Real-time Spatiotemporal Stereo Matching Using the Dual-Cross-Bilateral Grid

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Overview

We introduce a real-time stereo matching technique based on a reformulation of Yoon and Kweon's adaptive support weights algorithm. We use the bilateral grid to achieve a speedup of 200× compared to a straightforward full-kernel GPU implementation, making our technique **the fastest on the Middlebury website**.

We present a spatiotemporal extension that **incorporates temporal evidence in real time** (>14 fps). Our method visibly reduces flickering and outperforms per-frame approaches in the presence of image noise.

Our datasets and **source code for all our techniques** are available on our project website.

Motivation

Yoon and Kweon's adaptive support weights are a popular non-global stereo matching technique. Results are good, but the algorithm is slow, taking about a minute for Tsukuba. Our aim is to **speed up their technique by several orders of magnitude**, hence making it practical for real-time use.

Adaptive Support Weights

Yoon & Kweon's technique relies on aggregation of support over large window sizes and weights that adapt according to similarity and proximity to the central pixel in the window. The weight between two pixels is given by

$$w(\mathbf{p},\mathbf{q}) = \exp\left(-\frac{\Delta E(\mathbf{p},\mathbf{q})}{\gamma_c} - \frac{\|\mathbf{p}-\mathbf{q}\|}{\gamma_p}\right).$$

Starting from cost space $C(\mathbf{p}, d)$, with pixel $\mathbf{p} = (x, y)$ in the left image and disparity hypothesis d, the aggregated costs are

$$C'(\mathbf{p},d) = \frac{1}{k}\cdot\sum_{\mathbf{q}\in N_\mathbf{p}} w(\mathbf{p},\mathbf{q})\cdot w(\underline{\mathbf{p}},\underline{\mathbf{q}})\cdot C(\mathbf{q},d),$$

where $\underline{\mathbf{p}} = (x - d, y)$ is the corresponding pixel in the right image and $N_\mathbf{p}$ ranges over the 35×35 pixel support window.

Dual-Cross-Bilateral Aggregation

Yoon & Kweon's technique is similar to a bilateral filter in that it smoothes the cost space while preserving edges in both input images. In the bilateral filtering framework, we call this kind of filter a **dual-cross-bilateral filter** (DCB).

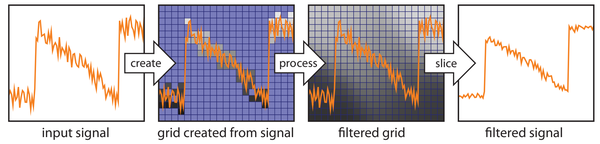
We reformulate their approach using Gaussian weights, the *de facto* standard in bilateral filtering. This yields

$$w(\mathbf{p},\mathbf{q}) = G_{\sigma_r}(\Delta E(\mathbf{p},\mathbf{q}))\cdot\sqrt{G_{\sigma_s}(\|\mathbf{p}-\mathbf{q}\|)},$$

where σ_r and σ_s are similarity and proximity parameters. Our DCB aggregation improves on our implemenation of Yoon & Kweon in the *nonocc* and *all* categories in almost all cases.

Bilateral Grid

Full-kernel implementations of the bilateral filter are slow, so we use the bilateral grid which **runs faster and uses less memory** as σ increases.

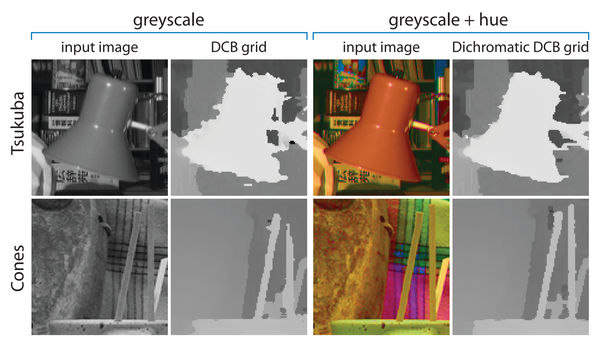


The DCB Grid

The bilateral grid can also be used for cross-bilateral filtering. Our **DCB grid** is an extension that takes into account the two input images as edge images, and accumulates cost space values instead of pixel values.

Our DCB grid runs at 13 fps or higher on all datasets, which is **more than 200× faster** than the full-kernel implementation.

