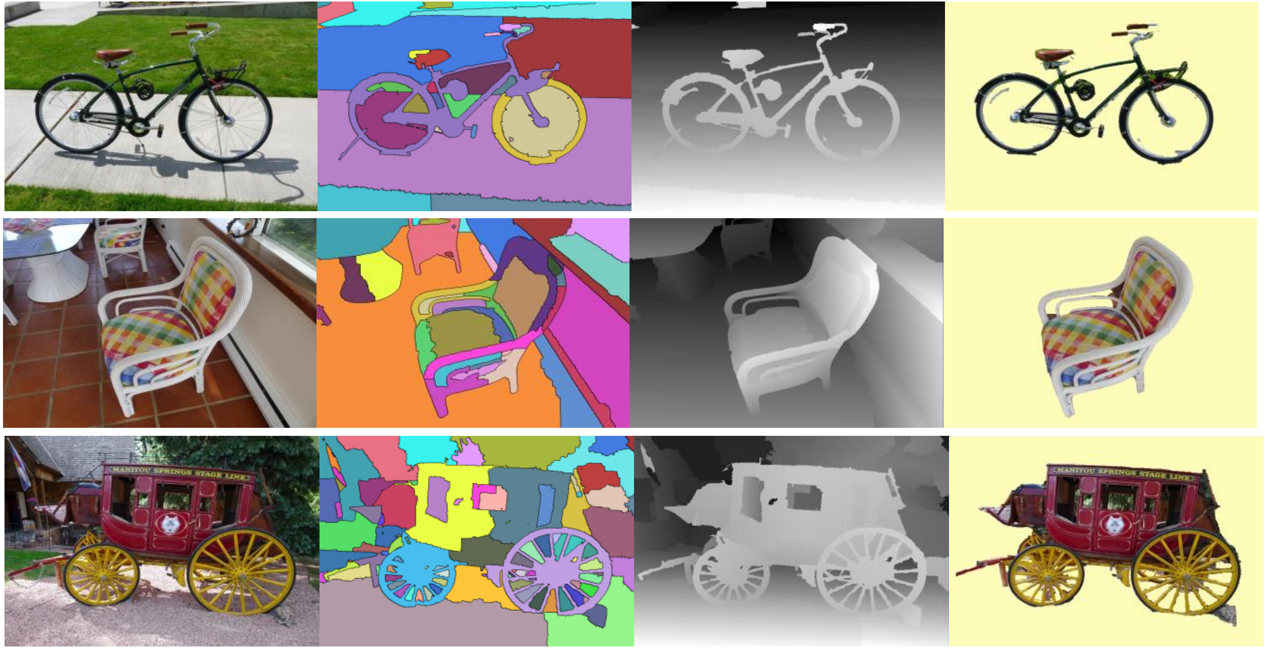
Discrete Optimization (Graph Cuts)



Novel Rendered View

Piecewise Planar Stereo ***Revisited***

[Kowdle, Sinha, Szeliski 2012]



Labeling Problems and Markov Random Fields

- Find a per-pixel label (disparity map) D, by minimizing energy:

$$E(D) = \mathrm{E}_{\mathrm{data}}(D) + \mathrm{E}_{\mathrm{smooth}}(D)$$

$$= \sum_{p \in I} C_p\left(d_p\right) + \sum_{(p,q) \in N} V_{pq}(d_p, d_q)$$

- Data and smoothness terms encode matching costs and prior
- Discrete or continuous labels
- Inference: Graph Cuts, Belief Propagation, PatchMatch, …

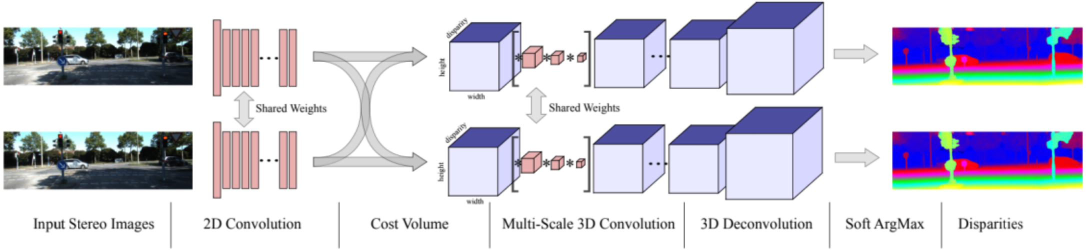
[Boykov+ 1998; Kolmogorov and Zabih 2002; Felzenszwalb and Huttenlocher 2004; Bleyer+ 2011; Besse+ 2012]

New Trends

- Learning the matching cost:
  - MC-CNN [Zbontar + Lecun 2015], Chen+ 2015, Luo+ 2016
- Continuous MRFs:
  - Piecewise Planar Stereo [Taniai+ 2017] (Top rank on Middlebury v3 since 2017)
- Deep stereo regression (end to end training)
  - FlowNet [Dosovitskiy+ 2015]
  - DispNet [Mayer+ 2016]
- Unsupervised learning
  - Left-Right Consistency Check → training samples, iterate … [Zhou+ ICCV 2017]

New Trends

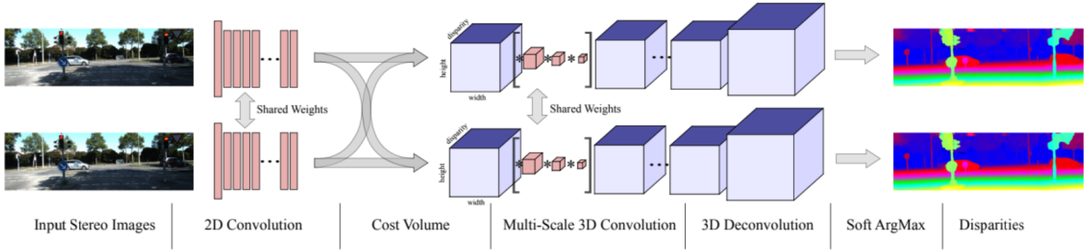
Kendall+ 2017



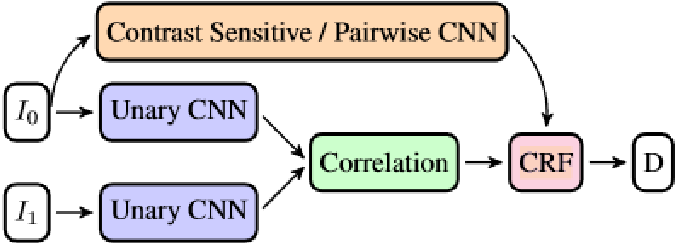
- **Return of "Correlation"**
  - DispNetCorr [Mayer+ 2016]
  - GC-Net [Kendall+ 2017]

New Trends

Kendall+ 2017



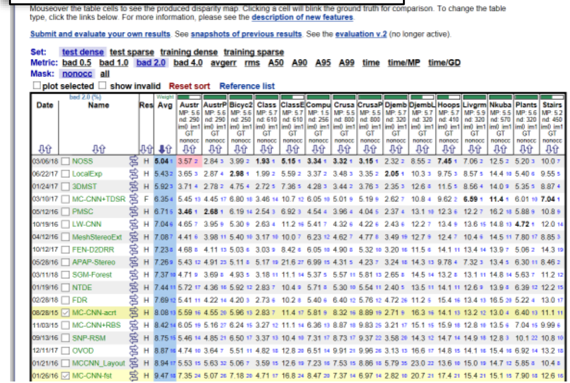
- **Return of "Correlation"**
  - DispNetCorr [Mayer+ 2016]
  - GC-Net [Kendall+ 2017]
- **Return of "CRFs"**
  - SGM-Nets [Seki and Pollefeys 2017]
  - Hybrid CNN-CRF [Knobelreiter+ 2017



Knobelreiter+ 2017

Analysis of Benchmarks (~June 2018)

Middlebury 2014



Mouseover the table cells to see the produced disparity map. Clicking a cell will blink the ground truth for comparison. To change the table type, click the links below. For more information, please see the description of new features.

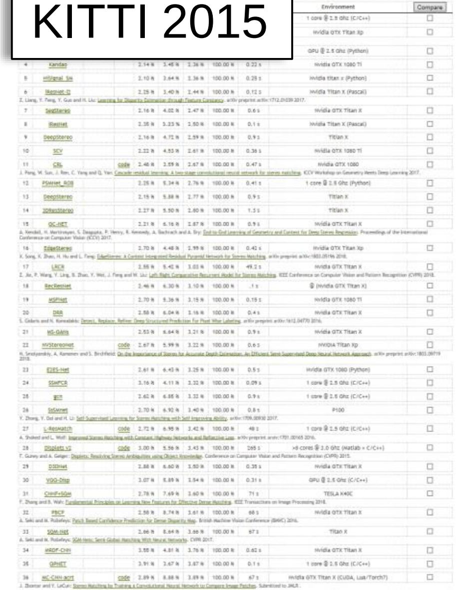
Submit and evaluate your own results. See snapshots of previous results. See the evaluation v.2 (no longer active).

Set: test dense test sparse training dense training sparse
Metric: bad 0.5 bad 1.0 bad 2.0 bad 4.0 avgerr rms A50 A90 A95 A99 time time/MP time/GD
Mask: nonocc all

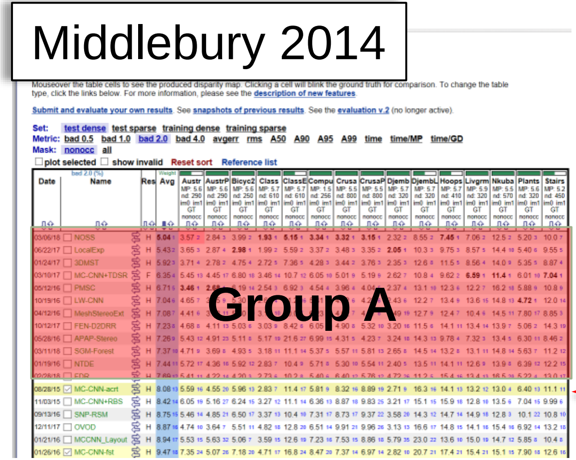
plot selected show invalid Reset sort Reference list

