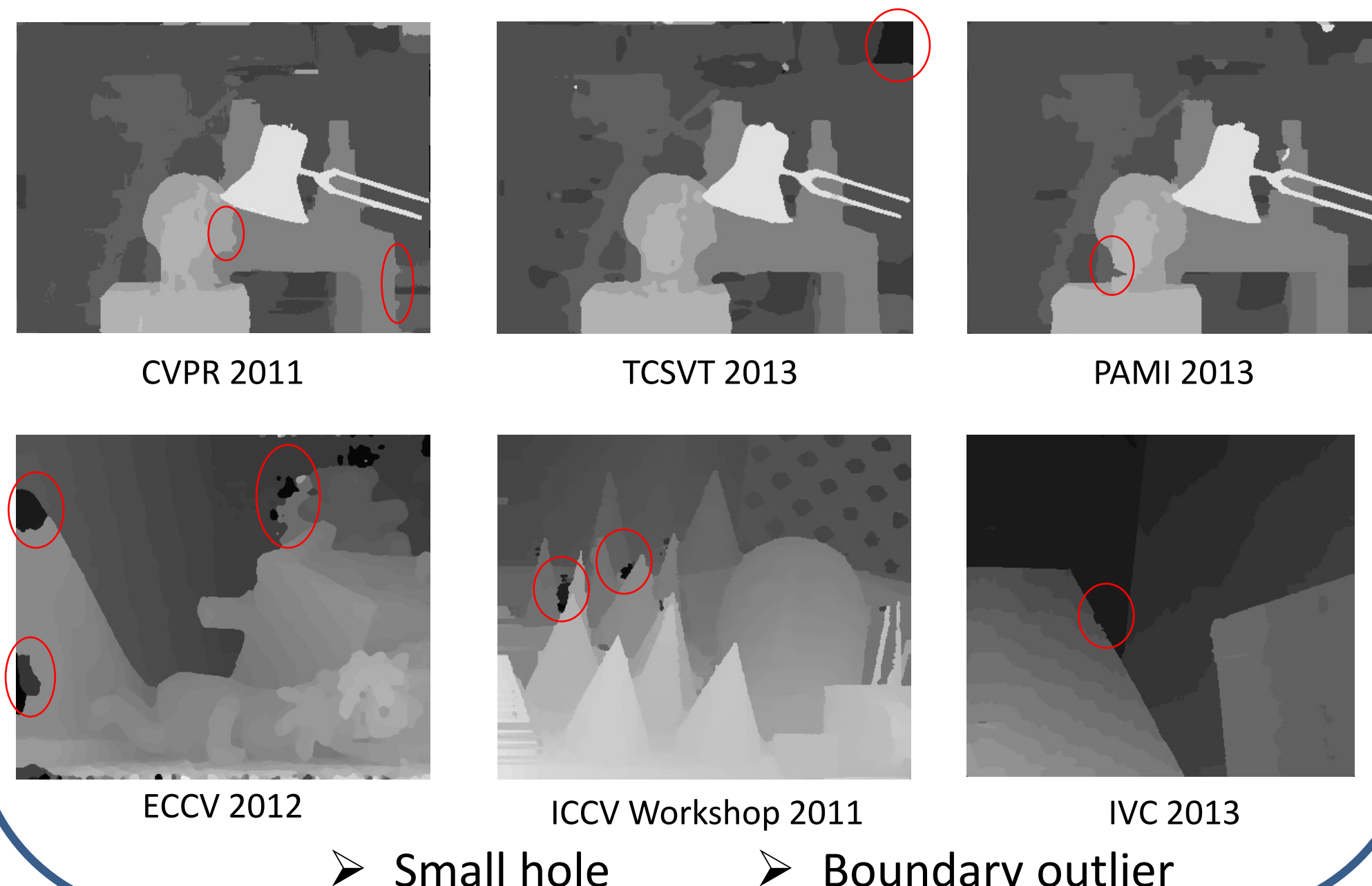# Cost-Volume Filtering-Based Stereo Matching with Improved Matching Cost and Secondary Refinement
