Seminars in Artificial Intelligence and Robotics

Computer Vision for Intelligent Robotics

Basics and hints on low level vision

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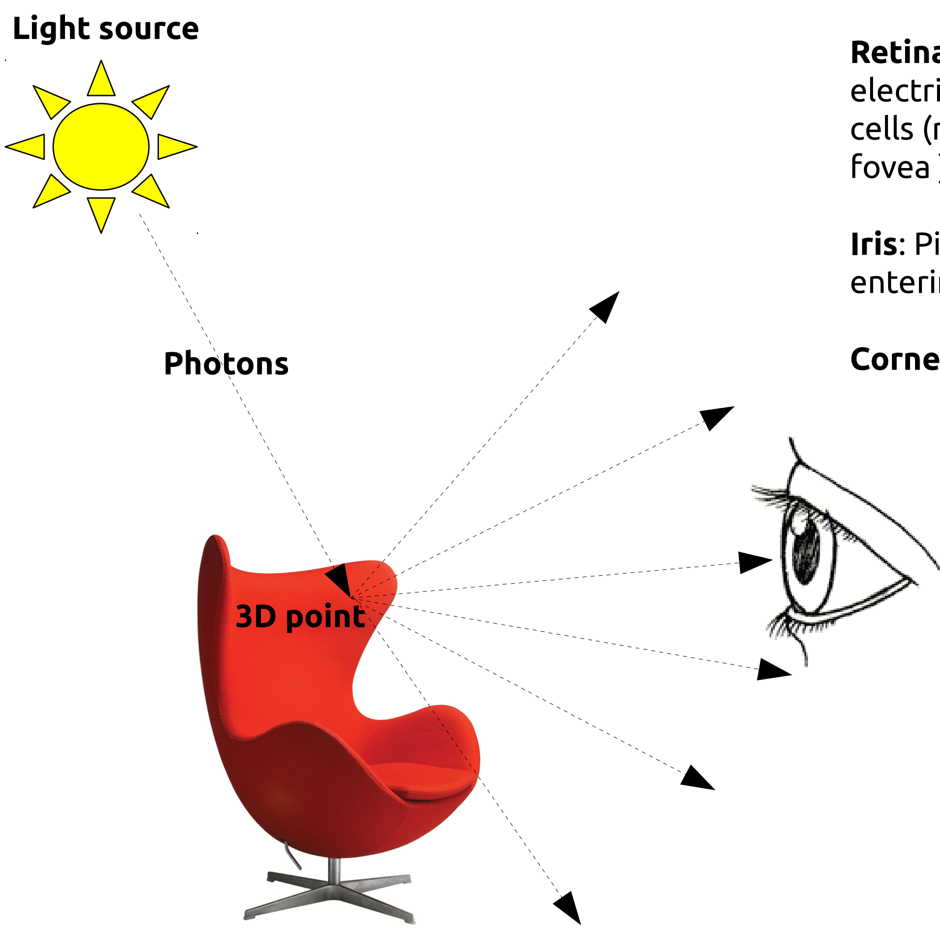
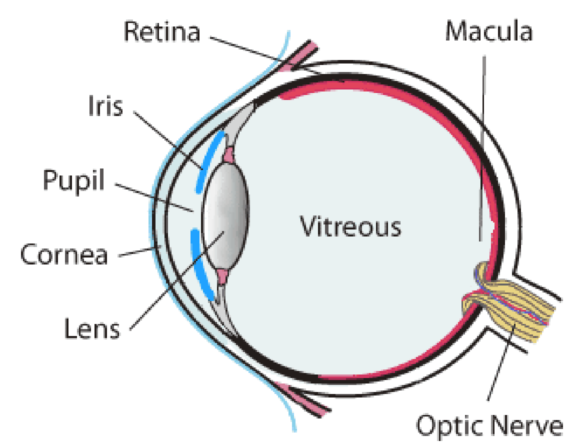
Capturing Light - human eye



Retina: Part of the eye that converts images into electrical impulses, i.e. it includes the photoreceptor cells (rods and cones, the latter densely packed in the fovea)