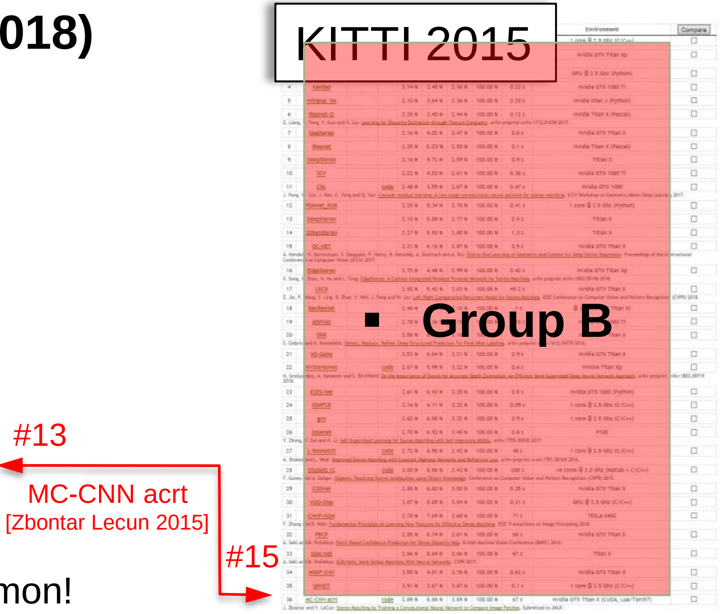
Date	Name (bad 2.0 (%))	Res	Avg (Weight)	Austr MP: 5.6 nd: 290 im0 im1 GT nonocc	AustrP MP: 5.6 nd: 290 im0 im1 GT nonocc	Bicyc2 MP: 5.6 nd: 250 im0 im1 GT nonocc	Class MP: 5.7 nd: 610 im0 im1 GT nonocc	ClassE MP: 5.7 nd: 610 im0 im1 GT nonocc	Compu MP: 1.5 nd: 256 im0 im1 GT nonocc	Crusa MP: 5.5 nd: 800 im0 im1 GT nonocc	CrusaP MP: 5.5 nd: 800 im0 im1 GT nonocc	Djemb MP: 5.7 nd: 320 im0 im1 GT nonocc	DjembL MP: 5.7 nd: 320 im0 im1 GT nonocc	Hoops MP: 5.7 nd: 410 im0 im1 GT nonocc	Livgrm MP: 5.9 nd: 320 im0 im1 GT nonocc	Nkuba MP: 5.5 nd: 570 im0 im1 GT nonocc	Plants MP: 5.6 nd: 320 im0 im1 GT nonocc	Stairs MP: 5.2 nd: 450 im0 im1 GT nonocc
03/06/18	NOSS	H	**5.04** 1	3.57 2	2.84 3	3.99 2	**1.93** 1	**5.15** 1	**3.34** 1	**3.32** 1	**3.15** 1	2.32 2	8.55 2	**7.45** 1	7.06 2	12.5 2	5.20 3	10.0 7
06/22/17	LocalExp	H	5.43 2	3.65 3	2.87 4	**2.98** 1	1.99 2	5.59 2	3.37 2	3.48 3	3.35 2	**2.05** 1	10.3 3	9.75 3	8.57 5	14.4 10	5.40 6	9.55 5
01/24/17	3DMST	H	5.92 3	3.71 4	2.78 2	4.75 4	2.72 5	7.36 5	4.28 3	3.44 2	3.76 3	2.35 3	12.6 8	11.5 5	8.56 4	14.0 9	5.35 5	8.87 4
03/10/17	MC-CNN+TDSR	F	6.35 4	5.45 13	4.45 17	6.80 18	3.46 14	10.7 12	6.05 10	5.01 9	5.19 9	2.62 7	10.8 4	9.62 2	**6.59** 1	**11.4** 1	6.01 10	**7.04** 1
05/12/16	PMSC	H	6.71 5	**3.46** 1	**2.68** 1	6.19 14	2.54 3	6.92 3	4.54 4	3.96 4	4.04 5	2.37 4	13.1 10	12.3 6	12.2 7	16.2 18	5.88 9	10.8 9
10/19/16	LW-CNN	H	7.04 6	4.65 7	3.95 9	5.30 9	2.63 4	11.2 16	5.41 7	4.32 6	4.22 6	2.43 6	12.2 7	13.4 9	13.6 15	14.8 13	**4.72** 1	12.0 14
04/12/16	MeshStereoExt	H	7.08 7	4.41 6	3.98 11	5.40 10	3.17 10	10.0 7	6.23 12	4.62 7	4.77 8	3.49 19	12.7 9	12.4 7	10.4 6	14.5 11	7.80 17	8.85 3
10/12/17	FEN-D2DRR	H	7.23 8	4.68 8	4.11 13	5.03 6	3.03 9	8.42 6	6.05 10	4.90 8	5.32 10	3.20 16	11.5 6	14.1 11	13.4 14	13.9 7	5.06 2	14.3 19
05/28/16	APAP-Stereo	H	7.26 9	5.43 12	4.91 23	5.11 8	5.17 19	21.6 27	6.99 15	4.31 5	4.23 7	3.24 18	14.3 13	9.78 4	7.32 3	13.4 5	6.30 11	8.46 2
03/11/18	SGM-Forest	H	7.37 10	4.71 9	3.69 8	4.93 5	3.18 11	11.1 14	5.37 5	5.57 11	5.81 13	2.65 8	14.5 14	13.2 8	13.1 11	14.8 14	5.63 7	11.2 12
01/19/16	NTDE	H	7.44 11	5.72 17	4.36 16	5.92 12	2.83 7	10.4 9	5.71 8	5.30 10	5.54 11	2.40 5	13.5 11	14.1 11	12.6 9	13.9 8	6.39 12	12.2 15
02/28/18	FDR	H	7.69 12	5.41 11	4.22 14	4.20 3	2.73 6	10.2 8	5.40 6	6.40 12	5.76 12	4.72 26	11.2 5	15.4 16	13.4 13	16.5 20	5.22 4	13.0 17
08/28/15	MC-CNN-acrt	H	8.08 13	5.59 16	4.55 20	5.96 13	2.83 7	11.4 17	5.81 9	8.32 16	8.89 19	2.71 9	16.3 16	14.1 13	13.2 12	13.0 4	6.40 13	11.1 11
11/03/15	MC-CNN+RBS	H	8.42 14	6.05 19	5.16 27	6.24 15	3.27 12	11.1 14	6.36 13	8.87 18	9.83 25	3.21 17	15.1 15	15.9 18	12.8 10	13.5 6	7.04 15	9.99 6
09/13/16	SNP-RSM	H	8.75 15	5.46 14	4.85 21	6.50 17	3.37 13	10.4 10	7.31 17	8.73 17	9.37 22	3.58 20	14.3 12	14.7 14	14.9 18	12.8 3	10.1 22	10.8 10
12/11/17	OVOD	H	8.87 16	4.74 10	3.64 7	5.51 11	4.82 18	12.8 20	6.51 14	9.91 21	9.96 26	3.13 13	16.6 17	14.8 15	14.1 16	15.4 16	6.92 14	13.2 18
01/21/16	MCCNN_Layout	H	8.94 17	5.53 15	5.63 32	5.06 7	3.59 15	12.6 19	7.23 16	7.53 15	8.86 18	5.79 35	23.0 22	13.6 10	15.0 19	14.7 12	5.85 8	10.4 8
01/26/16	MC-CNN-fst	H	9.47 18	7.35 24	5.07 26	7.18 20	4.71 17	16.8 24	8.47 20	7.37 14	6.97 14	2.82 10	20.7 21	17.4 21	15.4 21	15.1 15	7.90 18	12.6 16

KITTI 2015



Analysis of Benchmarks (~June 2018)





- Group A and B have no methods in common!
- Group A: MC-CNN variants; no other “deep learning” technique!
- Group B: U-nets, ResNet, 3D convolutions, RNNs, End to end learning, …

Summary

- Dataset bias exists.
- Middlebury stereo pairs from different scenes; makes learning difficult.
- Need a better way to evaluate “deep stereo regression”.

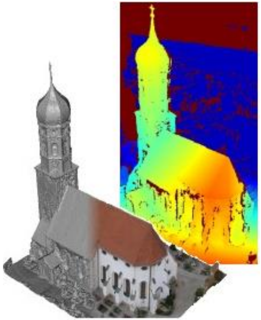
Must train **one** model on combined training set and submit to all benchmarks!

Outline

- Stereo Matching: New Trends
- **Semi-Global Stereo Matching (SGM)**
  - SGM with Surface Orientation Priors
  - Learning to Fuse Proposals
- Stereo Scene Flow with Motion Segmentation
- Camera Trajectory Planning for Aerial 3D Scanning
- Deep 6-DoF Object Pose Prediction

Semi Global Matching [Hirschmüller 2005]

- MRF inference (Graph Cuts, BP, ..) too slow
- SGM: Approximate even more; use heuristics
  - Widely used: assisted driving, robotics, aerial mapping …
  - Runs on GPUs, FPGAs …



Scanline Optimization (1D)

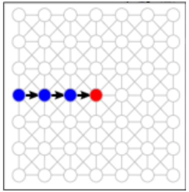
Minimize:

$$E(D) = \sum_{p \in I} C_p\left(d_p\right) + \sum_{(p,q) \in N} V_{pq}(d_p, d_q)$$

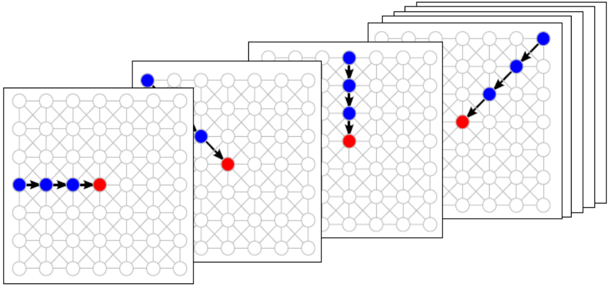
- Consider the above problem on a 1D scanline.
- Compute an aggregated matching cost

$$L_{\mathbf{r}}(\mathbf{p}, d) = C_{\mathbf{p}}(d) + \min_{d' \in \mathcal{D}}(L_{\mathbf{r}}(\mathbf{p} - \mathbf{r}, d') + V(d, d')).$$

  - $\mathbf{r} = (1, 0)$: start at leftmost pixel, scan left



Semi Global Matching (SGM)



- For 8 directions
  - calculate aggregated costs

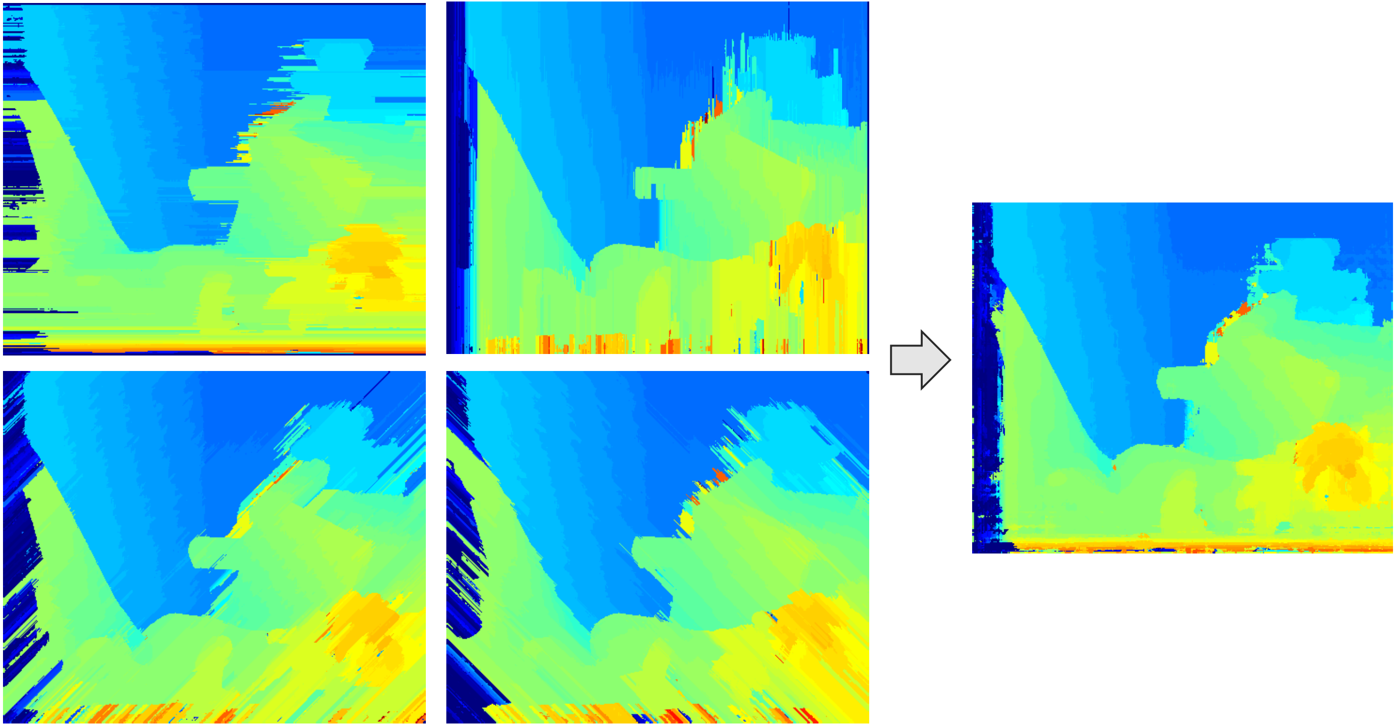
$$L_{\mathbf{r}}(\mathbf{p}, d) = C_{\mathbf{p}}(d) + \min_{d' \in \mathcal{D}} (L_{\mathbf{r}}(\mathbf{p} - \mathbf{r}, d') + V(d, d')).$$

