Robot Vision: Stereo Matching

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Outline

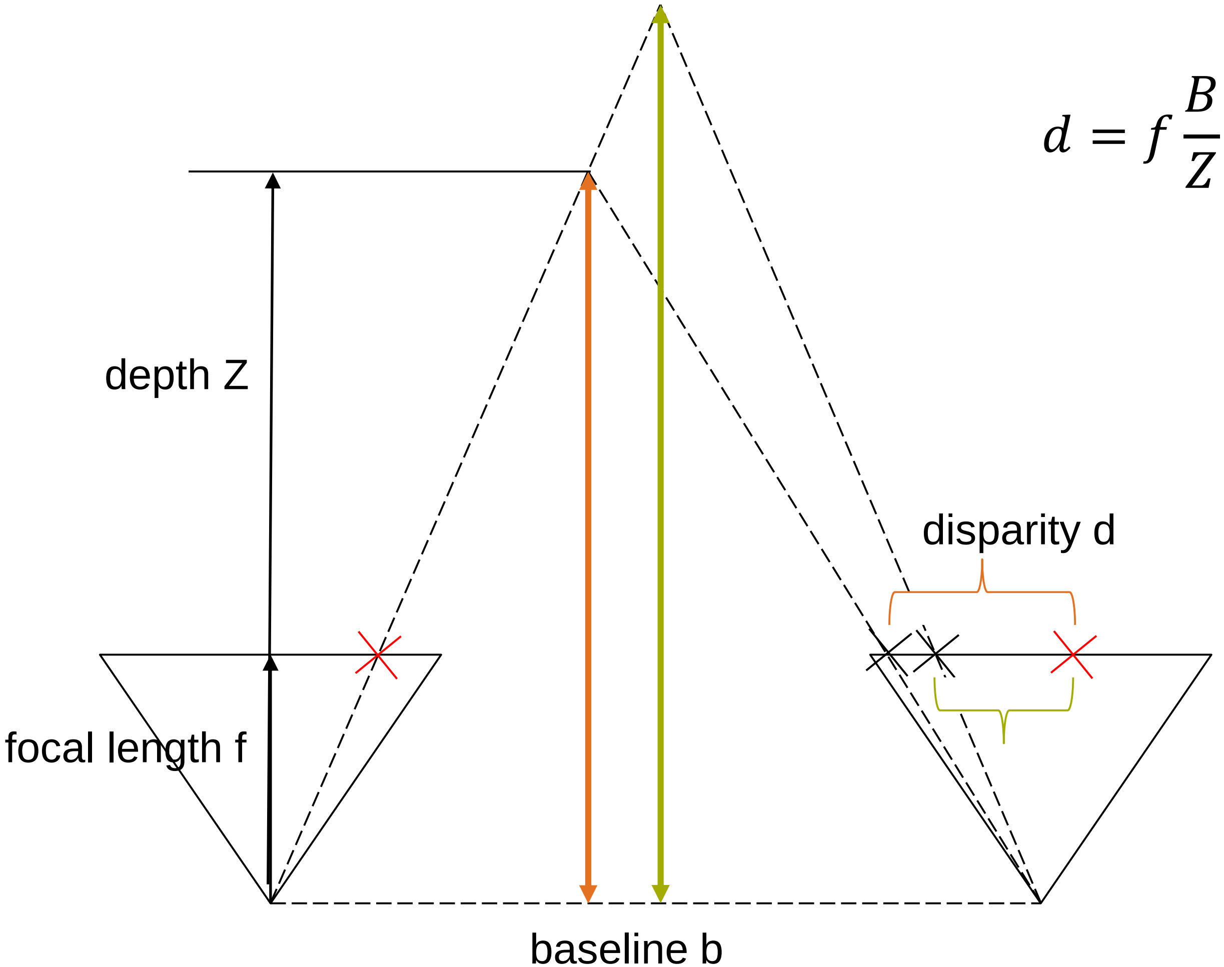
- Geometric relations for stereo matching
- Dense matching process
- Census Transform
- Dynamic programming
- Semiglobal matching
- Stereo matching with CNN’s
- Monocular depth estimation

Dense matching

- SfM only gives sparse 3D data
- Only feature points (e.g. SURF) are triangulated – for most pixel no 3D data is computed
- Dense image matching computes a 3D point for every pixel in the image (1MP image leads to 1 million 3D points)
- Dense matching algorithms need camera poses as prerequisite

Geometric relation

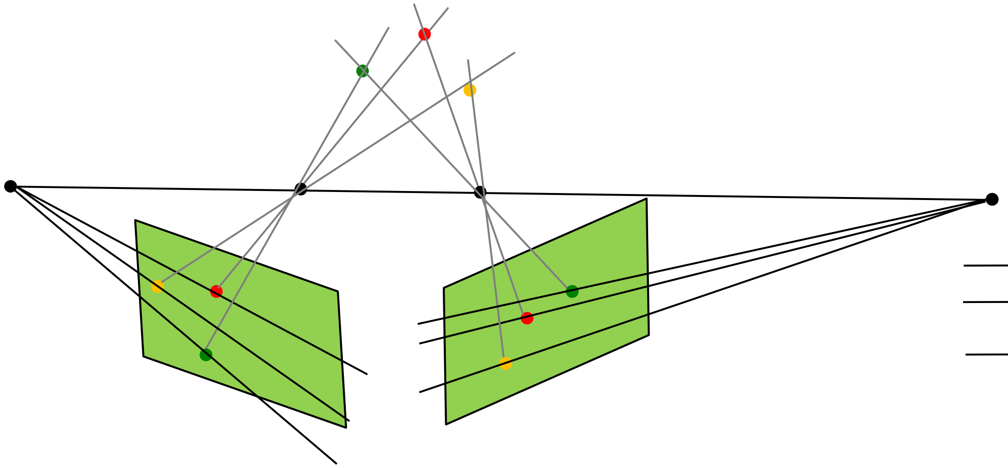
- Stereo normal case
- Depth Z [m] can be computed from disparity d [pixel]



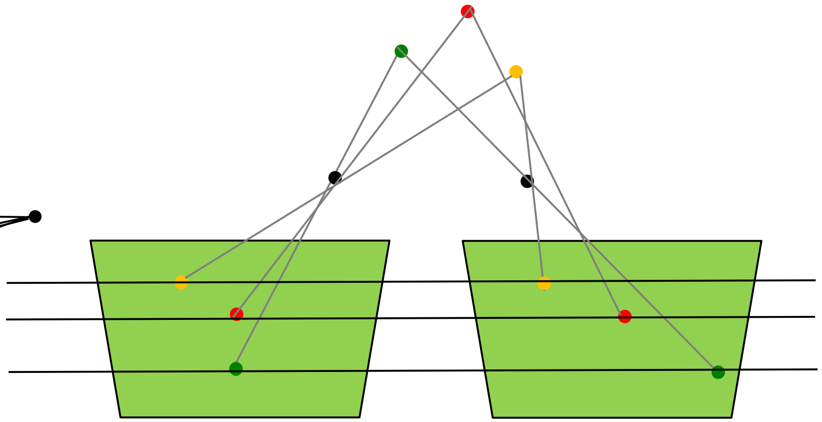
$$d = f\,\frac{B}{Z}$$

Rectification

- Image transformation to simplify the correspondence search
  - Makes all epipolar lines parallel
  - Image x-axis parallel to epipolar line
  - Corresponds to parallel camera configuration



Before rectification



„Stereo normal case“

Dense matching process

Left View

I_l

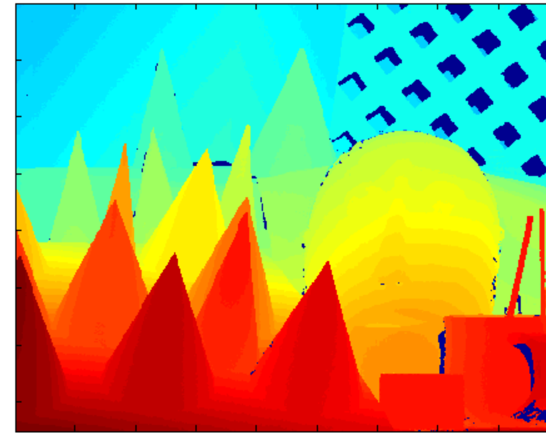
+

Right View

I_r

=

*



Disparity image

D

- Estimate disparity (depth) for all pixels in the left image.
  - Evaluate similarity measure for every possible pixel location on the line (e.g. NCC, SAD)

- Disparity *d*: Offset between pixel *p* in the left image and its corresponding pixel *q* in the right image.