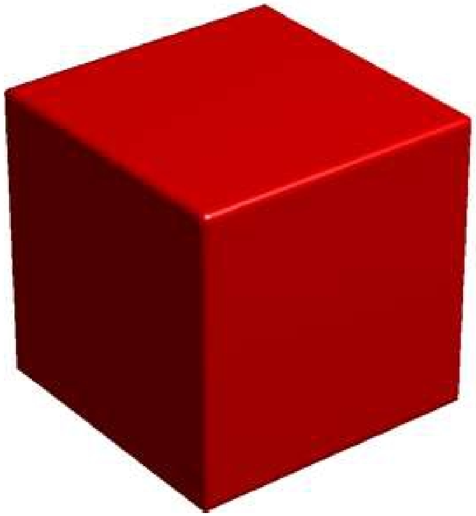
Iris: Pigmented tissue that controls amount of light entering eye by varying size of the **pupil**

Cornea + **Lens**: natural lens of eye



Surface reflectance

Lambertian reflectance: Computer vision algorithms often assume that the color and brightness intensity of a point on a surface does not change with the vantage point

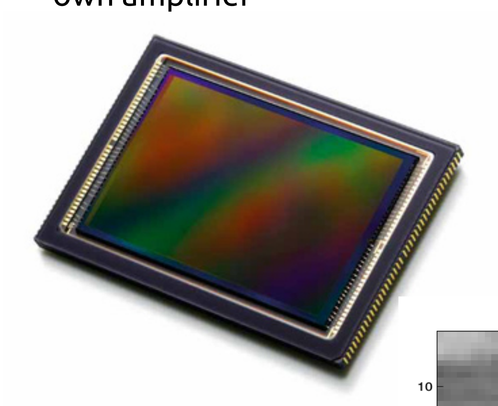


This is **not** true in general! But it is very hard to deal with non-lambertian reflectance...

Capturing Light – digital cameras

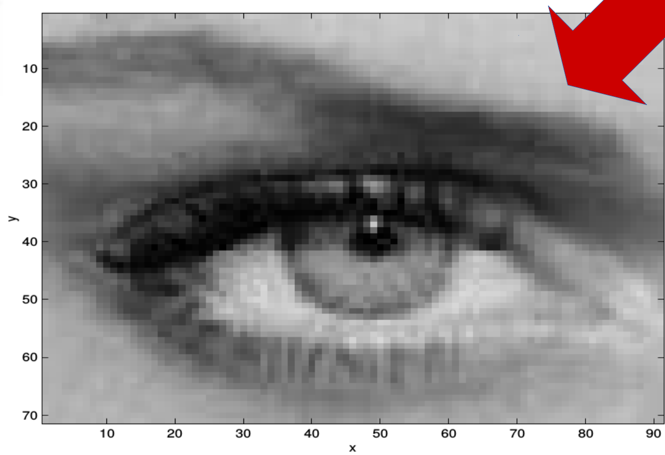
A continuous scene is framed by a discrete array

A CMOS sensor: array of photoreceptors, each sensor has its own amplifier



Provide a a two-dimensional brightness array: the **image**

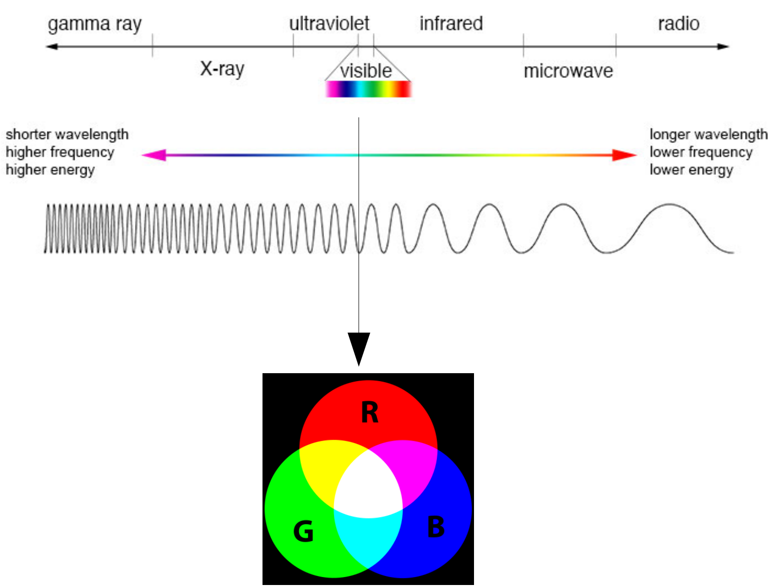
188	186	188	187	168	130	101	99	110	113	112	107	117	140	153	153	156	158	156	153
189	189	188	181	163	135	109	104	113	113	110	109	117	134	147	152	156	163	160	156
190	190	188	176	159	139	115	106	114	123	114	111	119	130	141	154	165	160	156	151
190	188	188	175	158	139	114	103	113	126	112	113	127	133	137	151	165	156	152	145
191	185	189	177	158	138	110	99	112	119	107	115	137	140	135	144	157	163	158	150
193	183	178	164	148	134	118	112	119	117	118	106	122	139	140	152	154	160	155	147
185	181	178	165	149	135	121	116	124	120	122	109	123	139	141	154	156	159	154	147
175	176	176	163	145	131	120	118	125	123	125	112	124	139	142	155	158	158	155	148
170	170	172	159	137	123	116	114	119	122	126	113	123	137	141	156	158	159	157	150
171	171	173	157	131	119	116	113	114	118	125	113	122	135	140	155	156	160	160	152
174	175	176	156	128	120	121	118	113	112	123	114	122	135	141	155	155	158	159	152
176	174	174	151	123	119	126	121	112	108	122	115	123	137	143	156	155	152	155	150
175	169	168	144	117	117	127	122	109	106	122	116	125	139	145	158	156	147	152	148
179	179	180	155	127	121	118	109	107	113	125	133	130	129	139	153	161	148	155	157
176	[illegible]	181	153	122	115	113	106	105	109	123	132	131	131	140	151	157	149	156	159
180	[illegible]	[illegible]	147	115	110	111	107	107	105	120	132	133	133	141	150	154	148	155	157
[illegible]	[illegible]	[illegible]	141	113	111	115	112	113	105	119	130	132	134	144	153	156	148	152	151
[illegible]	[illegible]	[illegible]	140	114	114	118	113	112	107	119	128	130	134	146	157	162	153	153	148
[illegible]	[illegible]	[illegible]	142	114	114	116	110	108	104	116	125	128	134	148	161	165	159	157	149
[illegible]	[illegible]	[illegible]	138	109	110	114	110	109	97	110	121	127	136	150	160	163	158	156	150