- Finally, sum the costs and select per-pixel minima.

$$S(\mathbf{p}, d) = \sum_{\mathbf{r}} L_{\mathbf{r}}(\mathbf{p}, d)$$

$$D_{\mathbf{p}} = \arg\min_{d} S(\mathbf{p}, d).$$

Semi Global Matching (SGM)

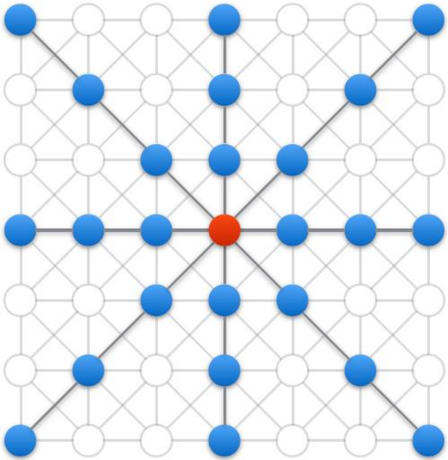


Semi Global Matching (SGM)

Approximates 2D MRF using 1D optimization

along 8 cardinal directions

$$E(D) = \sum_{\mathbf{p}} C_{\mathbf{p}}(d_{\mathbf{p}}) + \sum_{\mathbf{p},\mathbf{q} \in \mathcal{N}} V(d_{\mathbf{p}}, d_{\mathbf{q}})$$



- Related to Belief Propagation, TRW-S

  [Drory et al. 2014]

Semi Global Stereo Matching with Surface Orientation Priors



Daniel Scharstein
Middlebury College

Tatsunori Taniai
RIKEN, Tokyo

Sudipta Sinha
Microsoft Research

3DV 2017

Semi Global Matching [Hirschmüller 2005]

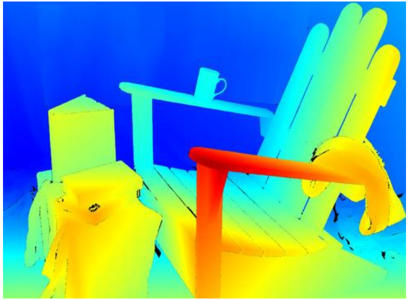
Approximates 2D MRF using 1D optimization along 8 cardinal directions

$$E(D) = \sum_{\mathbf{p}} C_{\mathbf{p}}(d_{\mathbf{p}}) + \sum_{\mathbf{p},\mathbf{q} \in \mathcal{N}} V(d_{\mathbf{p}}, d_{\mathbf{q}})$$

$$\begin{cases} 0 & \text{if } d = d' \end{cases}$$

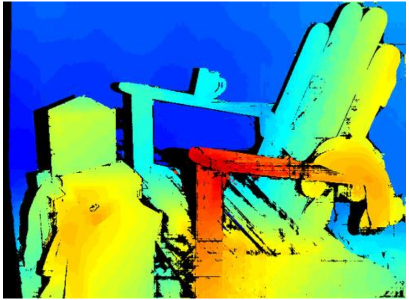
- Fronto parallel bias
- Inaccurate on slanted untextured surfaces

Left Image

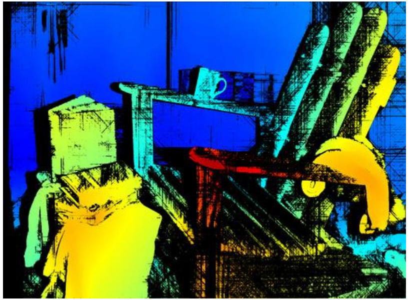


Ground Truth

SGM* (quarter resolution)



SGM* (full resolution (6 MP))



* Confidence measure used to prune uncertain pixels (black holes)

SGM-P: SGM with orientation priors

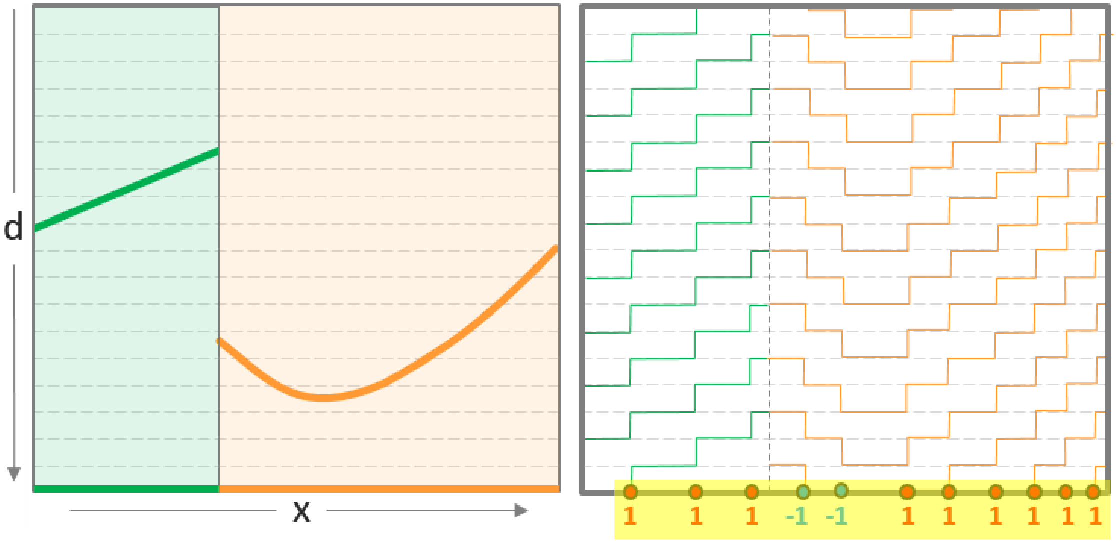
[Scharstein, Taniai, Sinha, 3DV 2017]

- What if we knew the surface slant?

Idea:

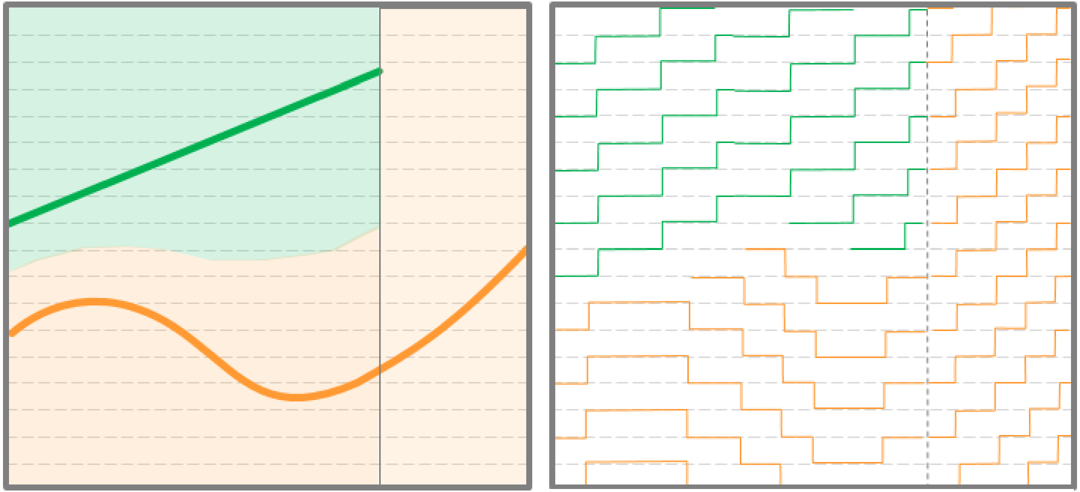
- *Rasterize* disparity surface prior (at arbitrary depth)
- Adjust $V(d, d')$ to follow discrete disparity "steps"

SGM-P: 2D orientation priors



$$V_S(d_{\mathbf{p}}, d'_{\mathbf{p}}) = V(d_{\mathbf{p}} + j_{\mathbf{p}}, d'_{\mathbf{p}})$$

SGM-P: 3D orientation priors

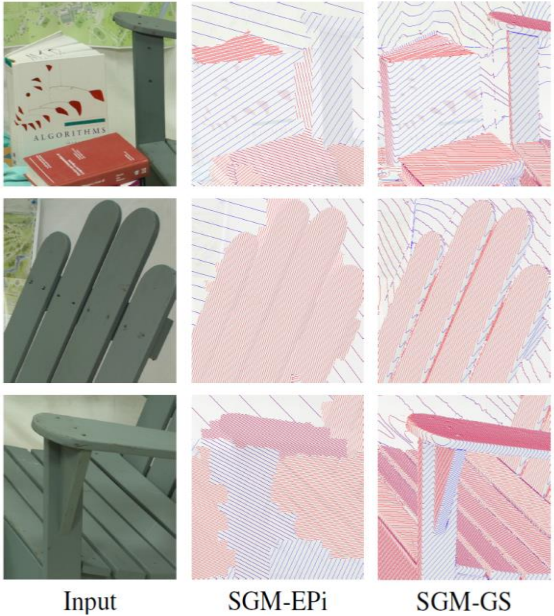


$$V_S(d_{\mathbf{p}}, d'_{\mathbf{p}}) = V(d_{\mathbf{p}} + j_{\mathbf{p}}(d_{\mathbf{p}}), d'_{\mathbf{p}})$$

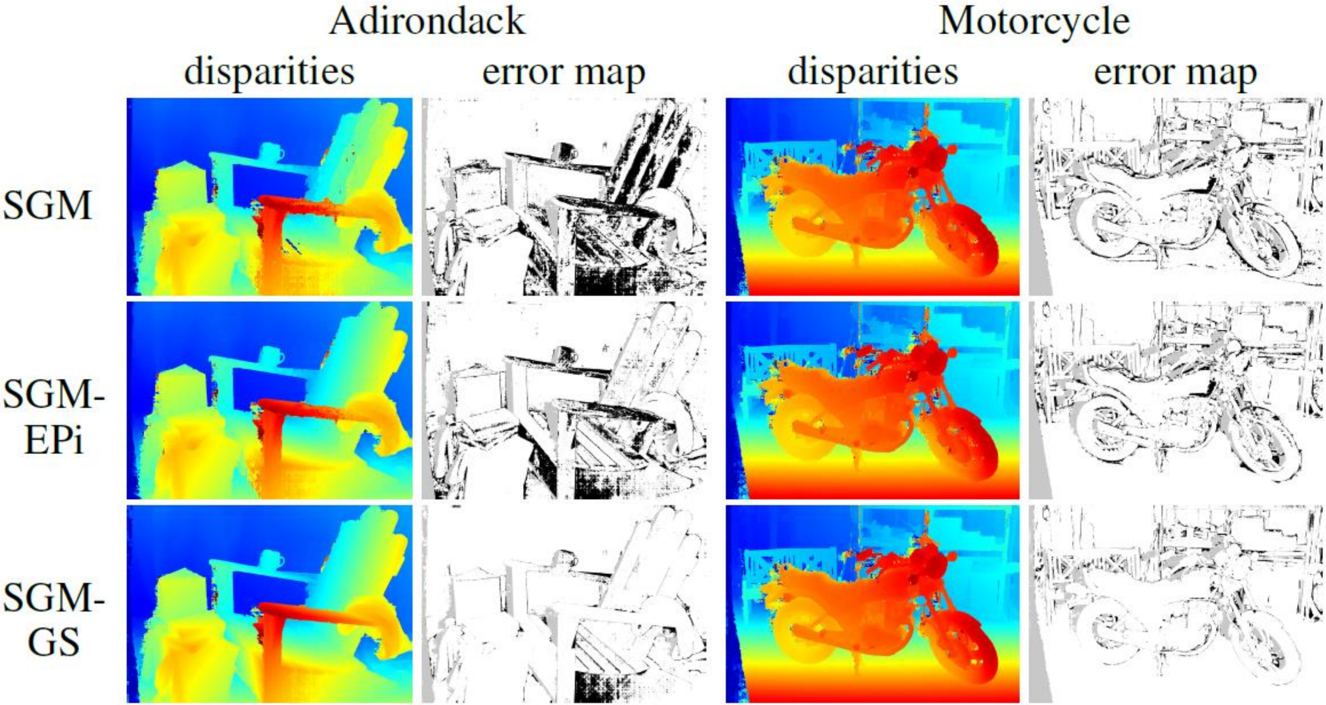
Jump locations vary with disparity

SGM-P: Where do we get priors?