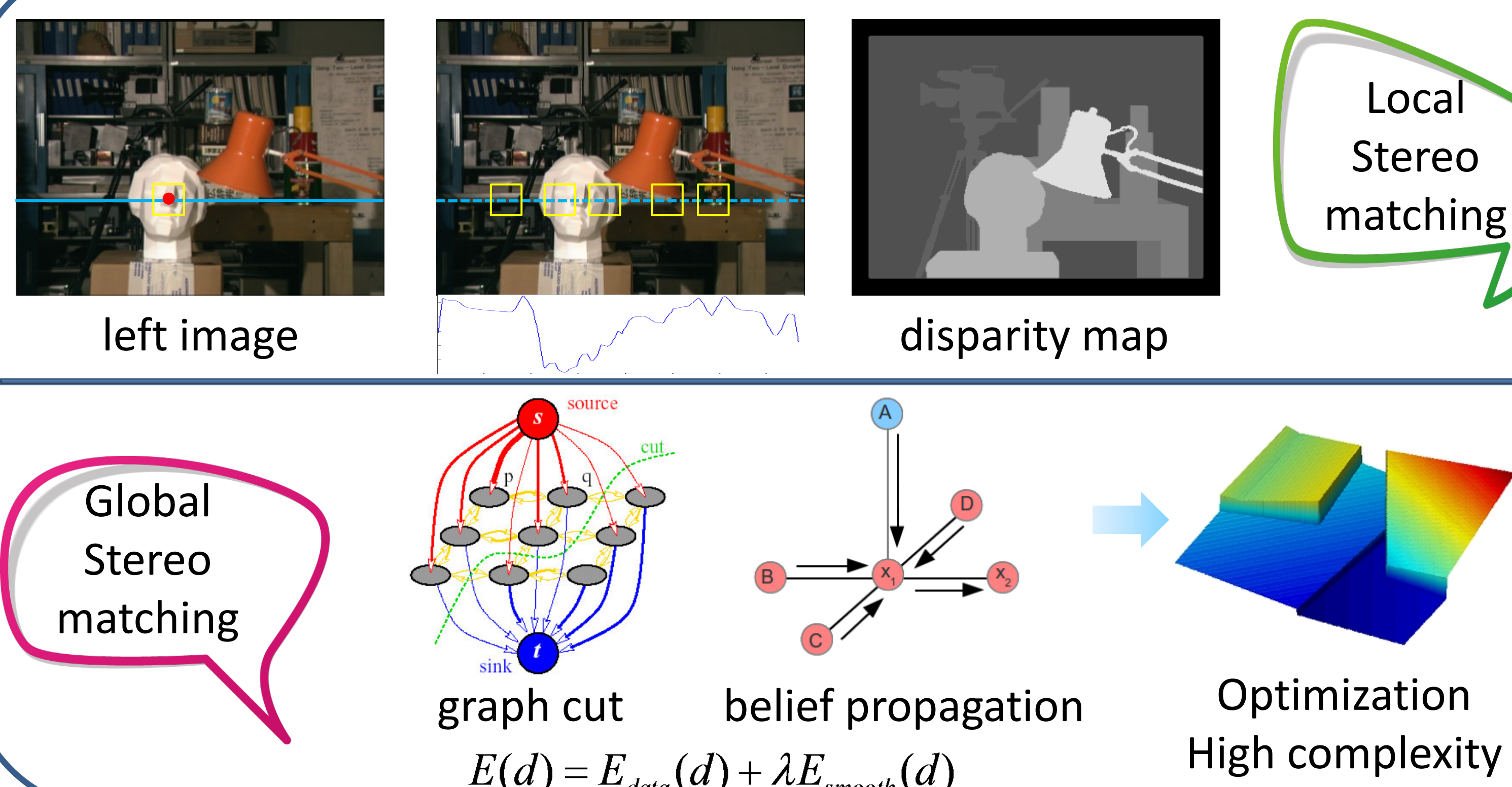
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Motivation