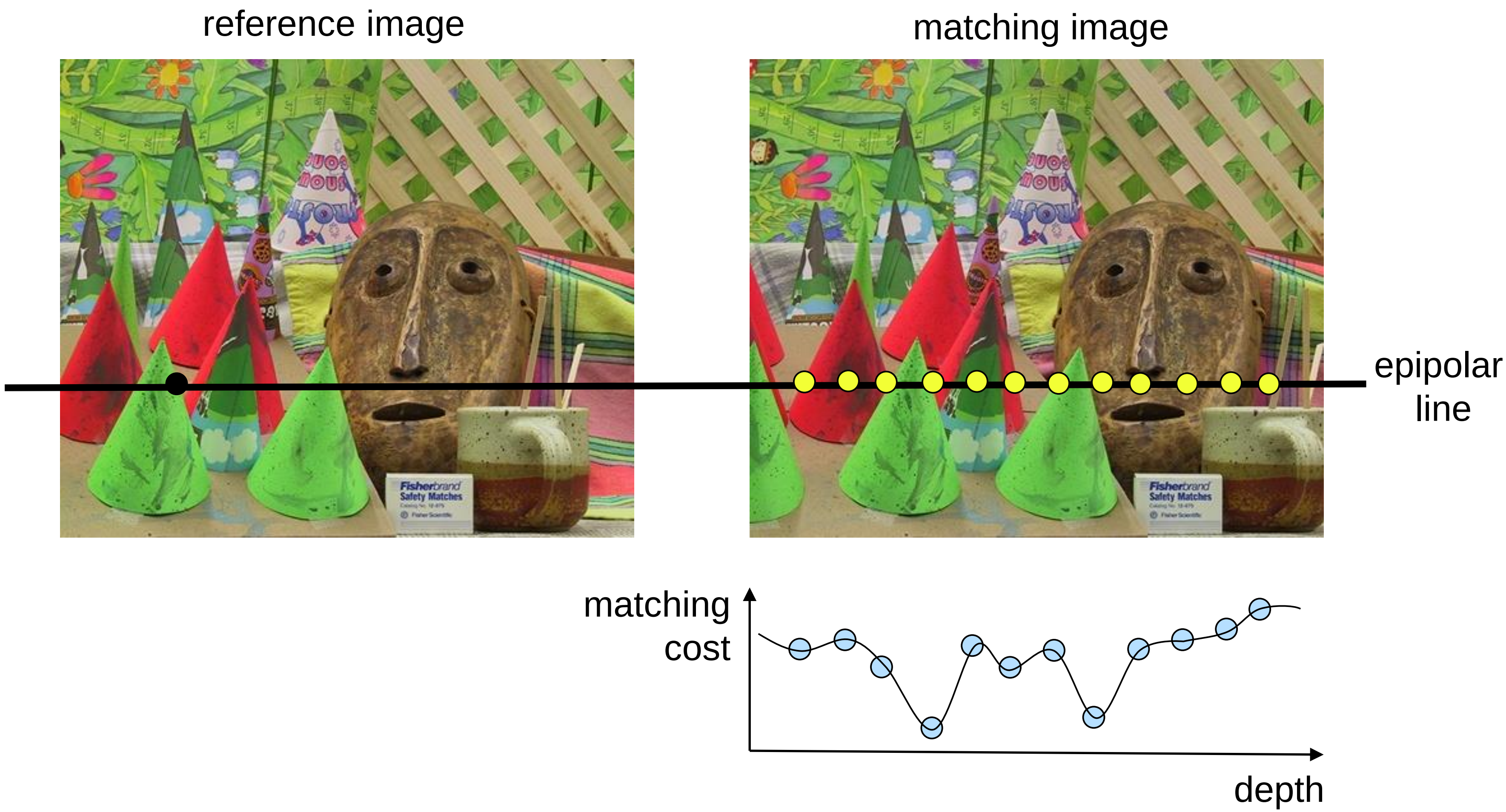
Census Transform

- A popular block matching cost
- Good robustness to image changes (e.g. brightness)
- Matching cost is computed by comparing bit strings using the Hamming distance (**efficient**)
- Bit strings encode if a pixel within a window is greater or less than the central pixel (0 .. if center pixel is smaller, 1 .. if center pixel is larger or equal)

89	63	72
67	**55**	64
58	51	49

00000011

Dense matching process



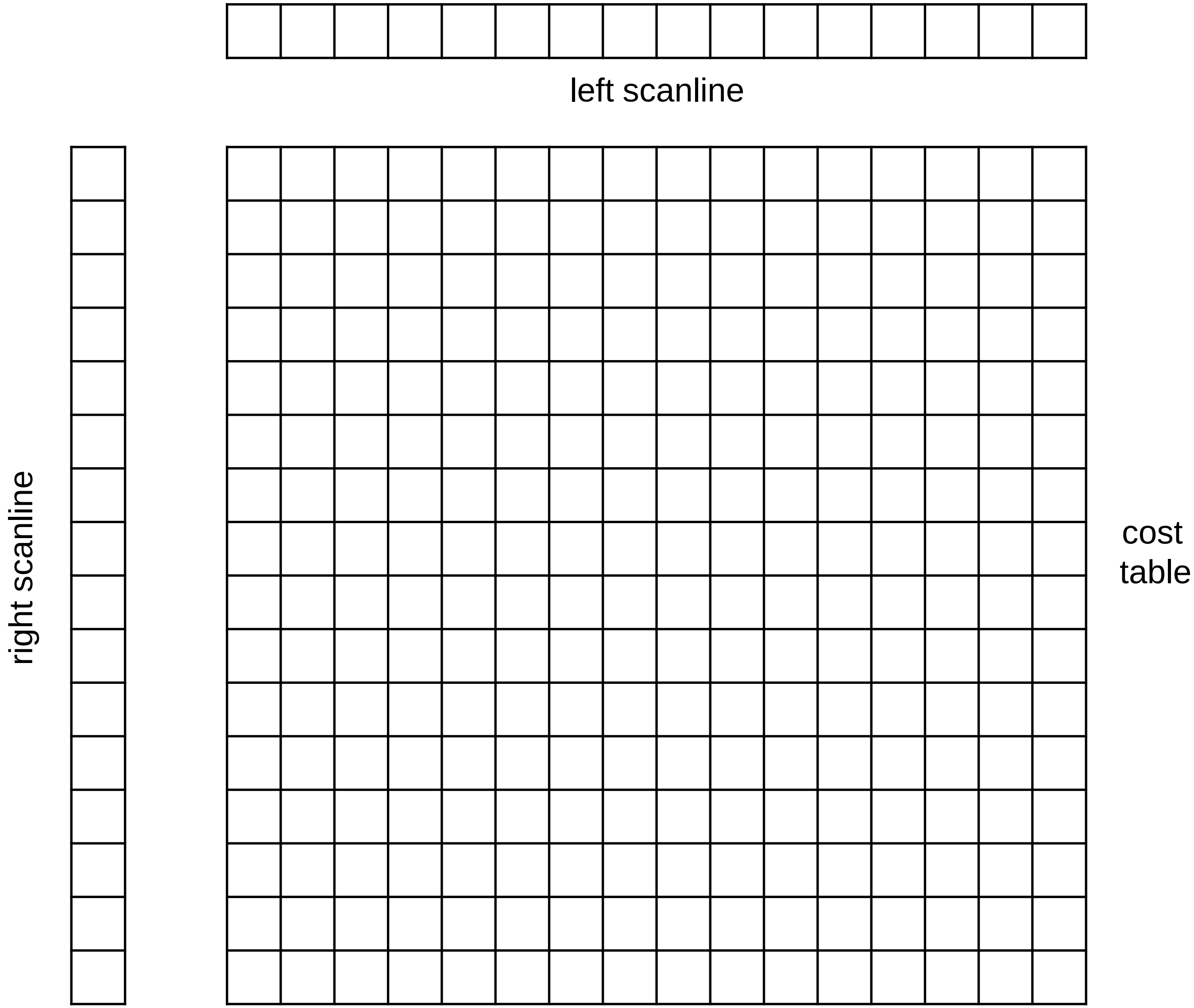
Disparity selection

- Single scanline based
  - Winner takes all (WTA)
    Select the disparity with the lowest cost (i.e. the highest similarity)
  - Scanline optimization (Dynamic programming)
    Select the disparities of the whole scanline such that the total (added up) costs for a scanline is minimal
- Global methods (Cost volume optimization)
  - Belief propagation
    Selects the disparities such that the total cost for the whole image is minimal
  - Semi-global Matching
    Approximates the optimization of the whole disparity image