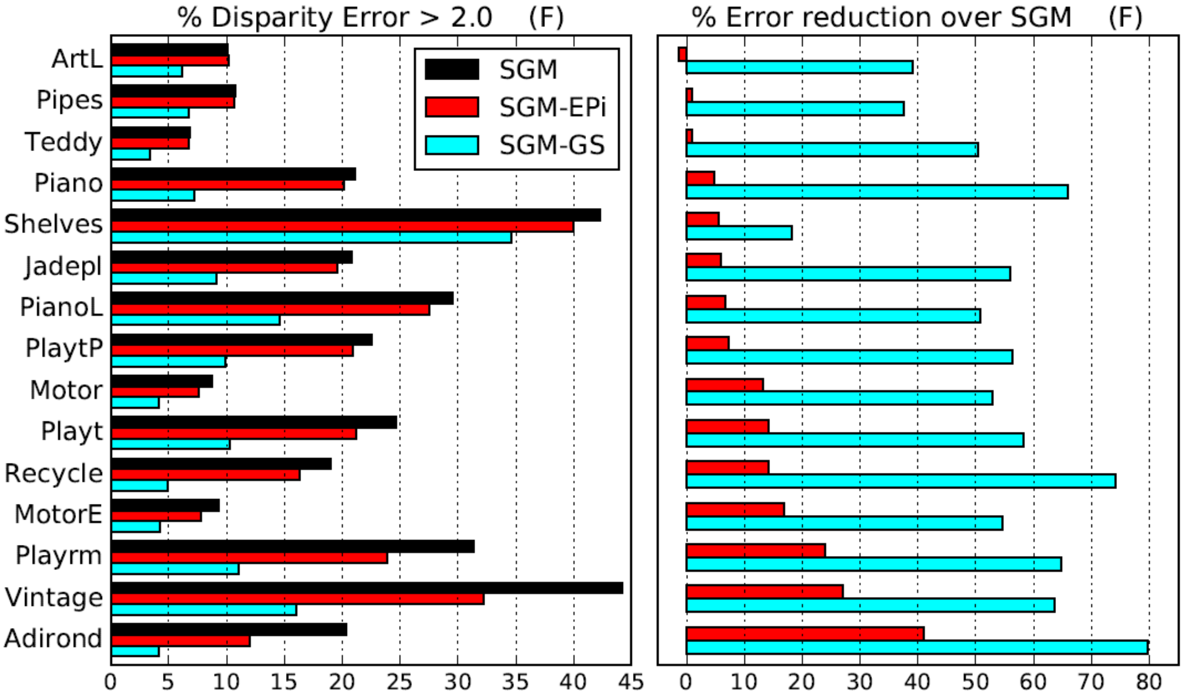
- Matched features + triangulation
- Matched features + plane fitting
- Low-res matching + plane fitting
- Ground truth oracle
- Semantic analysis
- Manhattan-world assumptions



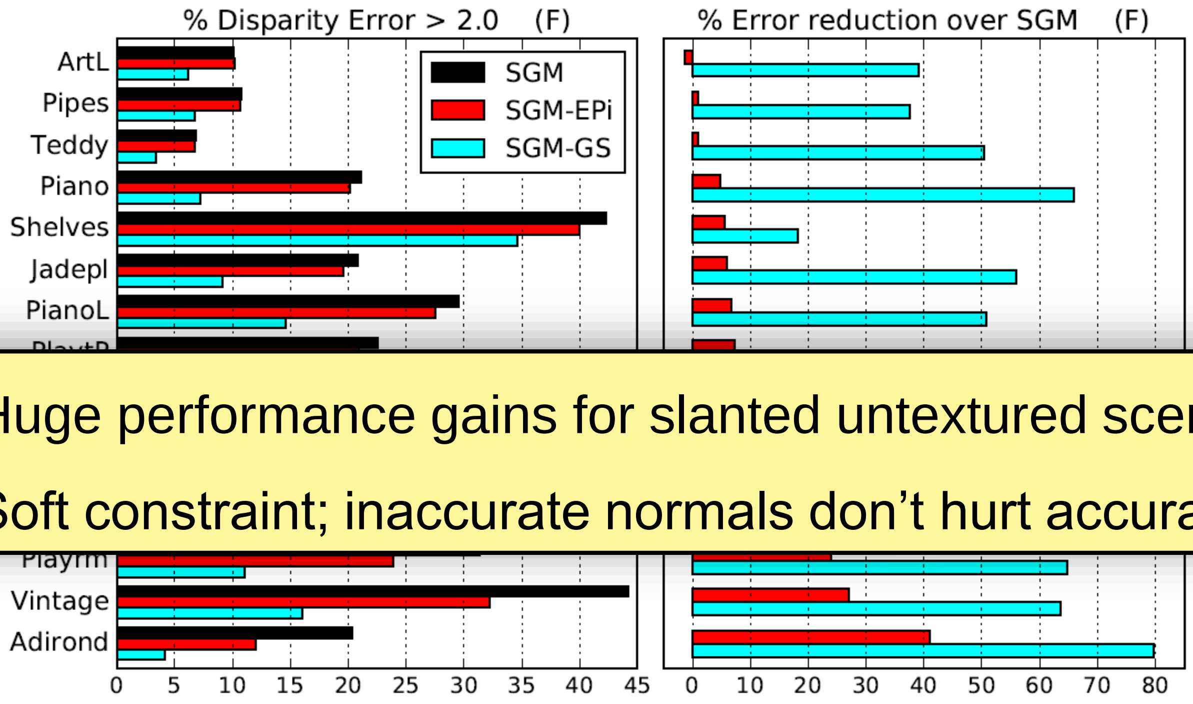
SGM-P: Results



SGM-P: Results



SGM-P: Results



- Huge performance gains for slanted untextured scenes
- Soft constraint; inaccurate normals don't hurt accuracy

Learning to Fuse Proposals from Multiple Scanline Optimizations in Semi-Global Matching

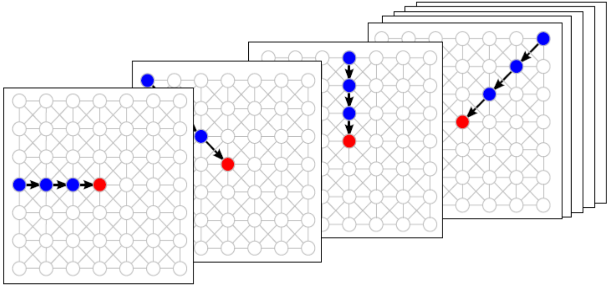
Johannes Schönberger
ETH Zurich

Sudipta Sinha
Microsoft Research

Marc Pollefeys
Microsoft / ETH Zurich

ECCV 2018 (to appear)

Semi Global Matching (SGM)



- For 8 directions
  - calculate aggregated costs

$$L_{\mathbf{r}}(\mathbf{p}, d) = C_{\mathbf{p}}(d) + \min_{d' \in \mathcal{D}} (L_{\mathbf{r}}(\mathbf{p} - \mathbf{r}, d') + V(d, d')).$$

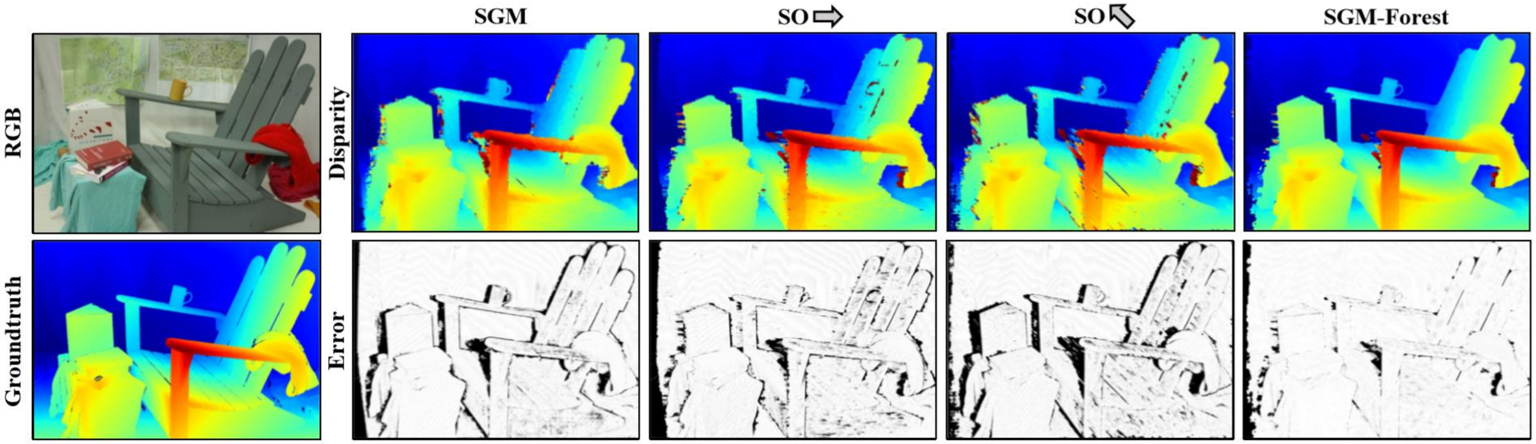
- Finally, sum the costs and select per-pixel minima.

Ad-hoc step

$$S(\mathbf{p}, d) = \sum_{\mathbf{r}} L_{\mathbf{r}}(\mathbf{p}, d)$$

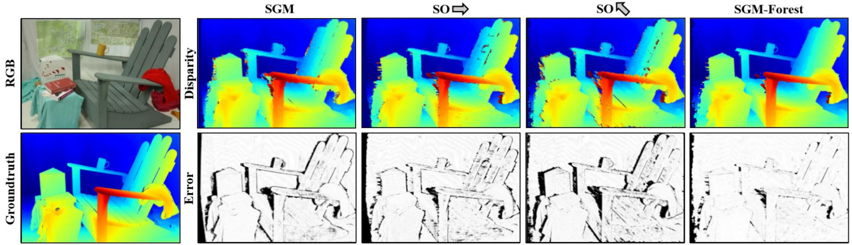
$$D_{\mathbf{p}} = \arg\min_{d} S(\mathbf{p}, d).$$

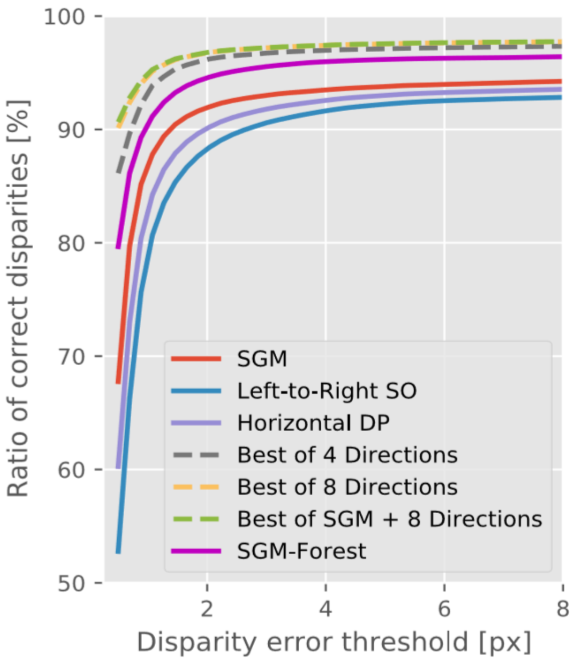
Main Idea



- Treat the 1D SO results as candidate solutions
- We propose to learn a function to select the best proposal
  - **SGM-Forest** is based on random forest classifiers