Although local method has achieved accuracy comparable to global method, outliers still exist in the final disparity map.
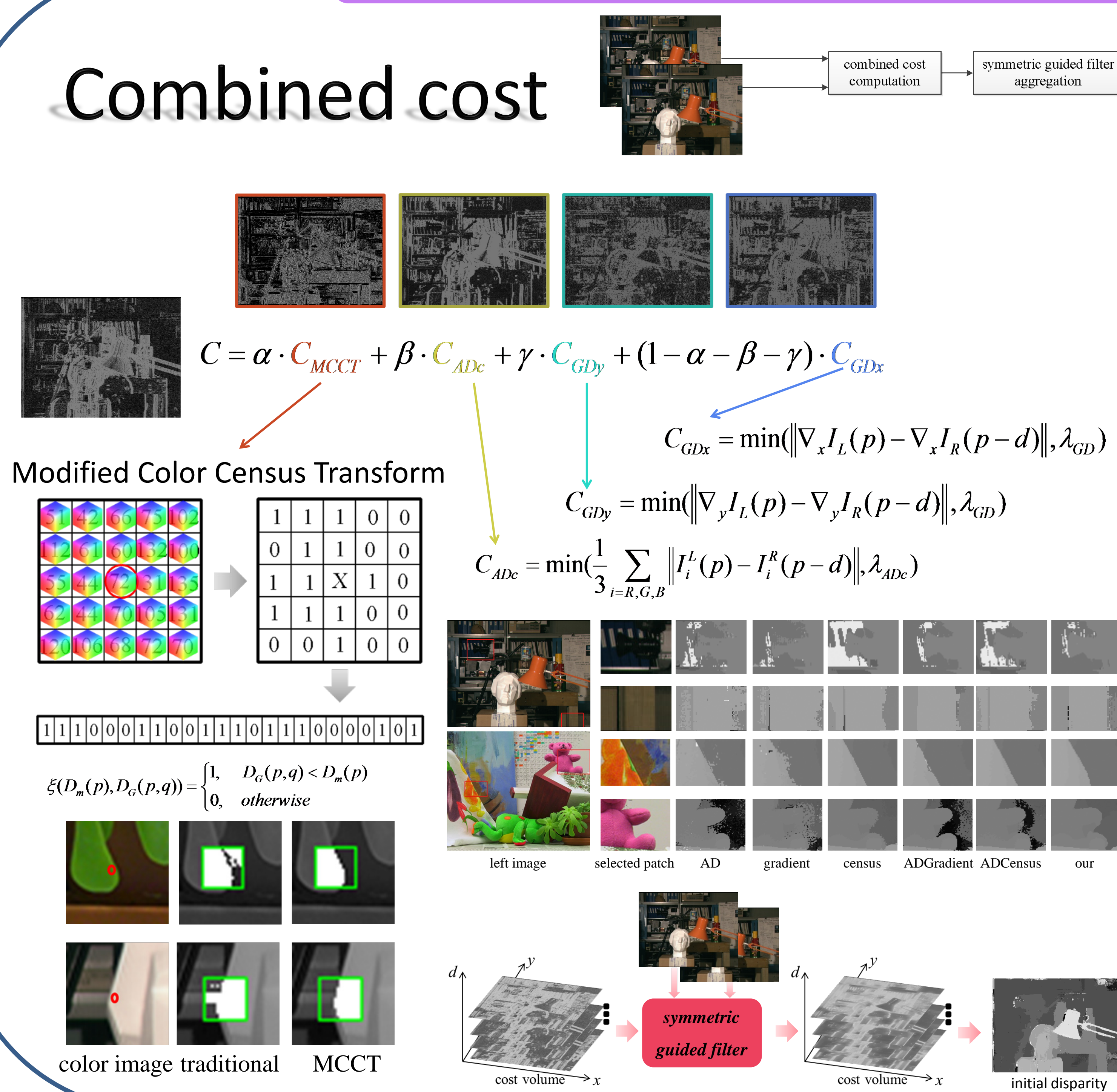