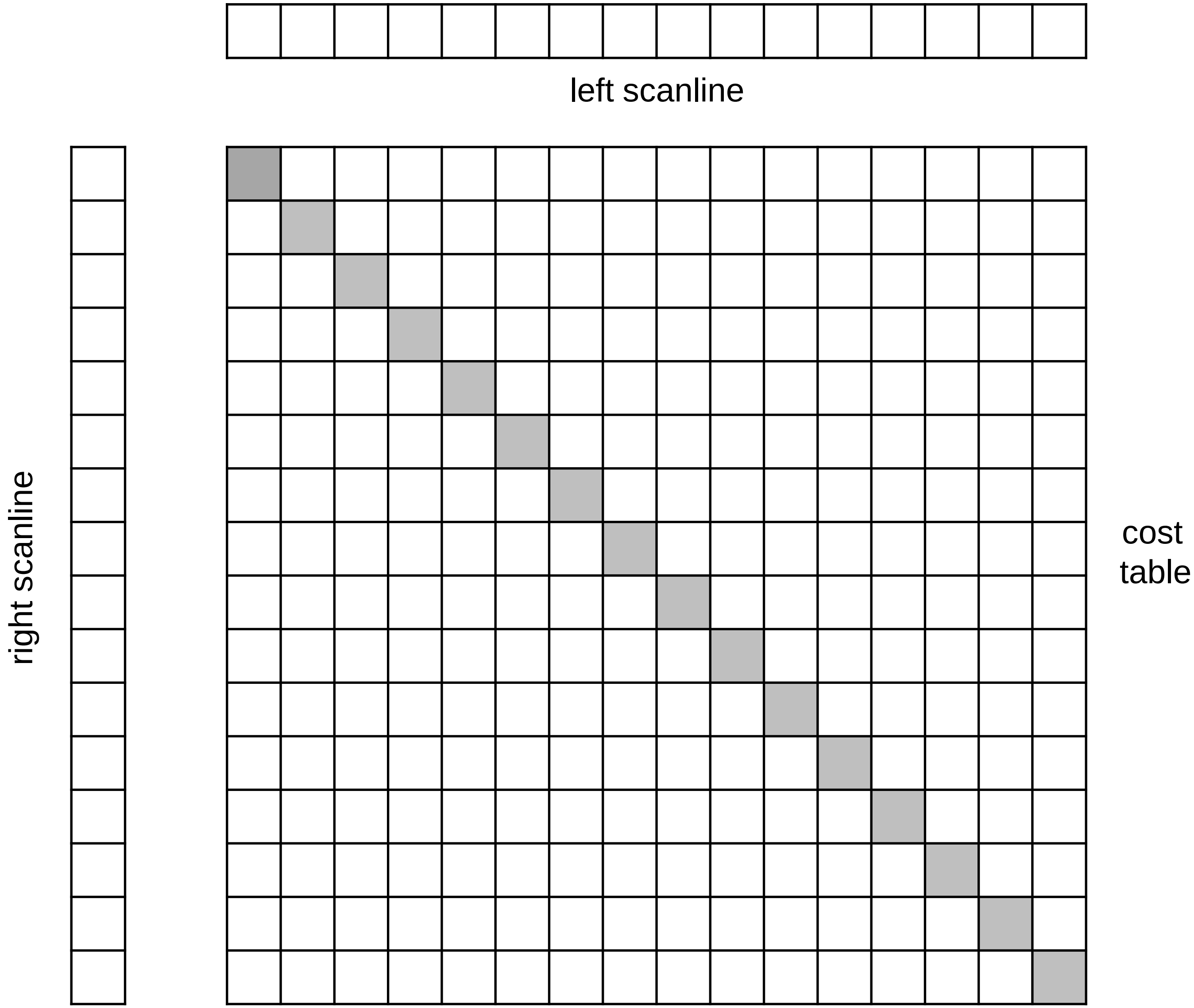
Scanline optimization

- Frequently called “dynamic programming” because of the programming scheme for efficient cost calculation. This naming is historic and does not reflect the method well. In fact it is an application of the Viterbi-Algorithm.
- Cost calculation based on a 2D grid