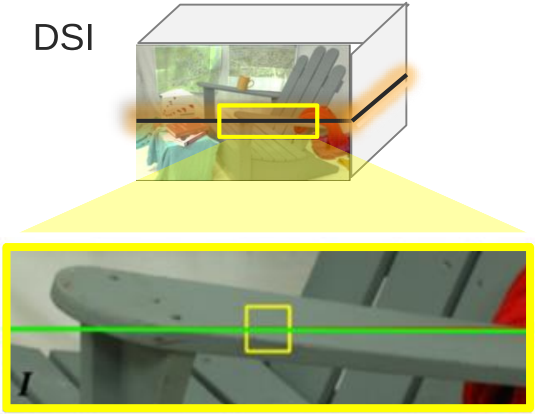
Main Idea

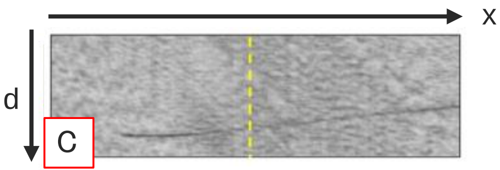




- "Best of k directions" oracle gives an upper bound
- Large gap between SGM and oracle
- SGM-Forest closes the gap a fair bit

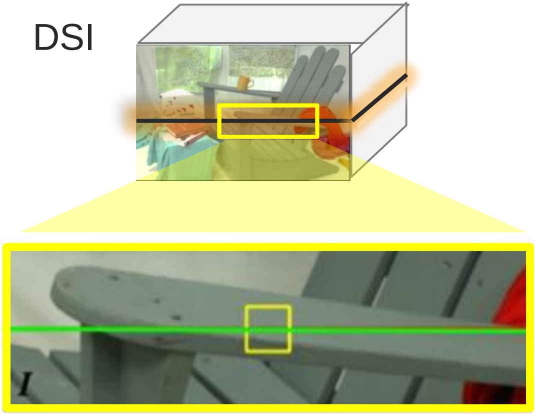
Analyzing the Scanline Optimization Costs

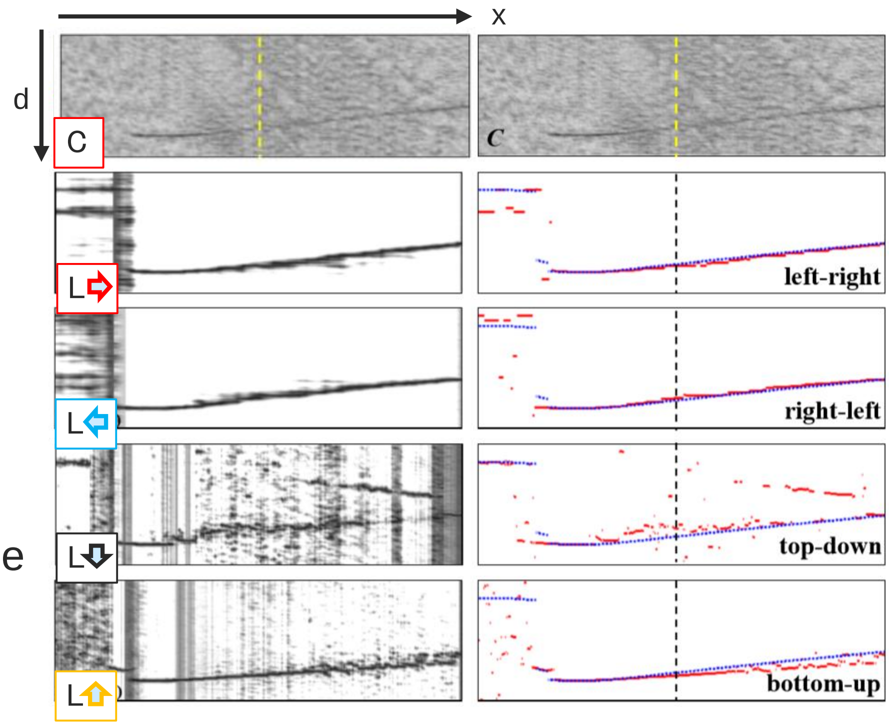




- C: unary cost volume
- L: scanline opt. cost volume
- Horizontal slices for the green scanline

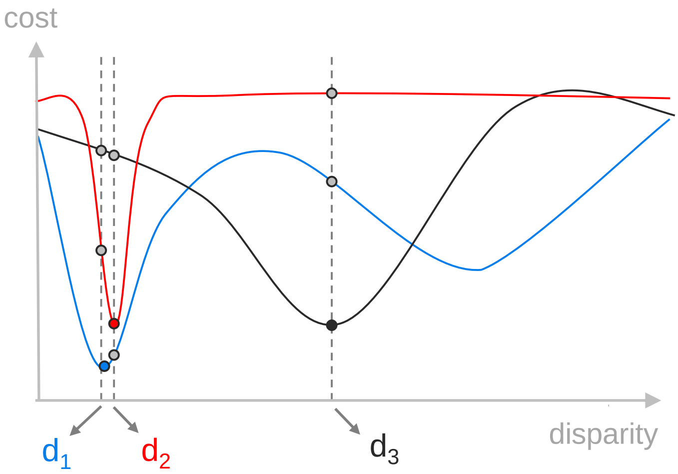
Analyzing the Scanline Optimization Costs

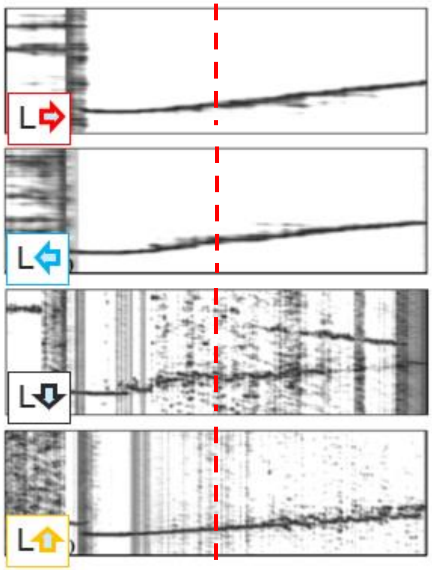




- C: unary cost volume
- L: scanline opt. cost volume
- Horizontal slices for the green scanline

Proposed Method





Feature vector:

$$f = [d_1, d_2, d_3, c_{11}, c_{12}, c_{13}, c_{21}, c_{22}, c_{23}, c_{31}, c_{32}, c_{33}]$$

Proposed Method

1. Run 1D Scanline Opt. to obtain ***k*** disparity map proposals
2. At each pixel
   - Construct $\boldsymbol{k^2 + k}$ dimensional feature vector
   - Do Random Forest Inference
     - outputs probabilities for selecting ***k*** proposals
   - Select best disparity
   - Refine disparity
     - Compute probability-weighted average of inlier disparities.
3. Post-processing (using probability image)
   - At each pixel ***p***, find neighboring pixels with high probability and color similar to that of ***p;*** then compute the median filter.

Results

Ablation study: Middlebury 2014 training set (15 pairs) used for evaluation

Method	Left View Scanlines	Right View Scanlines	Filtering	Training Dataset	bad 0.5px [%]	bad 1px [%]	bad 2px [%]	bad 4px [%]	Time [s]
		all							
SGM	all			–	65.58	36.08	20.66	16.24	**3.0**
SGM – $\min_d L_{\mathbf{r}}(\mathbf{p}, d)$	all			–	66.79	38.35	23.32	18.36	3.1
SGM – $\min_d \text{median}_{\mathbf{r}} L_{\mathbf{r}}(\mathbf{p}, d)$	all			–	67.53	39.75	23.34	18.12	3.2
SGM-SVM	all			M	60.89	32.59	20.31	16.16	323.7
SGM-MLP	all			M	60.49	32.61	20.25	16.14	21.0
SGM-Forest	horiz+vert			M	61.09	32.69	18.02	13.19	5.7
	top-down			M	61.31	32.85	18.31	13.37	5.8
	bottom-up			M	61.38	32.91	18.42	13.43	5.8
	all			M	60.28	32.15	17.90	13.14	6.1
	all	•		M	60.18	32.08	17.69	12.91	6.3
	all	•	•	E	59.89	30.69	16.78	11.67	8.2
	all	•	•	K	59.70	30.61	16.72	11.67	8.2
	all	•	•	M	**59.20**	**30.58**	**16.57**	**11.62**	8.2

M: Midd 2005, K: KITTI, E: ETH3D

Results

Ablation study: Middlebury 2014 training set (15 pairs) used for evaluation

- Good cross-domain generalization; low dataset bias
- Random forest inference: fast (on CPU); parallelizable
- SGM Forest retains computational benefits of SGM

SGM – $\min_d L_{\mathbf{r}}(\mathbf{p}, d)$	all			–	66.79	38.35	23.32	18.36	3.1
SGM – $\min_d \operatorname{median}_{\mathbf{r}} L_{\mathbf{r}}(\mathbf{p}, d)$	all			–	67.53	39.75	23.34	18.12	3.2
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M: Midd 2005, K: KITTI, E: ETH3D

Results

Datacost	Method	Middlebury 2014 0.5px	1px	2px	4px	KITTI 2015 0.5px	1px	2px	4px	ETH3D 2017 0.5px	1px	2px	4px
all													
NCC	SGM	69.23	42.36	27.96	22.25	60.59	33.79	15.06	8.34	32.52	16.71	10.66	7.69
	SGM-F.	**64.00**	**37.22**	**22.85**	**17.09**	**52.39**	**25.80**	**10.11**	**4.69**	**22.48**	**11.26**	**6.36**	**4.35**
MC-CNN-fast	SGM	65.82	36.22	21.98	17.47	58.48	31.39	13.30	7.02	26.34	10.50	6.13	4.52
	SGM-F.	**62.04**	**32.96**	**18.22**	**13.16**	**51.03**	**24.05**	**8.73**	**3.78**	**17.62**	**7.17**	**3.66**	**2.51**
MC-CNN-acrt	SGM	65.58	36.08	20.66	16.24	57.24	28.55	9.54	5.26	39.03	16.34	9.14	6.67
	SGM-F.	**59.20**	**30.58**	**16.57**	**11.62**	**46.88**	**19.77**	**6.51**	**2.97**	**27.40**	**11.89**	**7.30**	**5.52**

Results

Datacost	Method	Middlebury 2014 0.5px	1px	2px	4px	KITTI 2015 0.5px	1px	2px	4px	ETH3D 2017 0.5px	1px	2px	4px
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[Zbontar and Lecun 2015]

- Matching cost (unary): NCC, MC-CNN (-fast, -acrt)
- SGM-Forest outperforms SGM in all cases

Benchmark Results

Middlebury 2014 (MC-CNN-acrt)					
Method	**non-occl.**		**all**		**Time**
LocalExp	5.43%	#1	11.7%	#1	881s
3DMST	5.92%	#2	12.5%	#3	174s
MC-CNN+TDSR	6.35%	#2	12.1%	#3	657s
PMSC	6.71%	#4	13.6%	#4	599s
LW-CNN	7.04%	#5	17.8%	#15	314s
MeshStereoExt	7.08%	#6	15.7%	#9	161s
FEN-D2DRR	7.23%	#7	16.0%	#11	121s
APAP-Stereo	7.26%	#8	13.7%	#5	131s
SGM-Forest	**7.37%**	**#9**	**15.5%**	**#8**	**88s**
NTDE	7.44%	#10	15.3%	#7	152s