CVPR 2011   TCSVT 2013   PAMI 2013

ECCV 2012   ICCV Workshop 2011   IVC 2013

➢ Small hole   ➢ Boundary outlier

Focus of this work

left image   disparity map

Local Stereo matching

Global Stereo matching

graph cut   belief propagation   Optimization High complexity

$$E(d) = E_{data}(d) + \lambda E_{smooth}(d)$$

➢ cost computation
➢ cost aggregation
➢ disparity computation or optimization
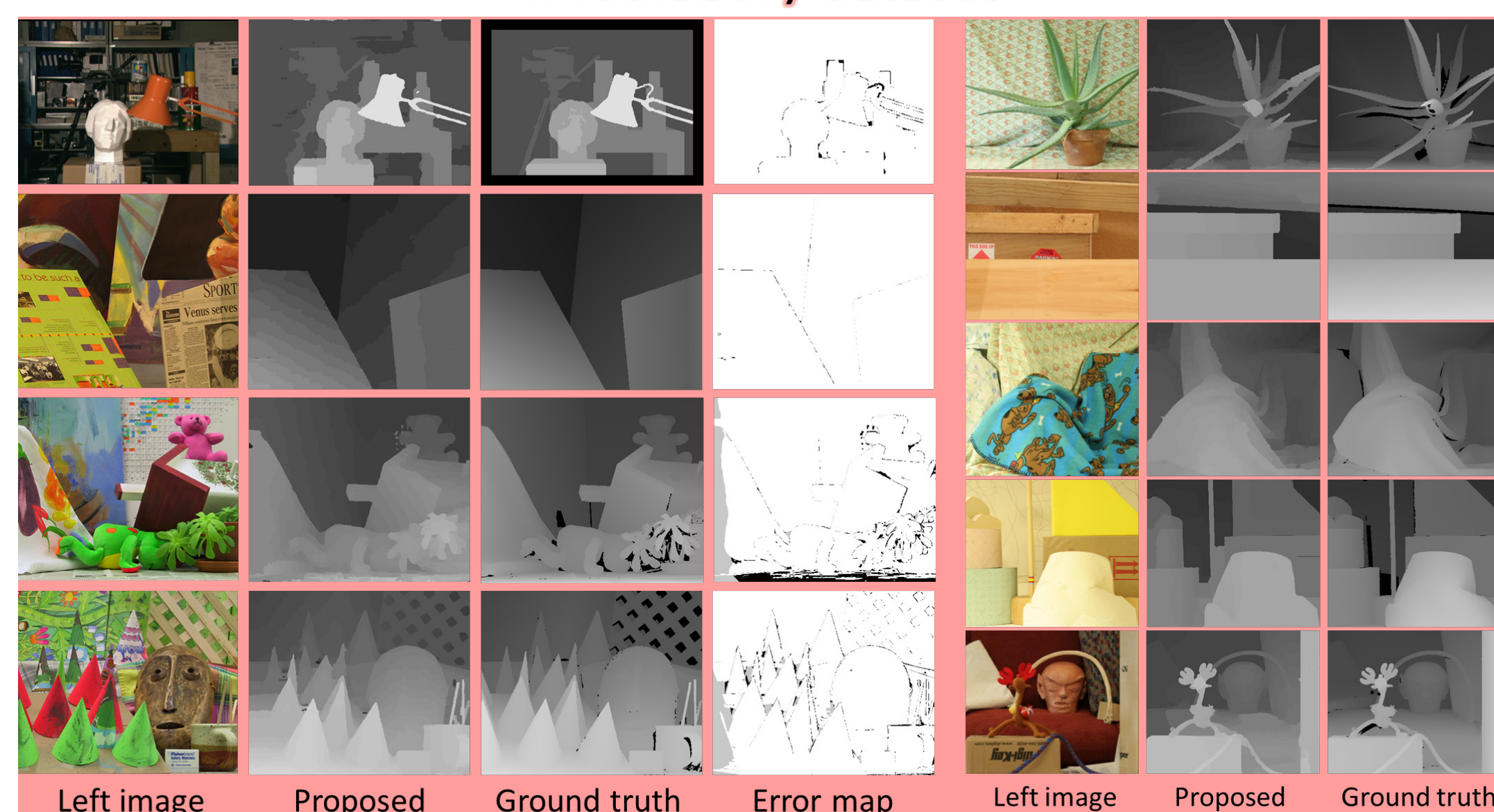➢ disparity refinement