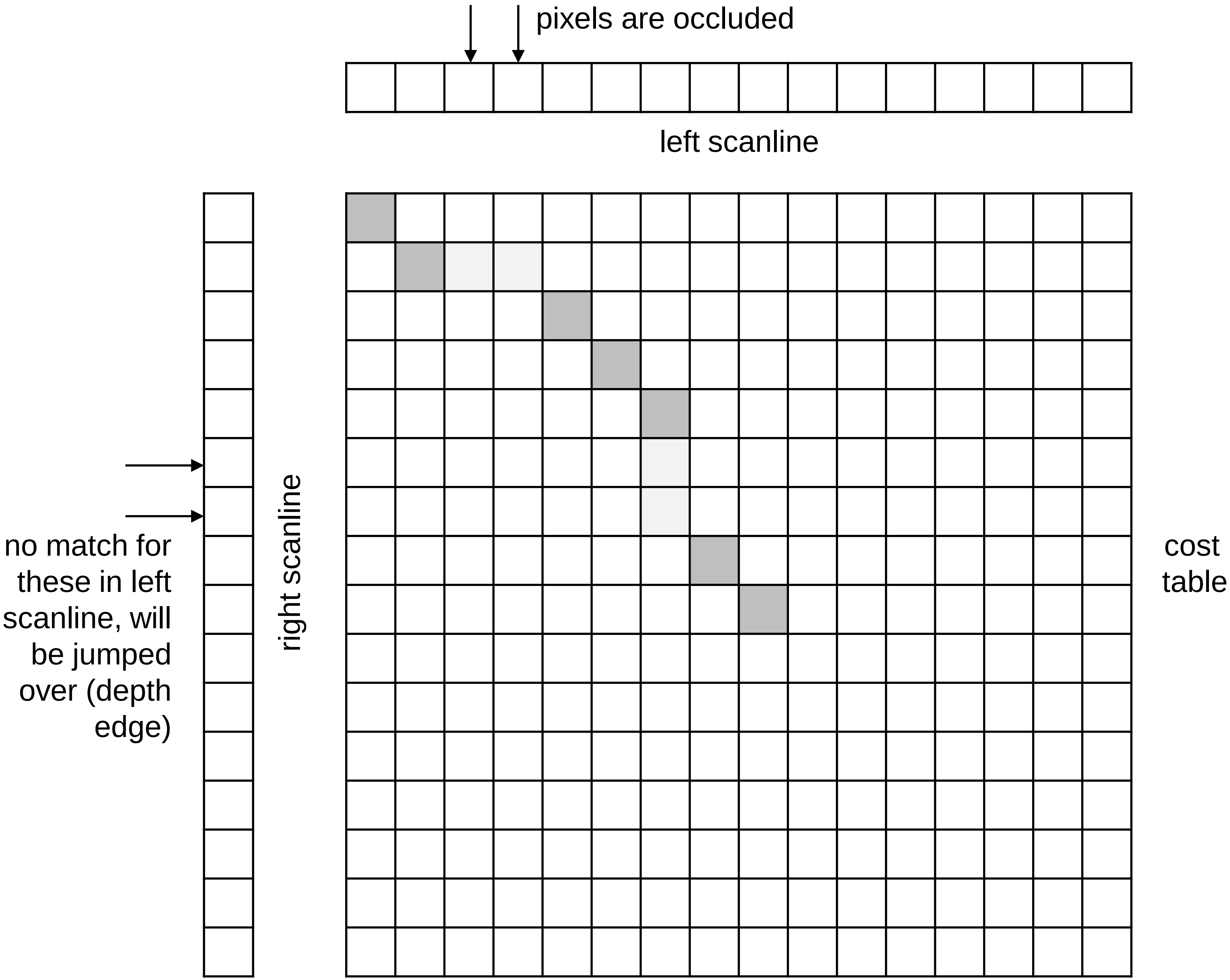
Scanline optimization



Scanline optimization



Scanline optimization

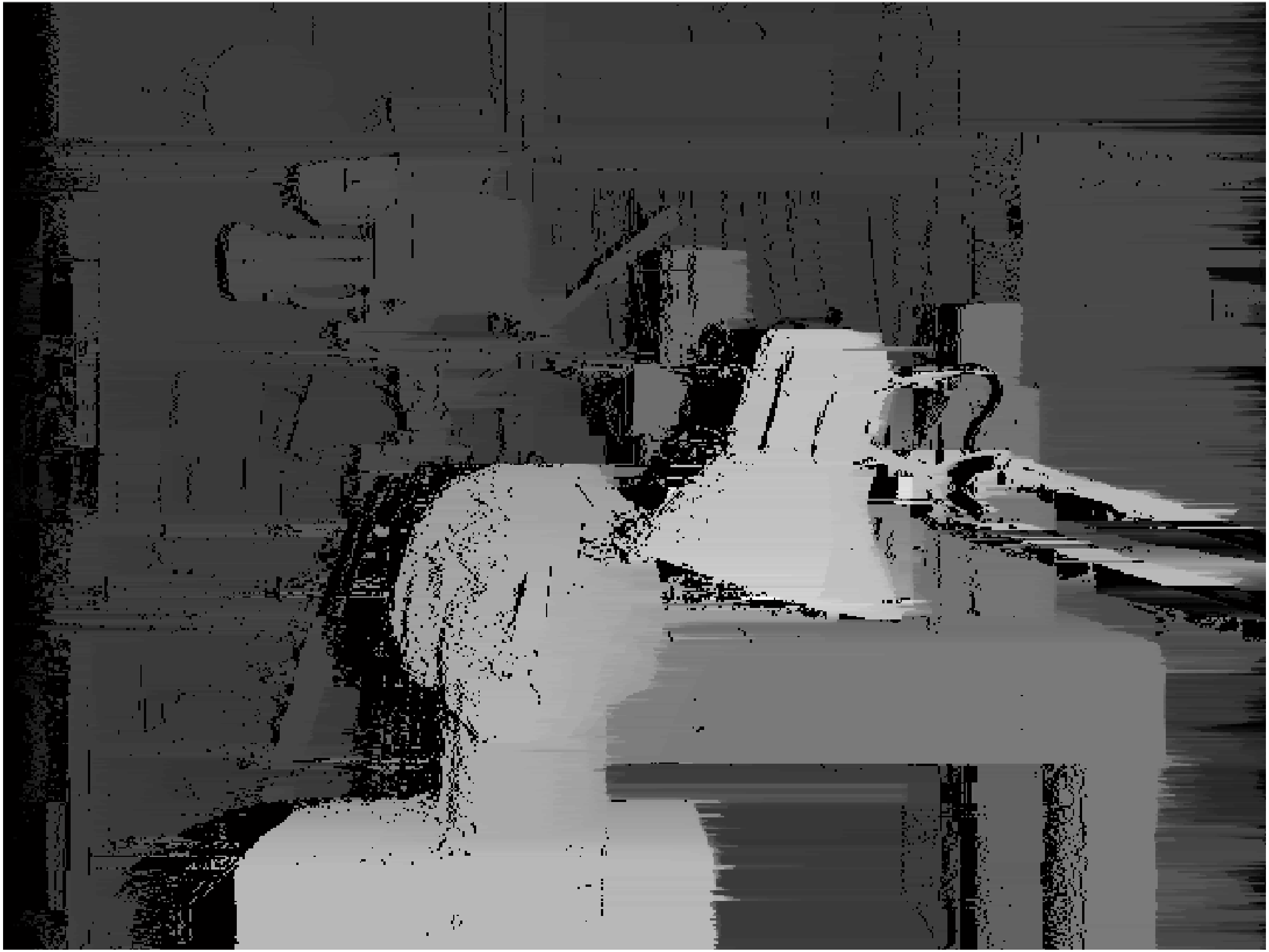


Scanline optimization complexity

- Exhaustive search: $O(h^n)$
  Example: scanline of length n=512 with h=100 disparities: 100^{512}

- Dynamic programming: $O(nh^2)$
  Example: scanline of length n=512 with h=100 disparities:
  512*100*100= 5,12 million operations

Scanline optimization streaking artifacts



Global methods

- Global methods
  - Global cost optimization in energy-minimization framework

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

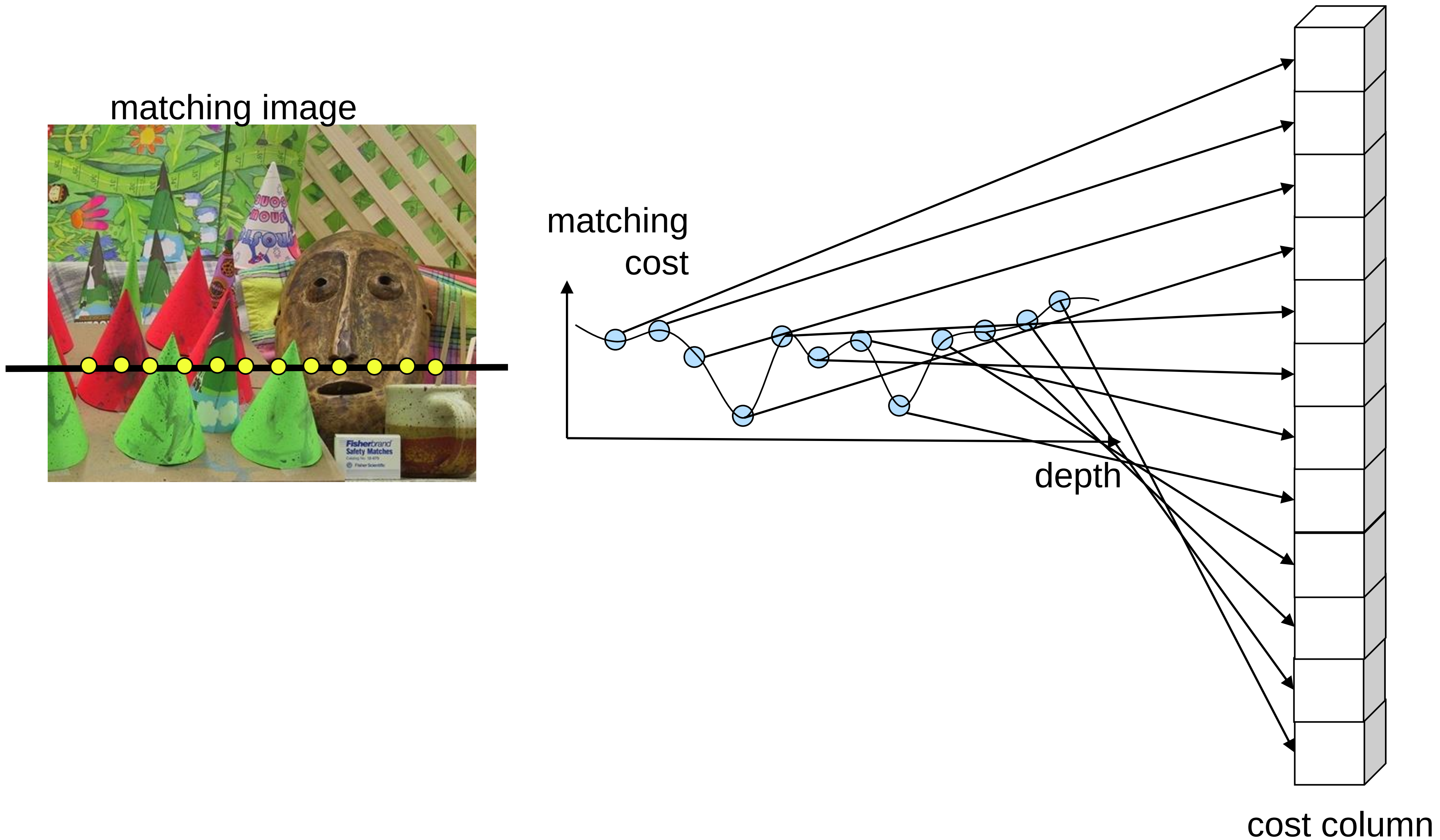
  - Data term:
    Agreement between cost function and input image pair