Middlebury 2014 (MC-CNN-fast)					
Method	**non-occl.**		**all**		**Time**
LocalExp	6.52 %	#1	12.1%	#1	846s
3DMST	7.08 %	#2	12.9%	#2	167s
APAP-Stereo	7.53%	#3	14.3%	#6	117s
FEN-D2DRR	7.89%	#4	14.1%	#4	73s
...					
MC-CNN-acrt	10.1%	#12	19.7%	#20	106s
...					
SGM-Forest	**11.1%**	**#19**	**17.8%**	**#14**	**9s**
...					
MC-CNN-fast	11.7%	#21	21.5%	#27	1s

KITTI 2015		
Method	**Error**	**Time**
CNNF+SGM	3.60% (#9)	71.0s
SGM-Net	3.66% (#11)	67.0s
MC-CNN-acrt	3.89% (#12)	67.0s
SGM-Forest	**4.38% (#14)**	**6.0s**
MC-CNN-WS	4.97% (#18)	1.4s
SGM_ROB [2]	6.38% (#27)	0.1s
SGM+C+NL	6.84% (#31)	270.0s
SGM+LDOF	6.84% (#32)	86.0s
SGM+SF	6.84% (#33)	2700.0s
CSCT+SGM+MF	8.24% (#35)	6.4ms

ETH3D 2017			
Method	**non-occl.**	**all**	**Time**
SGM-Forest	**5.40%**	**4.96%**	**5.21s**
SGM_ROB [2]	10.08%	10.77%	0.15s
MeshStereo	11.94%	11.52%	159.24s
SPS-Stereo	15.83%	15.04%	1.59s
ELAS	17.99%	16.72%	0.13s

Benchmark Results

Middlebury 2014 (MC-CNN-acrt)					
Method	non-occl.		all		Time
LocalExp	5.43%	#1	11.7%	#1	881s
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Method	non-occl.		all		Time
LocalExp	6.52 %	#1	12.1%	#1	846s
3DMST	7.08 %	#2	12.9%	#2	167s
APAP-Stereo	7.53%	#3	14.3%	#6	117s

- #1 on ETH3D
- #8 on Midd 2014, #14 on KITTI
- Significantly outperform all previous SGM variants
- SGM-ROB: [Hirschmuller 2008] impl.

SGM-Forest	**4.38% (#14)**	**6.0s**
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Outline

- Stereo Matching: New Trends
- Semi-Global Stereo Matching (SGM)
  - SGM with Surface Orientation Priors
  - Learning to Fuse Proposals
- **Stereo Scene Flow with Motion Segmentation**
- Camera Trajectory Planning for Aerial 3D Scanning
- Deep 6-DoF Object Pose Prediction

Fast Multi-frame Stereo Scene Flow with Motion Segmentation

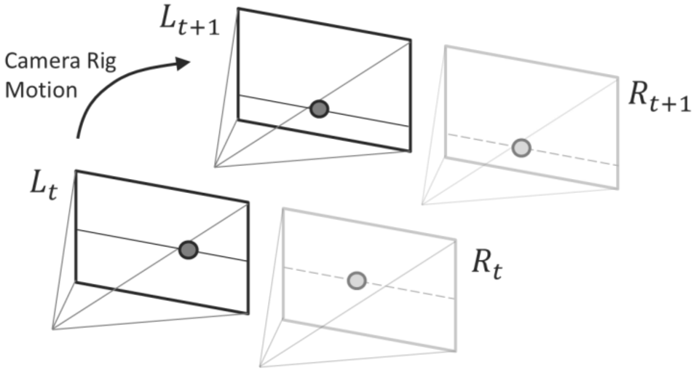
Tatsunori Taniai
RIKEN, Tokyo

Sudipta Sinha
Microsoft Research

Yoicho Sato
Univ. of Tokyo

CVPR 2017

Multi-frame Stereo Scene Flow



- Stereo video from moving stereo camera rig (calibrated)
- Scene Flow equivalent to stereo matching and optical flow estimation

Application

Object scene flow for autonomous vehicles

Menze and Geiger 2015

Action recognition by dense trajectories

Wang+ 2011

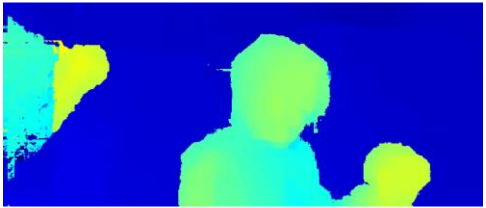
- Depth and flow sequences are useful in many applications

Motivation

Efficient, unified method for

- Stereo
- Optical Flow
- Moving object segmentation
- Visual Odometry (Camera ego-motion)

Disparity Map



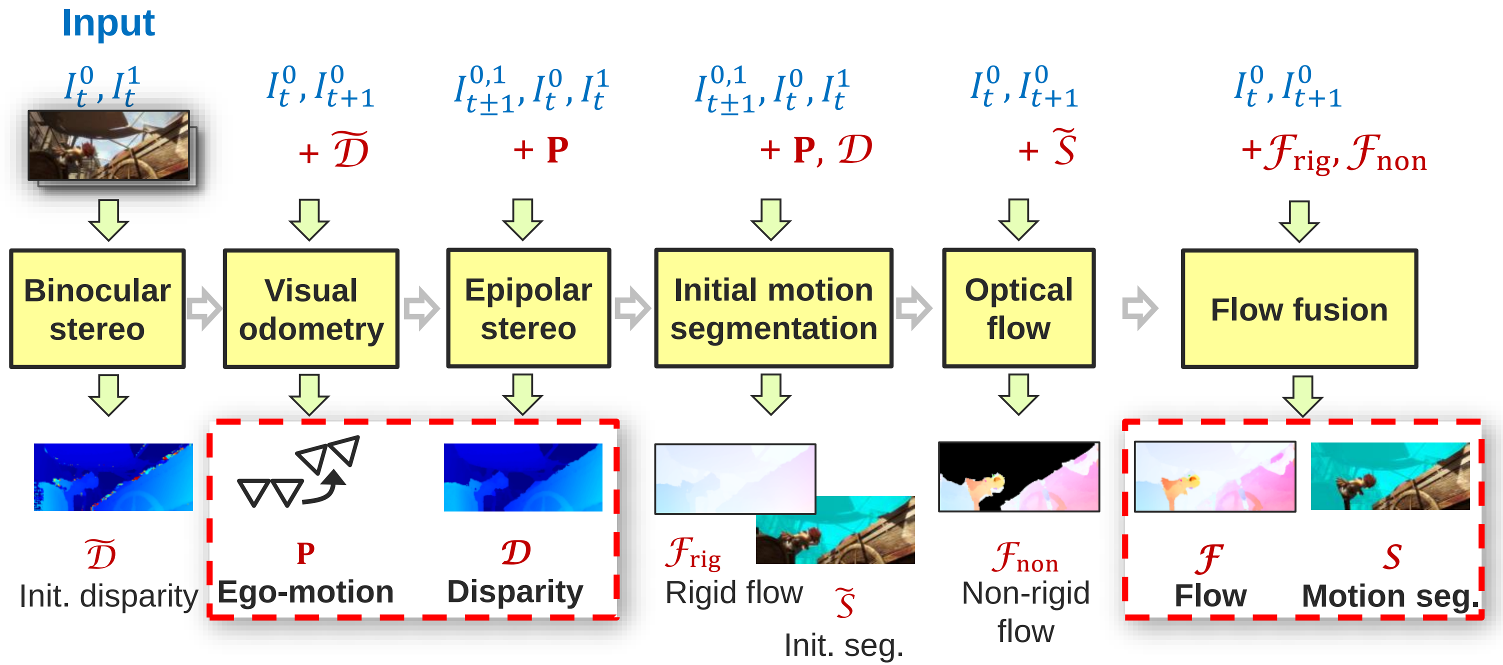
Optical Flow

Moving Object Segmentation

Main Idea: Dominant Rigid Scene Assumption

- Most of the scene is rigid; hence, camera motion determines the *rigid optical flow*.
- Given *rigid flow map*, only find regions with moving objects and recompute their flow.

Proposed Approach



Results – KITTI 2015 Scene Flow Benchmark (Nov 2016)

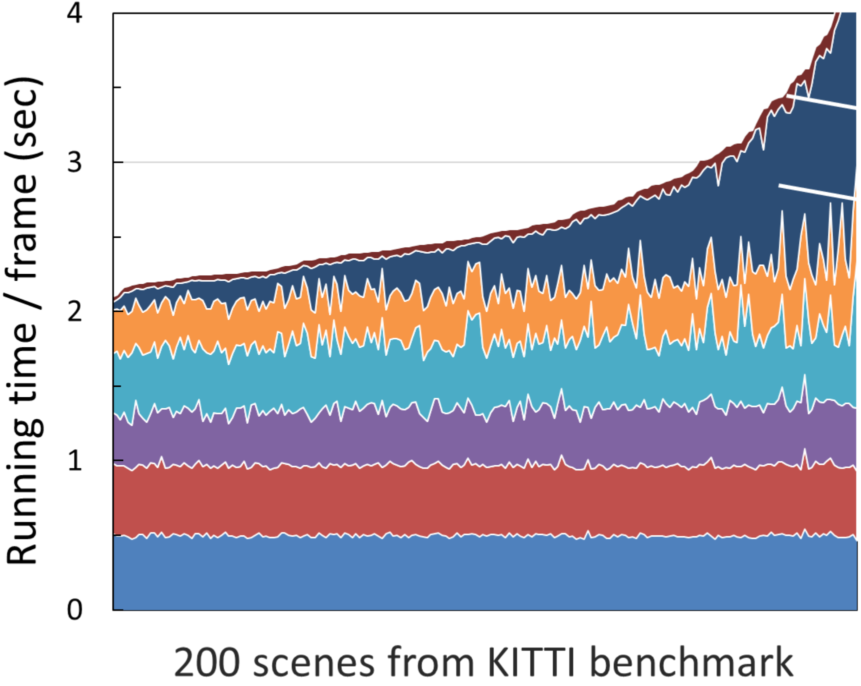
Rank	Method	D1-bg	D1-fg	D1-all	D2-bg	D2-fg	D2-all	Fl-bg	Fl-fg	Fl-all	SF-bg	SF-fg	SF-all	Time
1	PRSM [43]	**3.02**	**10.52**	**4.27**	**5.13**	**15.11**	**6.79**	**5.33**	**17.02**	**7.28**	**6.61**	**23.60**	**9.44**	300 s
2	OSF [30]	4.54	12.03	5.79	5.45	19.41	7.77	5.62	22.17	8.37	7.01	28.76	10.63	50 min
3	**FSF+MS** (ours)	5.72	11.84	6.74	7.57	21.28	9.85	8.48	29.62	12.00	11.17	37.40	15.54	2.7 s
4	CSF [28]	4.57	13.04	5.98	7.92	20.76	10.06	10.40	30.33	13.71	12.21	36.97	16.33	80 s
5	PR-Sceneflow [42]	4.74	13.74	6.24	11.14	20.47	12.69	11.73	27.73	14.39	13.49	33.72	16.85	150 s
8	PCOF + ACTF [10]	6.31	19.24	8.46	19.15	36.27	22.00	14.89	62.42	22.80	25.77	69.35	33.02	0.08 s (GPU)
12	GCSF [8]	11.64	27.11	14.21	32.94	35.77	33.41	47.38	45.08	47.00	52.92	59.11	53.95	2.4 s

200 road scenes with multiple moving objects

Rank	SF-all	Time
1	**9.44**	300 s
2	10.63	50 min
3	15.54	2.7 s
4	16.33	80 s
5	16.85	150 s
8	33.02	0.08 s (GPU)
12	53.95	2.4 s

Results – KITTI 2015 Scene Flow Benchmark (Nov 2016)