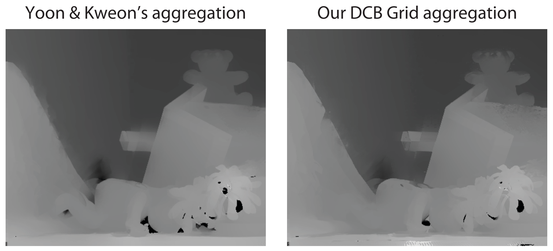
Dichromatic DCB Grid



Temporal DCB Grid

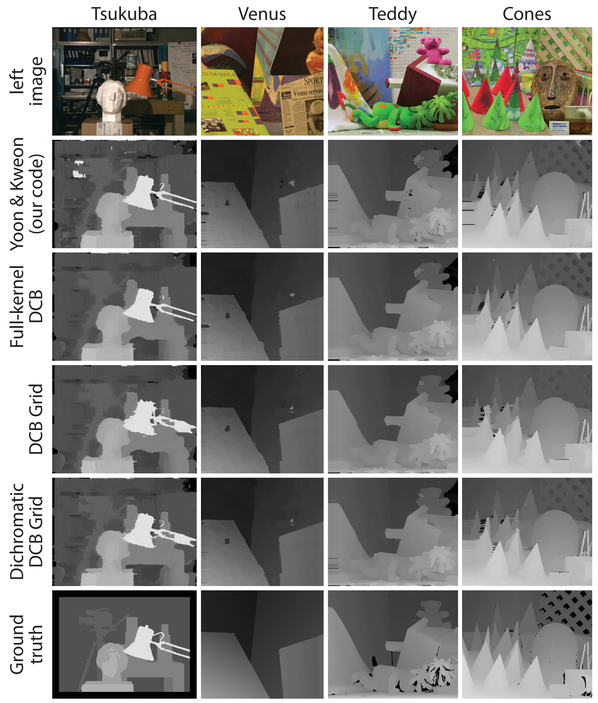
Per-frame techniques are insufficient to achieve temporally coherent disparity maps from stereo videos. We aggregate costs over a 3D spatiotemporal support window of 5 frames. The **run time is sublinear** in the number of frames: working with 5 frames only takes 76% longer than one frame.

Spatial-Depth Super-Resolution



fps	nonocc	all	disc	fps	nonocc	all	disc
0.15	17.1	17.4	41.7	17.0	19.9	19.2	42.5

Results



Run times (in ms)

Our techniques (in blue) run on an Nvidia Quadro FX 5800.

Technique	Tsukuba 384×288×16	Venus 434×383×20	Teddy 450×375×60	Cones 450×375×60
DCB Grid	14.2	25.7	75.8	75.0
Real-time GPU	30*	60*	200*	200*
Reliability DP	42	109	300*	300*
Dichromatic DCB Grid	188	354	1,070	1,070
Plane-fit BP	200*	400*	1,000*	1,000*
Y&K (our GPU impl.)	2,350	4,480	13,700	13,700
Full-kernel DCB	2,990	5,630	17,700	17,600
Yoon & Kweon	60,000	100,000*	300,000*	300,000*

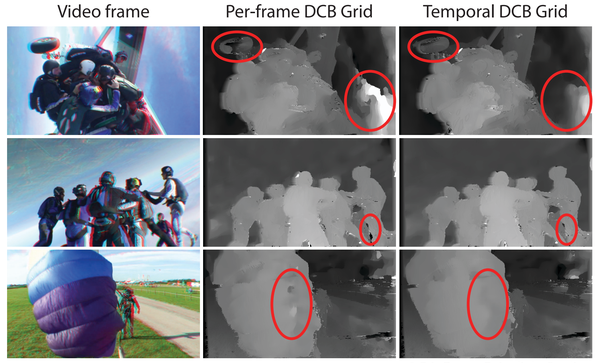
* Run times estimated from reported figures, to one significant digit.

Performance

Middlebury benchmarks for our techniques (in blue), Yoon & Kweon, and selected real-time techniques.

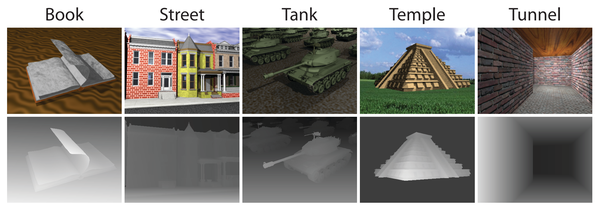
Technique	Rank	Tsukuba			Venus			Teddy			Cones		
		nonocc	all	disc	nonocc	all	disc	nonocc	all	disc	nonocc	all	disc
Plane-fit BP	19.4	**0.97**	**1.83**	**5.26**	**0.17**	**0.51**	**1.71**	**6.65**	**12.1**	**14.7**	4.17	10.7	10.6
Yoon & Kweon	32.8	1.38	1.85	6.90	0.71	1.19	6.13	7.88	13.3	18.6	3.97	9.79	**8.26**
Full-kernel DCB	47.7	3.96	4.75	12.9	1.36	2.02	10.4	9.10	15.9	18.4	**3.34**	**9.60**	**8.26**
Y&K (our GPU impl.)	48.2	4.39	5.29	8.10	1.30	2.07	8.31	9.39	16.3	18.4	3.68	9.96	8.42
Dichromatic DCB Grid	52.9	4.28	5.44	14.1	1.20	1.80	9.69	9.52	16.4	19.5	4.05	10.4	10.3
Real-time GPU	56.2	2.05	4.22	10.6	1.92	2.98	20.3	7.23	14.4	17.6	6.42	13.7	16.5
Reliability DP	59.7	1.36	3.39	7.25	2.35	3.48	12.2	9.82	16.9	19.5	12.9	19.9	19.7
DCB Grid	64.9	5.90	7.26	21.0	1.35	1.91	11.2	10.5	17.2	22.2	5.34	11.9	14.9

Qualitative Evaluation on Stereo Videos

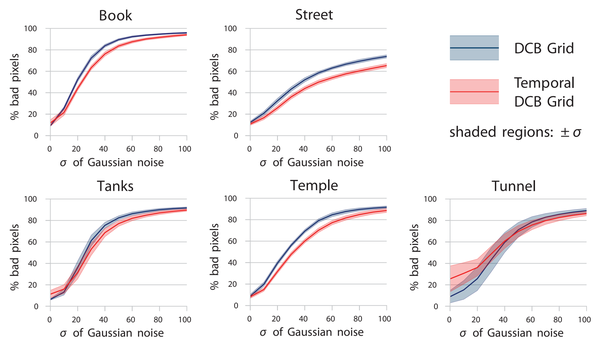


Ground Truth Stereo Videos

As there were no stereo videos with ground truth disparities, we created a set of 5 synthetic stereo videos with ground truth disparity maps, which we make available.



Quantitative Evaluation on Stereo Videos



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