Method

combined cost computation → symmetric guided filter aggregation → initial post-processing → "small hole" filling → "inconsistent region" detection and MOW

Combined cost

$$C = \alpha \cdot C_{MCCT} + \beta \cdot C_{ADc} + \gamma \cdot C_{GDy} + (1 - \alpha - \beta - \gamma) \cdot C_{GDx}$$

$$C_{GDx} = \min(\|\nabla_x I_L(p) - \nabla_x I_R(p-d)\|, \lambda_{GD})$$

$$C_{GDy} = \min(\|\nabla_y I_L(p) - \nabla_y I_R(p-d)\|, \lambda_{GD})$$

$$C_{ADc} = \min\left(\frac{1}{3} \sum_{i=R,G,B} \|I_i^L(p) - I_i^R(p-d)\|, \lambda_{ADc}\right)$$

Modified Color Census Transform

$$\xi(D_m(p,q), D_G(p,q)) = \begin{cases} 1, & D_G(p,q) < D_m(p) \\ 0, & otherwise \end{cases}$$

color image traditional   MCCT

left image   selected patch   AD   gradient   census   ADGradient   ADCensus   our

symmetric guided filter

cost volume → cost volume → initial disparity

initial disparity map → "small hole" filling → edge detection → "inconsistent region" detection → MOW → final disparity map

color image → contrast enhancement → color segmentation

RADAR
Remaining Artifacts Detection and Refinement

"small hole" filling

"inconsistent region" detection   convex region

Modified OccWeight

using the most appropriate pixel to replace the center outlier pixel

square window

cross region

➢ MDC: Y.-C. Wang et al., TCSVT 2013
➢ OccWeight: W. Wang and C. Zhang, SOPO 2012
➢ RADAR-o: RADAR without initial refinement
➢ Proposed: RADAR-aided pipeline

Average error ratio — Nonocc, All, Disc — MDC, OccWeight, RADAR-o, Proposed

Experimental results

Middlebury dataset

Left image   Proposed   Ground truth   Error map   Left image   Proposed   Ground truth