CPU: 3.5 GHz × 4 Cores
Image: (1242 × 375) × 0.65 scale



0.07 sec Flow fusion

0.48 sec Optical flow

0.36 sec Initial segmentation

0.47 sec Epipolar stereo

0.38 sec Visual odometry

0.47 sec Binocular stereo

0.72 sec Initialization

2.72 sec per frame

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Submodular Trajectory Optimization for Aerial 3D Scanning

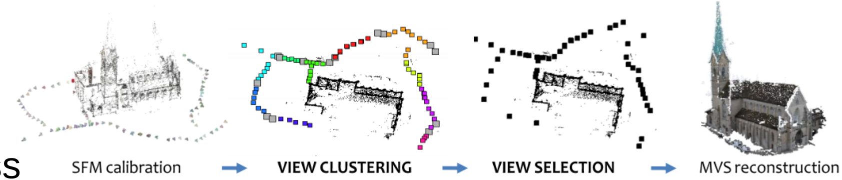
ICCV 2017

Mike Roberts[1,2] Debadeepta Dey[2] Anh Truong[3] Sudipta Sinha[2]
Shital Shah[2] Ashish Kapoor[2] Pat Hanrahan[1] Neel Joshi[2]

[1]Stanford University [2]Microsoft Research [3]Adobe Research

Related Work

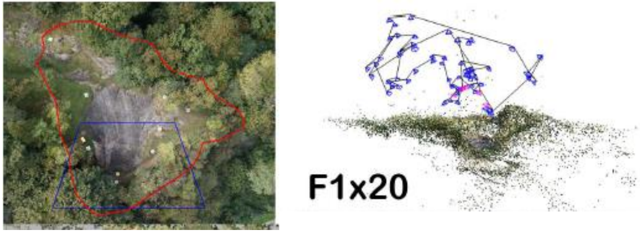
- View selection [Hornung+ 2011]
  - First, acquire dense imagery
  - Later, select subset & process



- Next-best-view planning
  - Information-gain maximization [Isler+ 2016]
  - Robotic RGB-D 3D scanning [Wu+ 2014]
  - No travel budget constraints

- Real-time Drone view planning

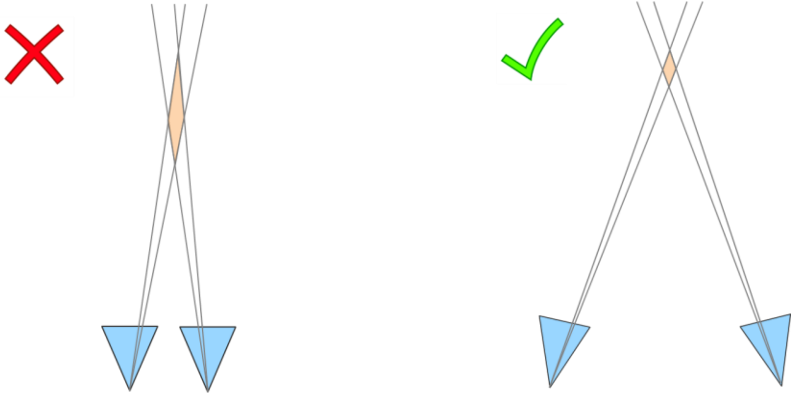
  [Mostegel+ 2016, Hepp+ 2018]
  - Greedy technique; heuristic-based



Planning the camera path

1. Fly an easy-to-generate trajectory
2. Compute coarse 3D model (SFM → MVS → mesh)
3. **Plan *optimized* trajectory**
4. Fly the computed trajectory
5. Run SFM + MVS on all images

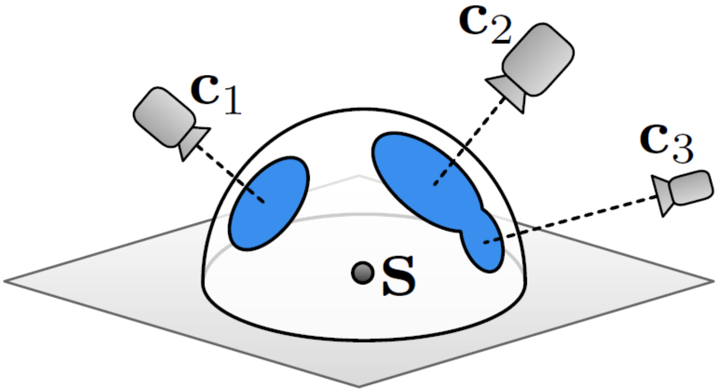
Heuristics Known to Work Well



We prefer images with

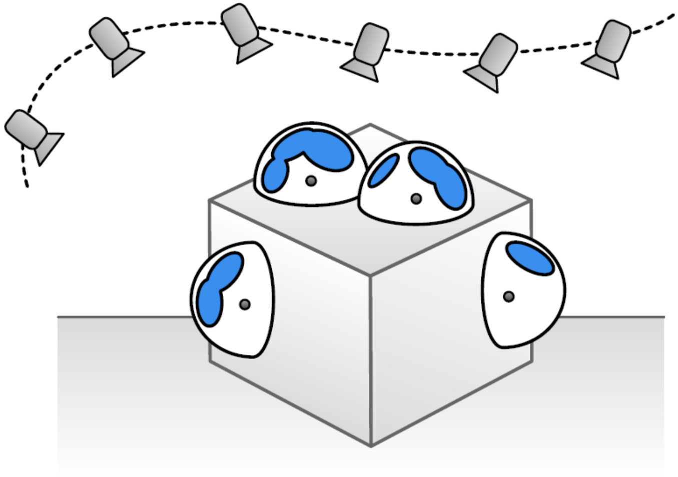
- diverging viewing angles
- close-up views
- fronto parallel views of surfaces

Coverage Measure



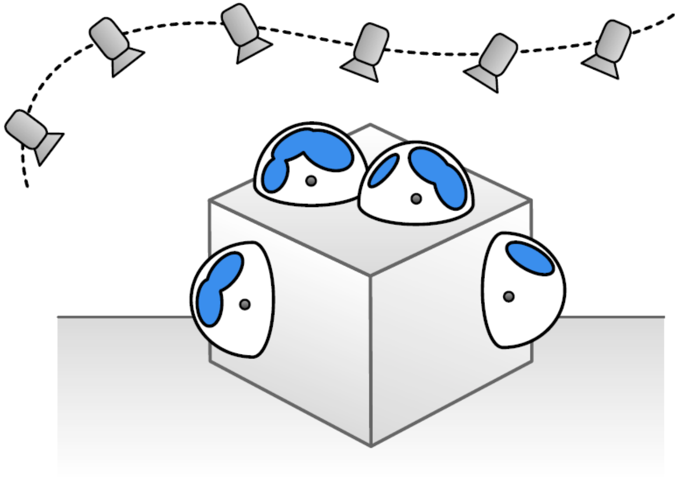
For a surface point S observed from multiple cameras, we define coverage as the area of the union of all the blue disks on a hemisphere.

Coverage Measure



Similarly, we define coverage for multiple surface points observed from multiple camera viewpoints.

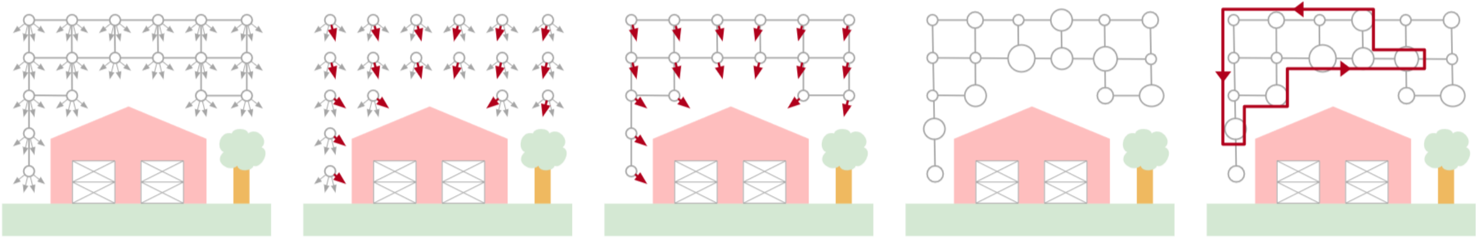
Coverage Measure



Submodular Function!

Similarly, we define coverage for multiple surface points observed from multiple camera viewpoints.

Planning Optimized Trajectories



Nodes = possible camera locations; edge weights = pairwise Euclidean distances.

Sub-problems:

1. Solve optimal set of orientations; ignoring path constraints
2. Then, find path by solving a *graph orienteering problem*

Solving for Camera Orientations

- Coverage *set* function is submodular
  - Adding new elements to an existing set gives diminishing returns
- Cardinality and Mutual Exclusion Constraint
  - Select exactly one look-at vector at each position

- Constrained submodular maximization
  - Always, pick the next best element with the most marginal reward
  - Greedy algorithm; good theoretical approximation guarantee

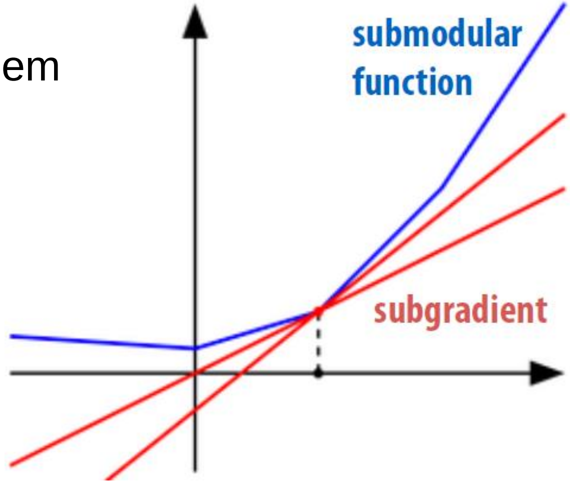
Solving for Camera Positions


(c) Coarsened problem
(d) Additive approximation to the coarsened problem
(e) Solve for the optimal closed path on the additive approximation

- Graph Orienteering Problem
  - NP-Hard; related to TSP and Knapsack
  - Find short paths that let you collect most rewards (at nodes).
- In standard orienteering, rewards are additive.
- But, our reward function is submodular, not additive!
- Hence, we must solve a *submodular orienteering problem.*

Solving for Camera Positions

- Choose a *good* sub-gradient (additive approximation) for our submodular function
- This gives us a regular orienteering problem
- Solve a integer linear program (ILP)



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Real-Time Seamless Single Shot 6D Object Pose Prediction

Bugra Tekin

EPFL

Sudipta Sinha

Microsoft Research

Pascal Fua

EPFL

CVPR 2018

3D Recognition, 2D-3D Model Alignment

Given a RGB image (with known intrinsics), recognize the object instances and predict their 3D position and orientation within the scene.