$$E_{data}(D) = \sum_{(p)} c(p, d)$$

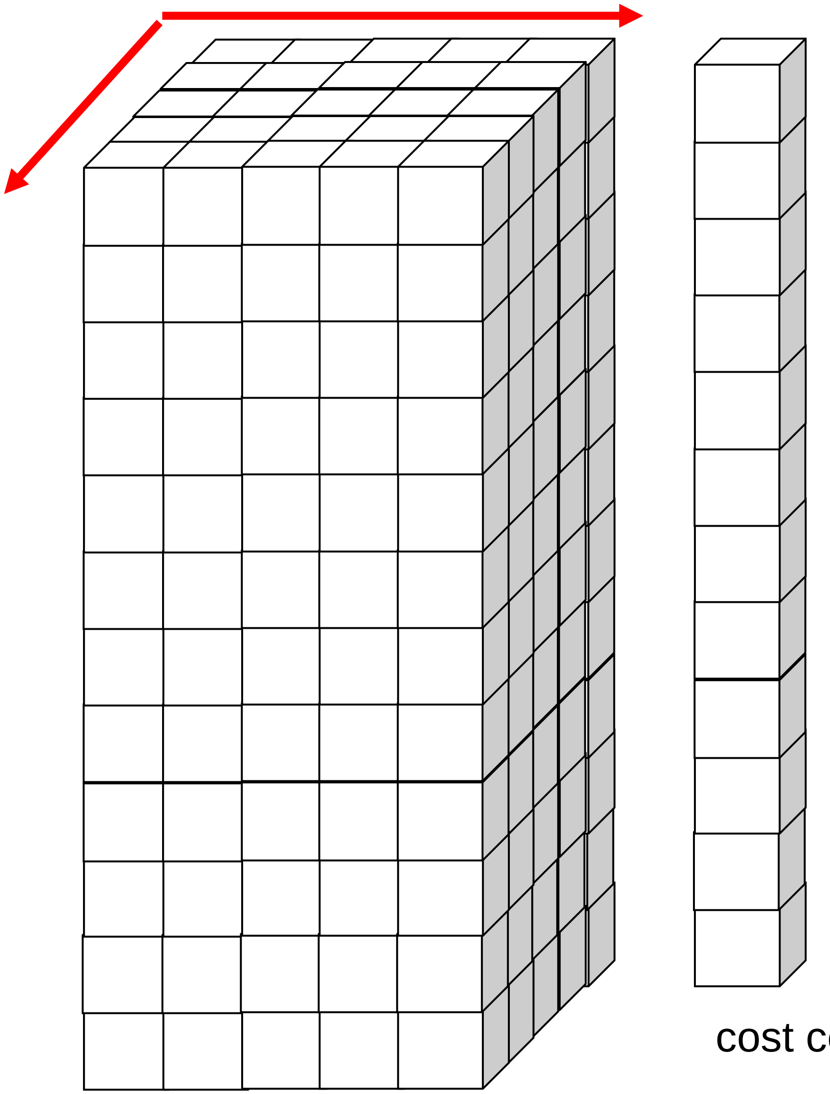
  - Smoothness term:
    Encoding the smoothness assumptions

$$E_{smooth}(D) = \sum_{(p)} \rho(d(u, v) - d(u+1, v))$$

Cost volume

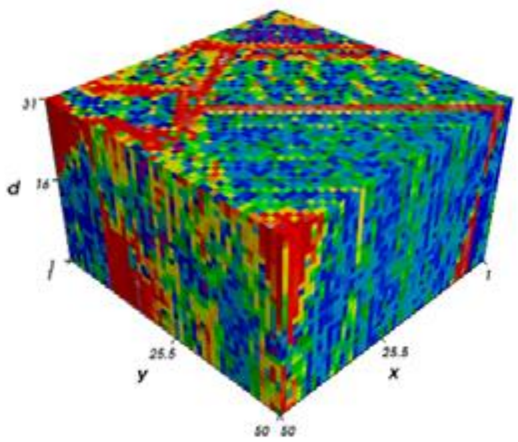


Cost volume

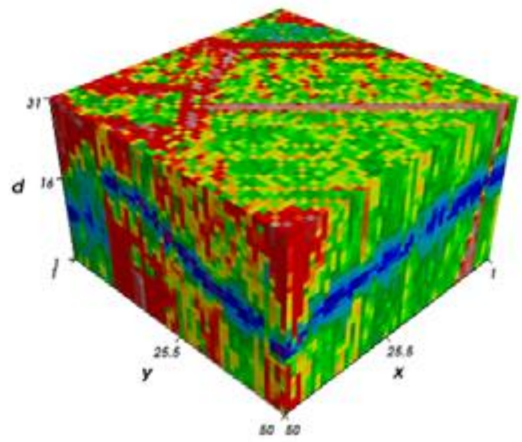


Semiglobal matching

- Cost Aggregation (Cost Optimization)



Cost Cube



Optimized Cost Cube

Goal: global minimization of

$$E(D) = \underbrace{\sum_{P} (C(p, D_p)}_{\text{Data term}} + \underbrace{\sum_{q \in N_p} P_1 \left[|D_p - D_q| = 1 \right] + \sum_{q \in N_p} P_2 \left[|D_p - D_q| > 1 \right]}_{\text{Regularization term}}$$

P_1 : Penalty factor for small jump

P_2 : Penalty factor for large jump

N_p : Neighborhood of p

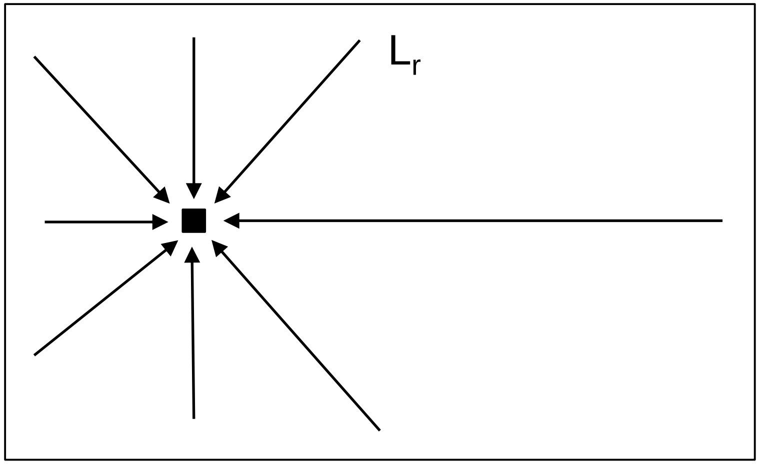
Semiglobal matching

- Path-wise approximation of aggregation

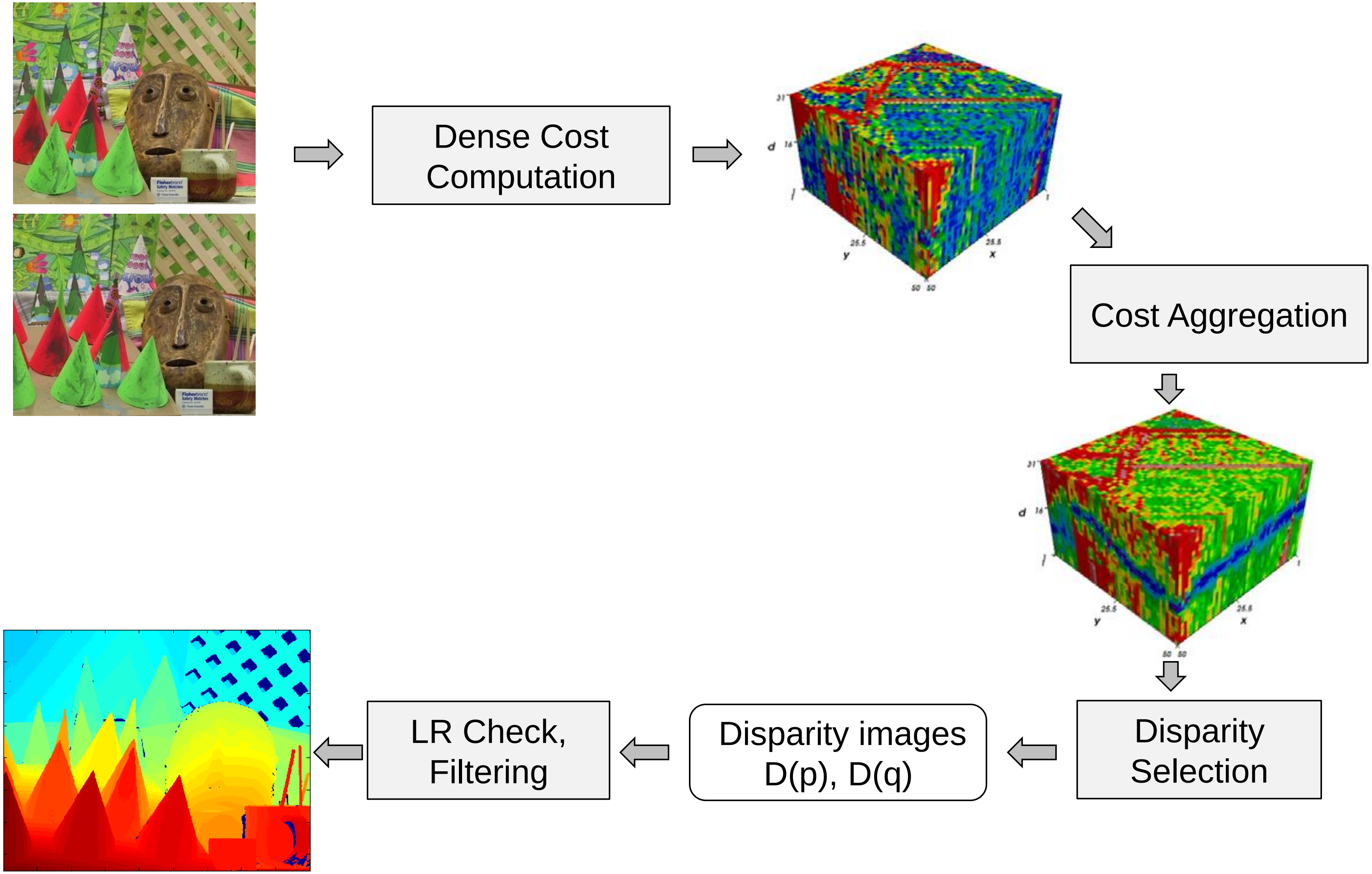
$$L_r(p,d) = C(p,d) + \min \begin{pmatrix} L_r(p-r,d), \\ P_1 + L_r(p-r,d-1), \\ P_1 + L_r(p-r,d+1), \\ P_2 + \min\limits_i L_r(p-r,i) \end{pmatrix}$$

p	Image coordinates
P_1	Cost for small height jump
P_2	Cost for large height jump
r	Path direction
L_r	Aggregated costs along r
d	Disparity

- Summation of *L* along 8 or 16 directions *r* $\quad S(p,d) = \sum_r L_r(p,d)$



Semiglobal matching



[Heiko Hirschmüller (2008), Stereo Processing by Semi-Global Matching and Mutual Information, in IEEE PAMI, Volume 30(2), February 2008, pp. 328-341.]