Real-world sequences

BookArrival / Balloons / Cafe / Newspaper

Left frames   RecursiveBF   CostFilter   DTAggr-P   HEBF   Proposed

Virtual view synthesis

BlockMatching   CostFilter   DTAggr-P   Proposed
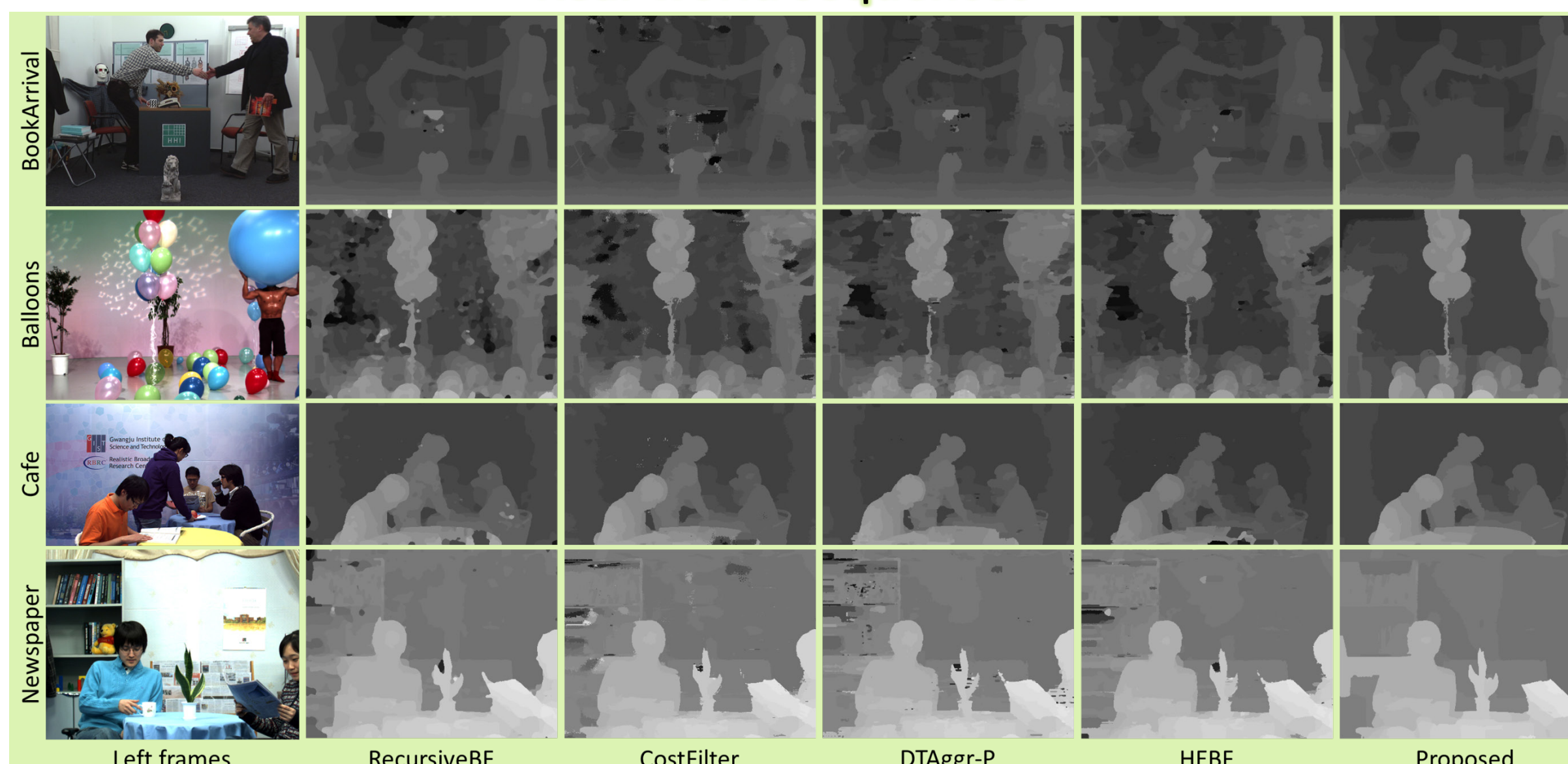
Quantitative evaluation compared with other local methods