Feature-based (RGB, RGB-D)

- Lowe 2001
- Rothganger+ 2005
- Lepetit+ 2005
- Lai+ 2010
- Hinterstoisser+ 2012

Coordinate Regression

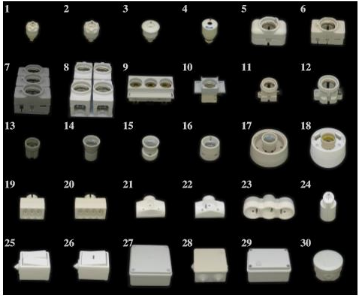
- Brachmann+ 2014, 2016

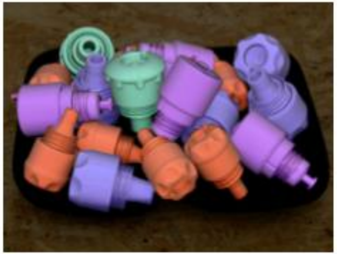
CNNs

- Rad + Lepetit 2017
- Kehl+ 2017
- Xiang+ 2017
- Tekin+ 2018
- Oberweger+ 2018

Texture-less Object 6D Pose Datasets

LINEMOD [2012]
15 objects





T-LESS [2017]
30 objects

YCB-VIDEO [2018]
21 objects

Deep 6-dof object pose estimation

- BB8 [Rad and Lepetit 2017]

image → CNN$_1$ → cropped image → CNN$_2$ → CNN$_3$ → 6D pose

2d detector · *pose estimator* · *pose refinement*

- SSD-6D [Kehl+ 2017]

image → CNN$_1$(~SSD) → 2D to 6D → CNN$_2$ → 6D pose

2d detector, viewpoint classifier · *heuristic* · *pose refinement*

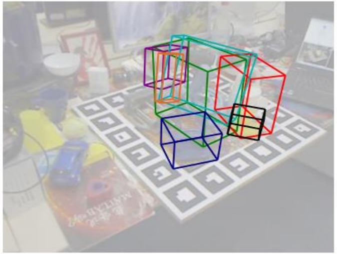
- Ours

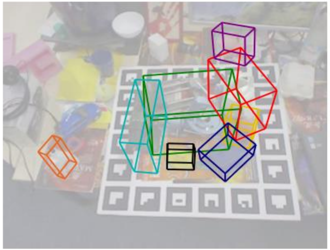
image → CNN$_1$(~YOLO) → PnP → 6D pose

3D bounding box corner predictor · *pose solver*

Our Method

- Single-shot 2D object detection (YOLO, SSD)
- Our CNN predicts 2D projections of 3D bounding box vertices (and the centroid). We run PnP solver on 9 2D-3D correspondences.
- Accurate, fast (50-90 fps); detects multiple objects in one pass.

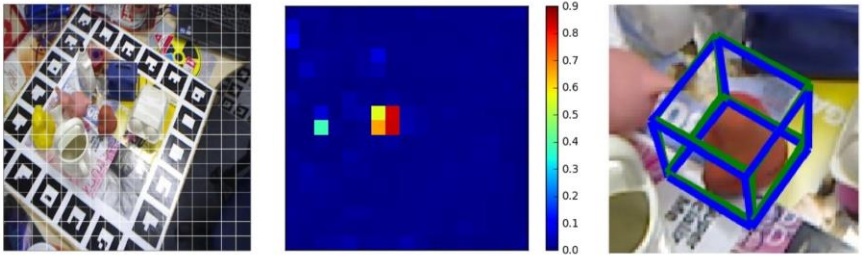




Our Method

Training:

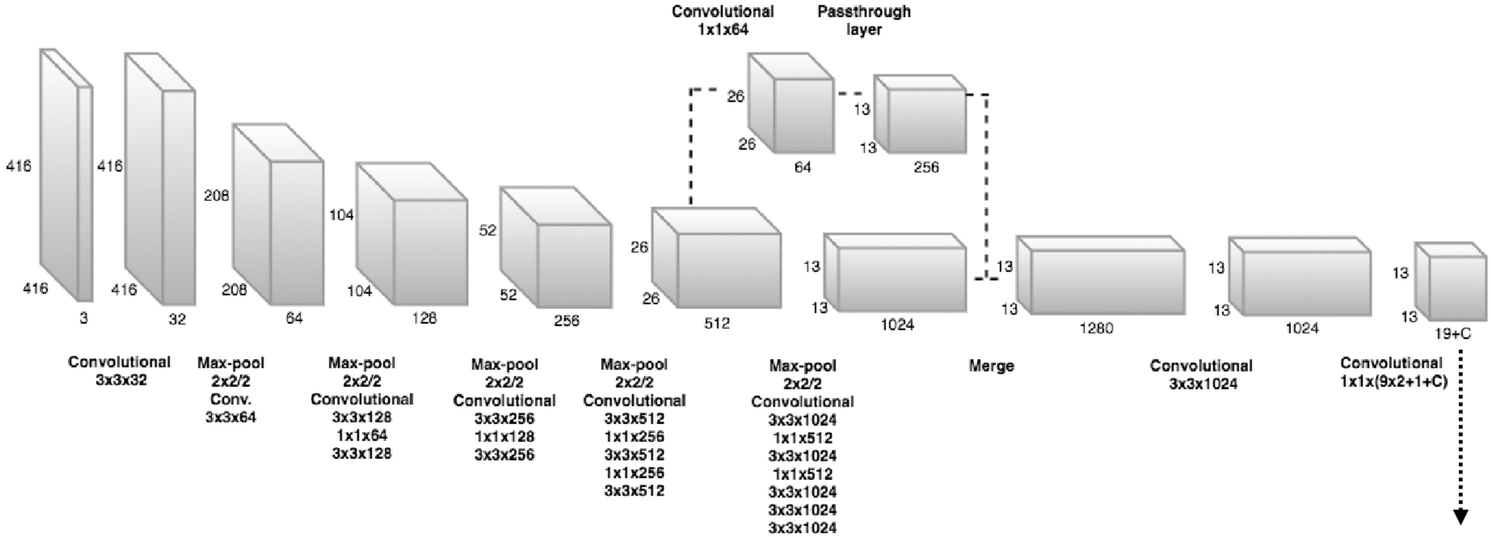
- ground truth 2D coordinates of the 9 control points are the targets
- modify YOLO loss function (for confidence estimation)
- data augmentation



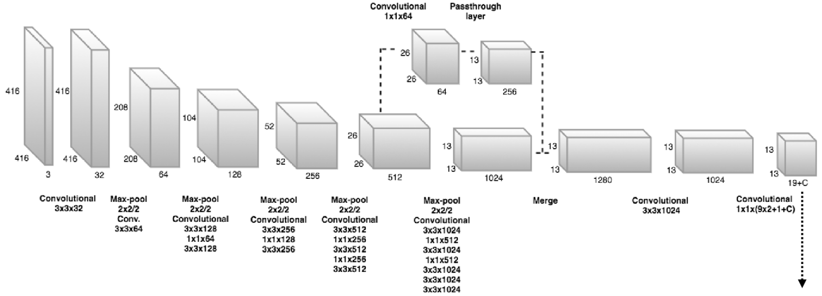
Testing:

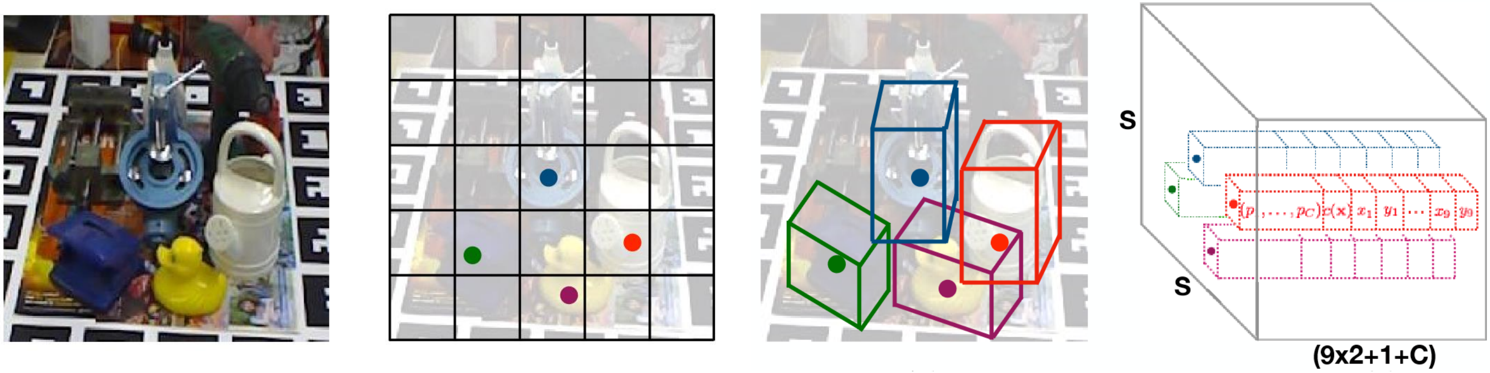
- Subpixel refinement
- PnP (RANSAC, least squares)

CNN Architecture



CNN Architecture





Results on LineMOD dataset

- Two accuracy metrics (2D image projection, 3D model overlap).
- Percentage of test images where the error was lower than specified thresholds.

2D metric

Method	w/o Refinement			w/ Refinement	
Object	Brachmann [2]	BB8 [25]	OURS	Brachmann [2]	BB8 [25]
Ape	-	***95.3***	92.10	85.2	**96.6**
Benchvise	-	80.0	**95.06**	67.9	90.1
Cam	-	80.9	**93.24**	58.7	86.0
Can	-	84.1	**97.44**	70.8	91.2
Cat	-	97.0	**97.41**	84.2	98.8
Driller	-	74.1	***79.41***	73.9	**80.9**
Duck	-	81.2	**94.65**	73.1	92.2
Eggbox	-	87.9	**90.33**	83.1	91.0
Glue	-	89.0	**96.53**	74.2	92.3
Holepuncher	-	90.5	**92.86**	78.9	95.3
Iron	-	78.9	***82.94***	83.6	**84.8**
Lamp	-	74.4	**76.87**	64.0	75.8
Phone	-	77.6	**86.07**	60.6	85.3
Average	69.5	83.9	**90.37**	73.7	89.3

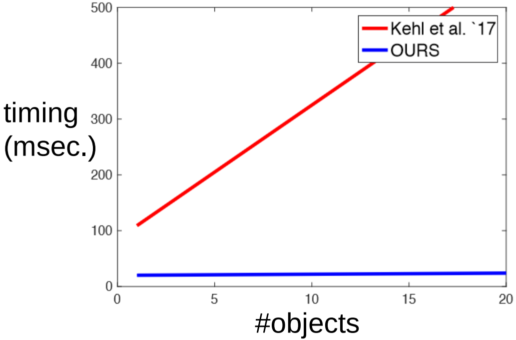
3D metric

Method	w/o Refinement				w/ Refinement		
Object	Brachmann [2]	BB8 [25]	SSD-6D [10]	OURS	Brachmann [2]	BB8 [25]	SSD-6D [10]
Ape	-	***27.9***	0	21.62	33.2	40.4	**65**
Benchvise	-	62.0	0.18	***81.80***	64.8	**91.8**	80
Cam	-	***40.1***	0.41	36.57	38.4	55.7	**78**
Can	-	48.1	1.35	***68.80***	62.9	64.1	**86**
Cat	-	***45.2***	0.51	41.82	42.7	62.6	**70**
Driller	-	58.6	2.58	***63.51***	61.9	**74.4**	73
Duck	-	***32.8***	0	27.23	30.2	44.3	**66**
Eggbox	-	40.0	8.9	***69.58***	49.9	57.8	**100**
Glue	-	27.0	0	***80.02***	31.2	41.2	**100**
Holepuncher	-	42.4	0.30	***42.63***	52.8	**67.2**	49
Iron	-	67.0	8.86	***74.97***	80.0	**84.7**	78
Lamp	-	39.9	8.20	***71.11***	67.0	**76.5**	73
Phone	-	35.2	0.18	***47.74***	38.1	54.0	**79**
Average	32.3	43.6	2.42	***55.95***	50.2	62.7	**79**

Results on LineMOD dataset

- Running Times:
  - On TitanX or similar GPU.
  - using cuDNN

Method	Overall speed for 1 object	Refinement runtime
Brachmann et al. [2]	2 fps	100 ms/object
Rad & Lepetit [25]	3 fps	21 ms/object
Kehl et al. [10]	10 fps	24 ms/object
OURS	50 fps	-



Method	2D projection metric	Speed
416 × 416	89.71	94 fps
480 × 480	90.00	67 fps
544 × 544	90.37	50 fps
688 × 688	90.65	43 fps

Up to 90 fps on smaller images

Conclusions

- New trends and challenges in stereo matching
- Improving Semi-Global Stereo (SGM) Matching
  - Incorporating orientation priors
  - Learned fusion step
- Fast scene flow with motion segmentation
- Camera path planning for improved multi-view stereo
- Deep single shot 6D object pose estimation

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