Stereo matching using CNN’s (Example MC-CNN)

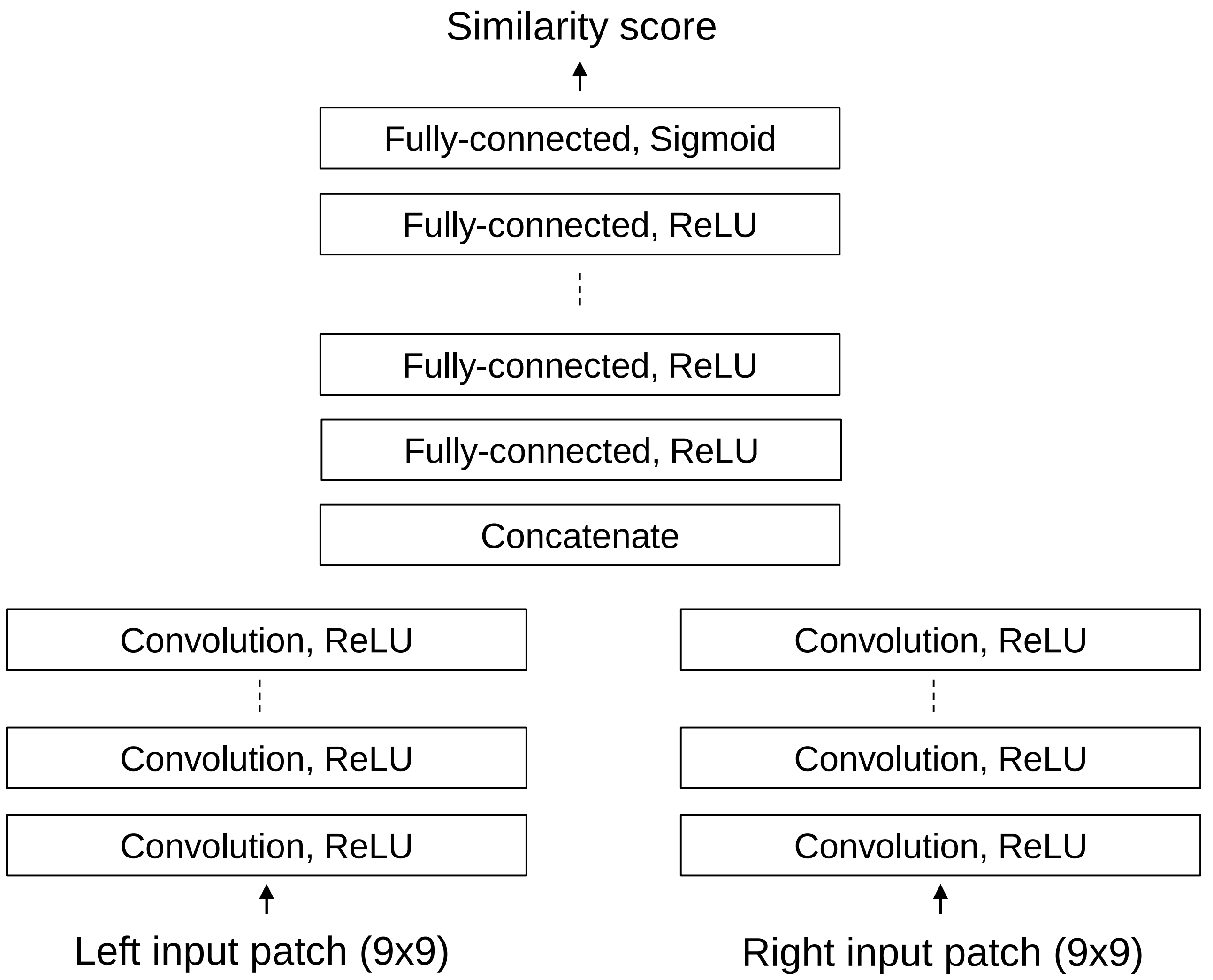
- Traditionally disparity estimation works along 3 steps
- CNN‘s can be used to replace these parts which replaces handcrafted models and thresholds with data-driven algorithms

Steps replaced by CNN’s

still SGM
implementation used

MC-CNN

- Using deep neural networks for similarity estimation



Performance of CNN based stereo

Middlebury Stereo Evaluation - Version 3

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

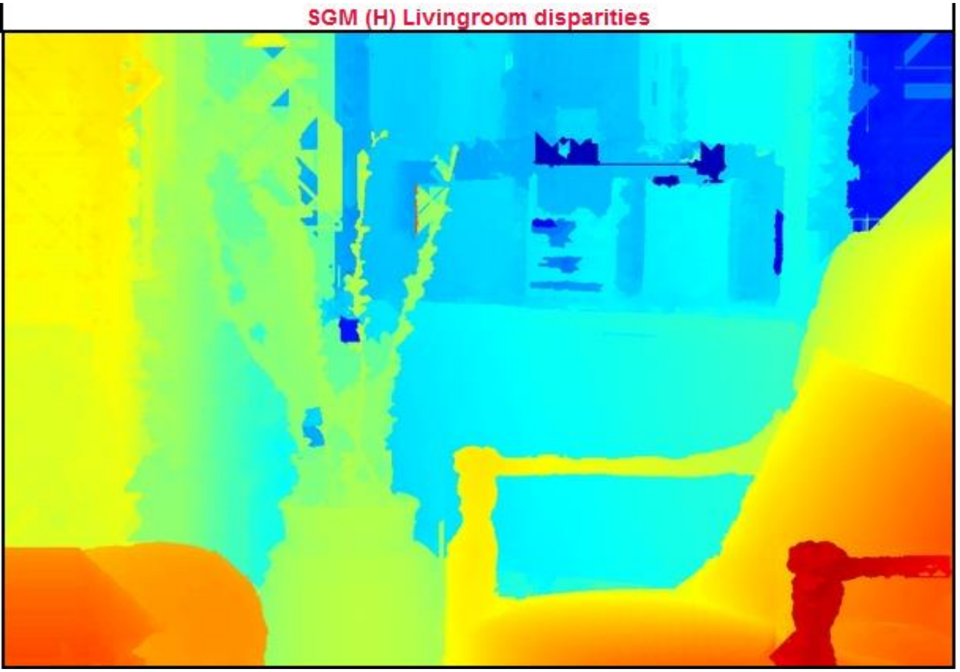
Metric: bad 0.5 bad 1.0 bad 2.0 bad 4.0 avgerr rms A50 A90 A95 A99 time time/MP time/GD