Algorithm	Rank (1.0)	Tsukuba			Venus			Teddy			Cones			Rank* (0.75)
		nonocc	all	disc	nonocc	all	disc	nonocc	all	disc	nonocc	all	disc	
ADCensus	2	1.07	1.48	5.73	0.09	0.25	1.15	4.10	6.22	10.9	2.42	7.25	6.95	27
Proposed	5	1.15	1.42	6.23	0.15	0.27	1.89	5.39	10.6	14.7	2.01	7.37	5.88	10
HEBF	27	1.10	1.38	5.74	0.22	0.33	2.41	6.54	11.8	15.2	2.78	7.98	7.36	20
CostFilterwCC	30	1.38	1.74	7.38	0.15	0.42	2.12	6.28	11.6	16.6	2.54	7.96	7.46	15
DTAggr-P	32	1.75	2.10	7.09	0.24	0.45	2.59	5.70	11.5	13.9	2.49	7.82	7.30	29
CostFilter	34	1.51	1.85	7.61	0.20	0.39	2.42	6.16	11.8	16.0	2.71	8.24	7.66	16
P-LinearS	45	1.10	1.67	5.92	0.53	0.89	5.71	6.69	12.0	15.9	2.60	8.44	6.71	44
RecursiveBF	58	1.85	2.51	7.45	0.35	0.88	3.01	6.28	12.1	14.3	2.80	8.91	7.79	30
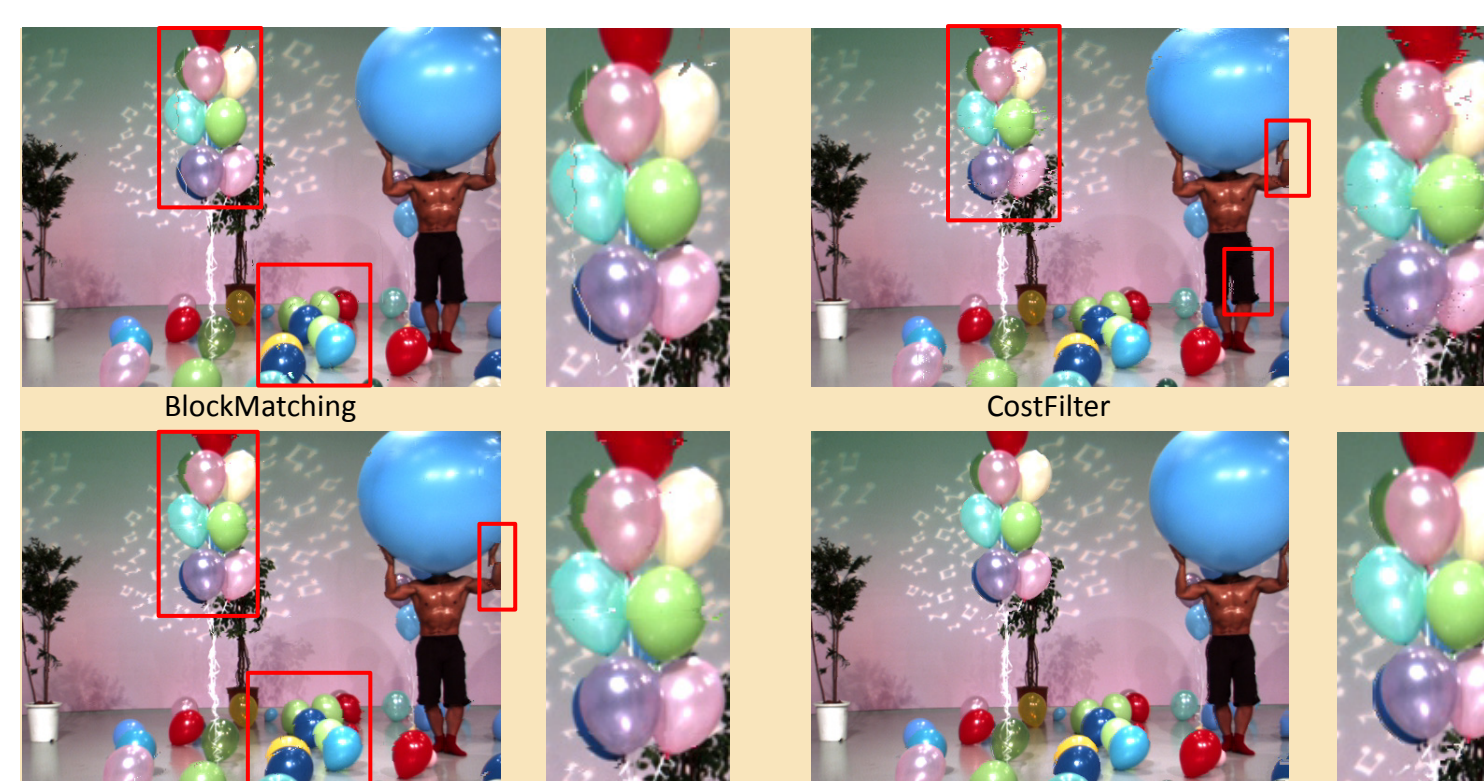
Complexity

The most time-consuming parts are the cost aggregation (symmetric guided filter) and the refinement pipeline. However, both of them can be paralleled for acceleration.

Time allocation
- 60.61% Cost aggregation
- 24.49% Refinement pipeline
- 14.90% Cost computation etc.

Acceleration on CPU — 3.2× — Before / After
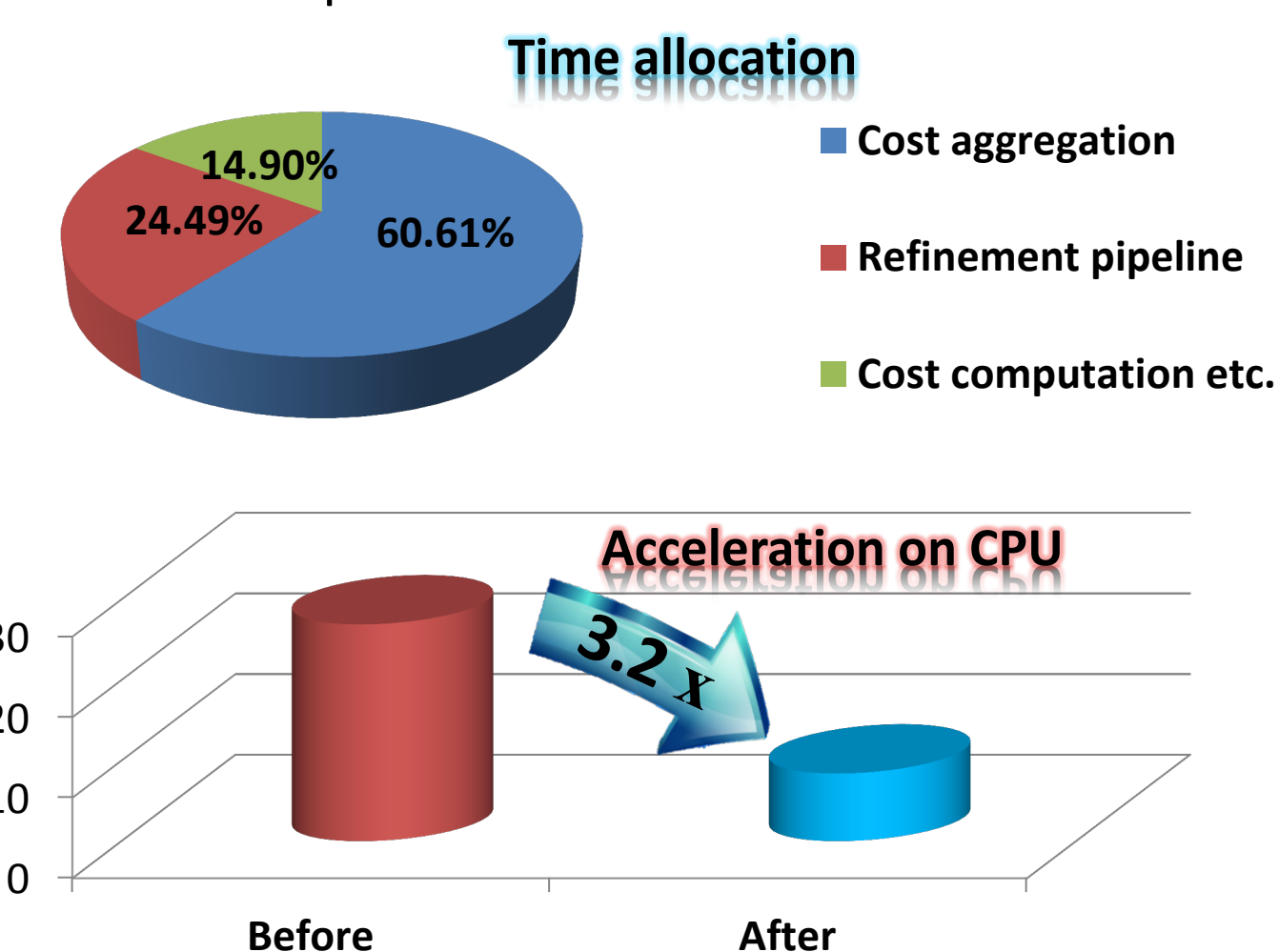
Conclusion

✓ Combined matching cost
✓ Secondary refinement scheme RADAR
✓ Perform well on both Middlebury and Real-world dataset