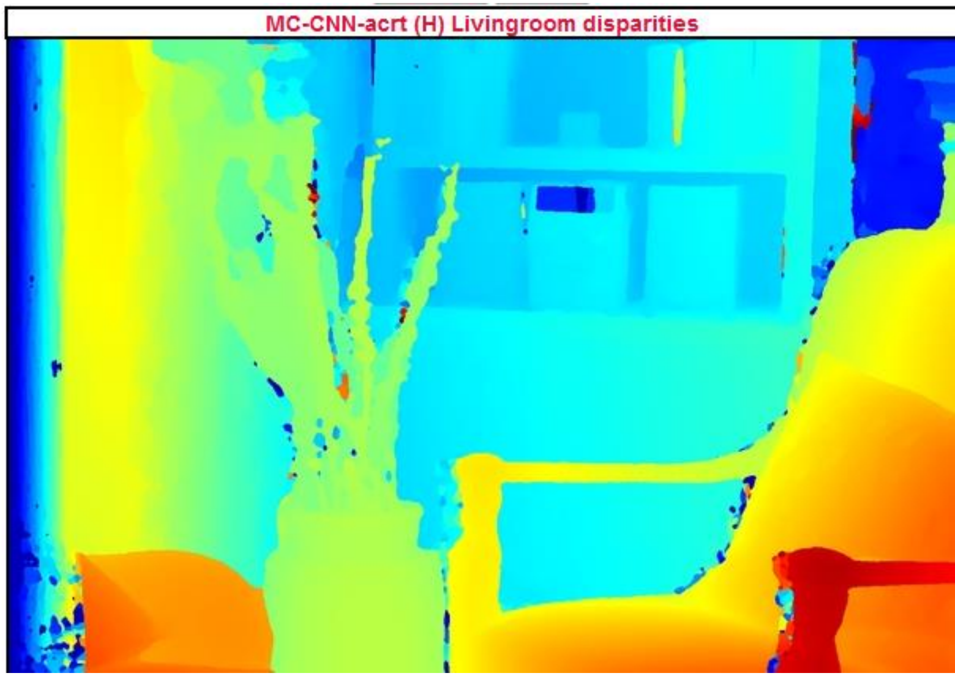
Mask: nonocc all

☑ plot selected ☐ show invalid **Reset sort** **Reference list**

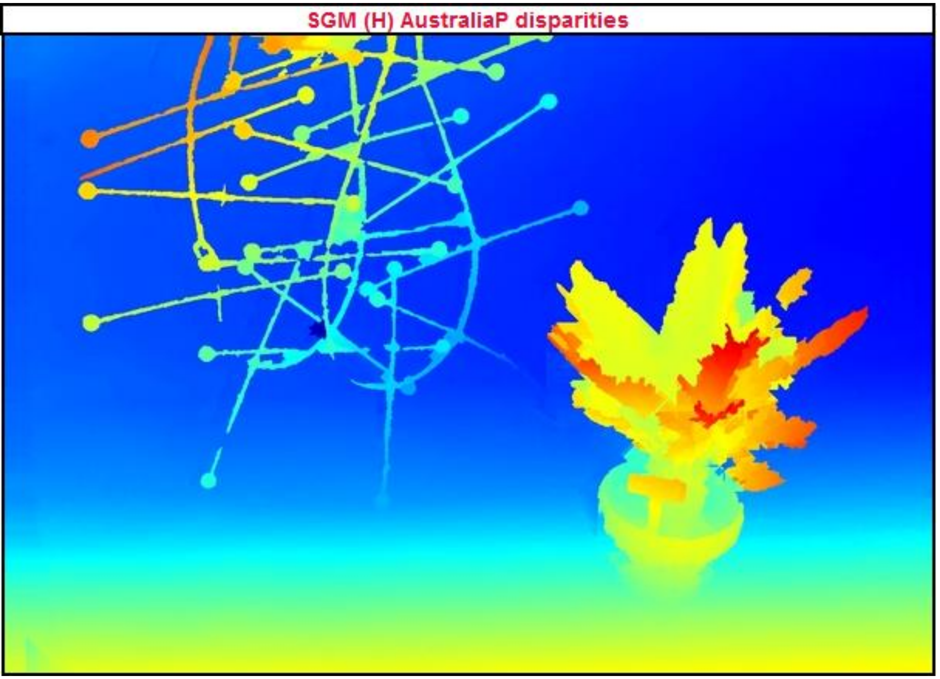
Date	bad 2.0 (%) Name		Res	Weight Avg	Austr MP: 5.6 nd: 290 im0 im1 GT nonocc	AustrP MP: 5.6 nd: 290 im0 im1 GT nonocc	Bicyc2 MP: 5.6 nd: 250 im0 im1 GT nonocc	Class MP: 5.7 nd: 610 im0 im1 GT nonocc	ClassE MP: 5.7 nd: 610 im0 im1 GT nonocc	Compu MP: 1.5 nd: 256 im0 im1 GT nonocc	Crusa MP: 5.5 nd: 800 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
08/28/15	☑ MC-CNN-acrt		H	**8.08** 1	5.59 20	4.55 25	5.96 17	2.83 10	11.4 25	5.81 14	8.32 23	8.89 27	2.71 15	16.3 23	14.1 18	13.2 18	13.0 5	6.40 16	11.1 15
07/28/14	☑ SGM		H	18.4 2	40.3 79	4.54 23	8.03 32	22.9 67	40.5 59	11.4 39	24.7 51	10.1 36	5.40 45	29.6 45	28.5 51	23.9 55	20.0 40	14.2 40	30.9 51

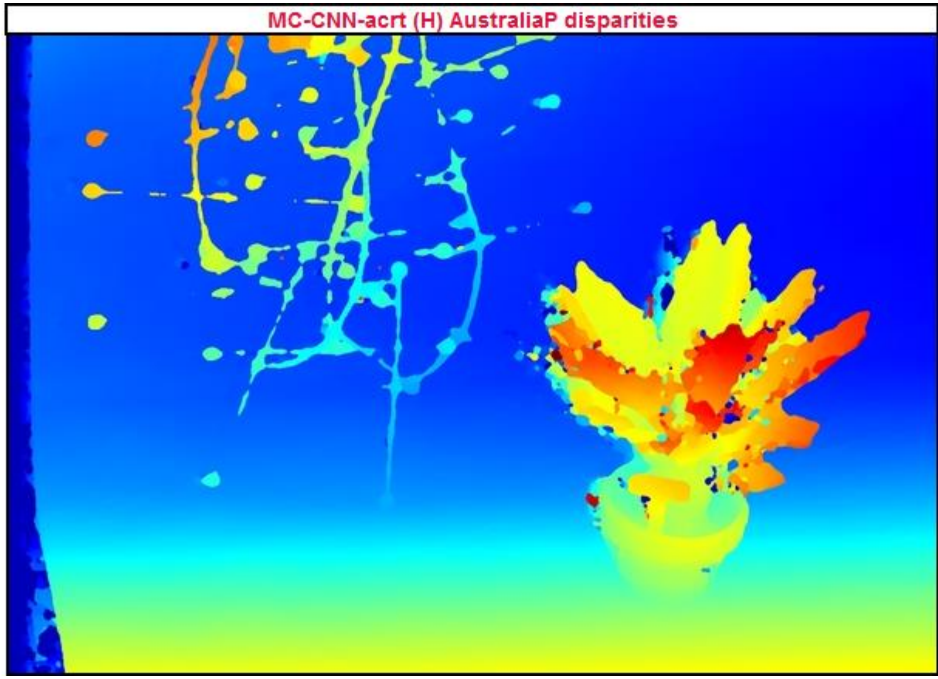
Example results



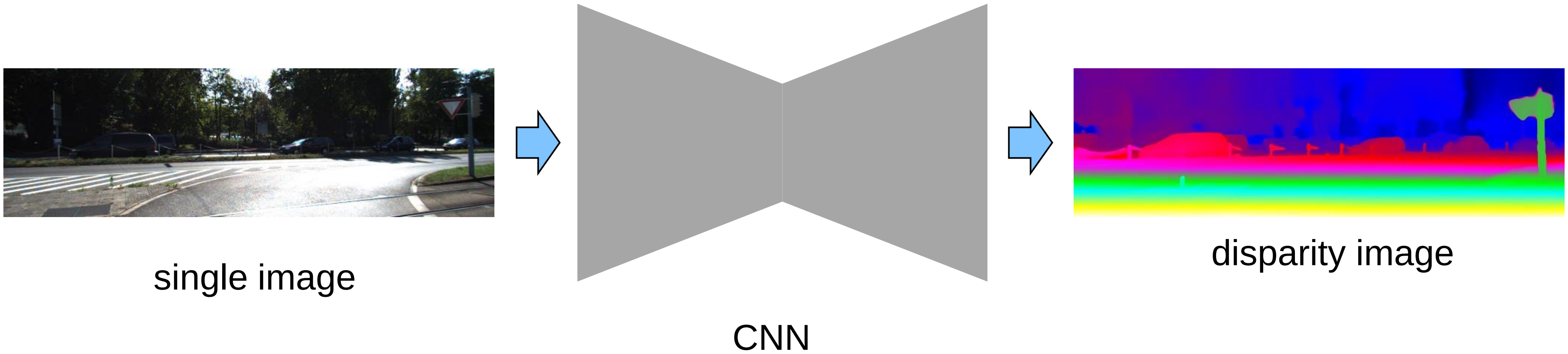


Example results

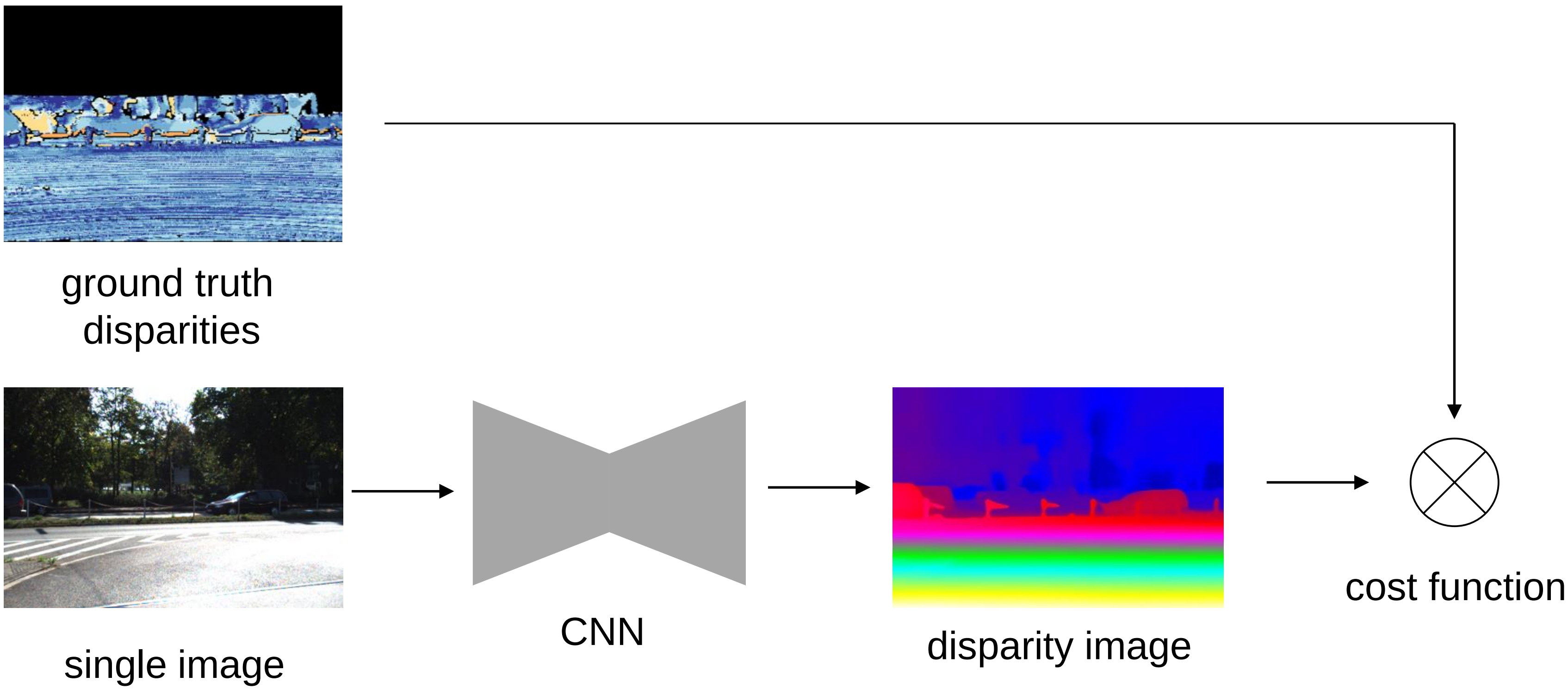




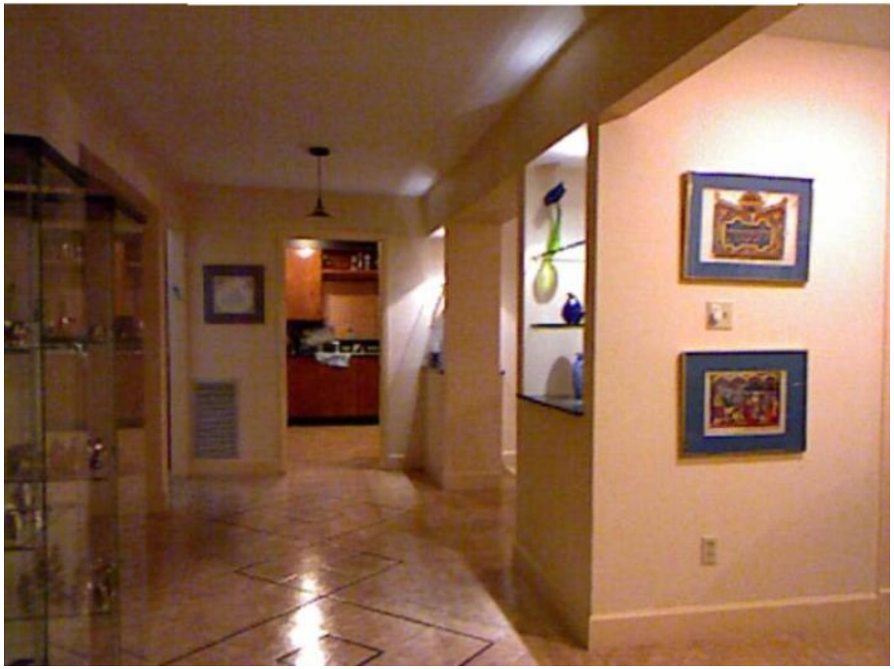
Monocular depth estimation



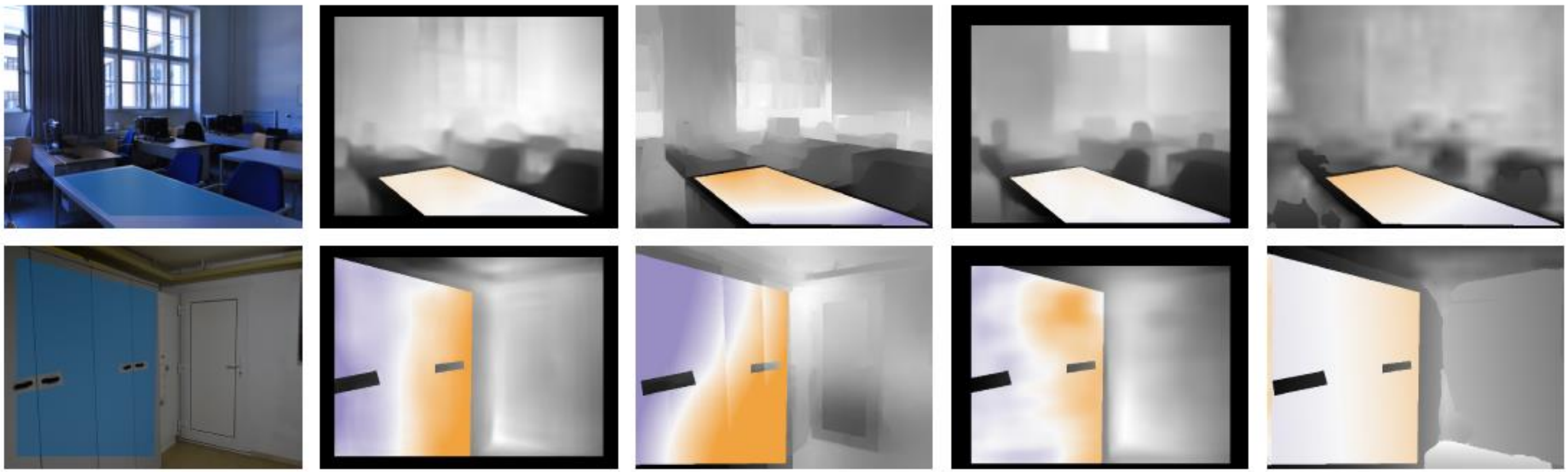
Monocular depth estimation - Training



How well does it work?



Planarity errors



(a) RGB (b) Eigen and Fergus (2015) (VGG) (c) Liu et al. (2015) (d) Li et al. (2017) (e) Liu et al. (2018)

Figure 4.25: Visual results after applying *planarity errors* (PEs) on different planar regions (top: table, bottom: wall). RGB with corresponding plane masks (■) (a). Predictions using different methodologies (b-e). Colors in the predictions correspond to orthogonal differences of projected depths towards the reference plane

Koch, Tobias; Liebel, Lukas; Fraundorfer, Friedrich; Körner, Marco: Evaluation of CNN-Based Single-Image Depth Estimation Methods. Proceedings of the European Conference on Computer Vision Workshops (ECCV-WS), Springer International Publishing, 2019

Limits of current method

- Network estimates depth for a picture on a flat wall
- NO absolute scale measurements as in real stereo setup!

Koch, Tobias; Liebel, Lukas; Fraundorfer, Friedrich; Körner, Marco: Evaluation of CNN-Based Single-Image Depth Estimation Methods. Proceedings of the European Conference on Computer Vision Workshops (ECCV-WS), Springer International Publishing, 2019