A "**picture**" of the image: a picture is different representation of the image, i.e. a scene that produces on the imaging sensor the same image as the original scene.

Perceive colors: the RGB model

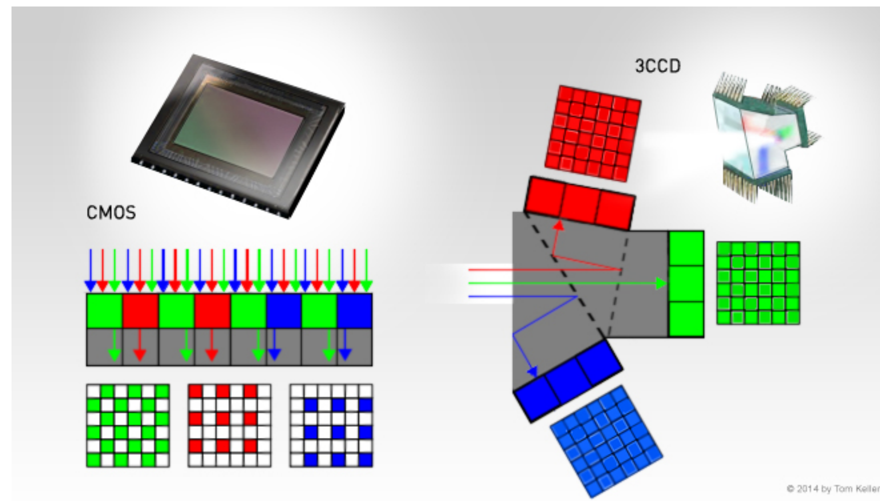
Currently, 3 approaches:



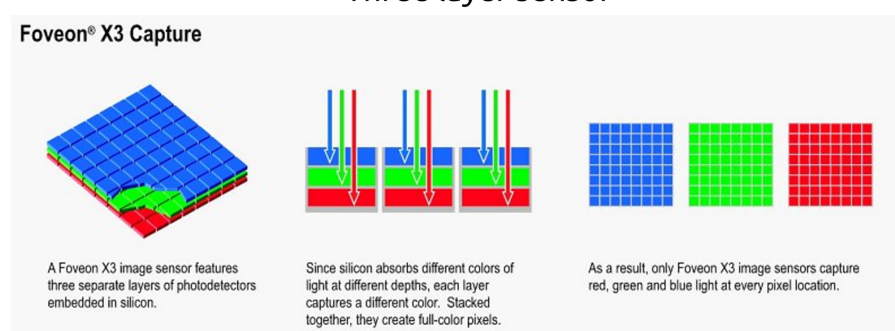
Additive color system: the **RGB model**

Bayer pattern

3 sensors

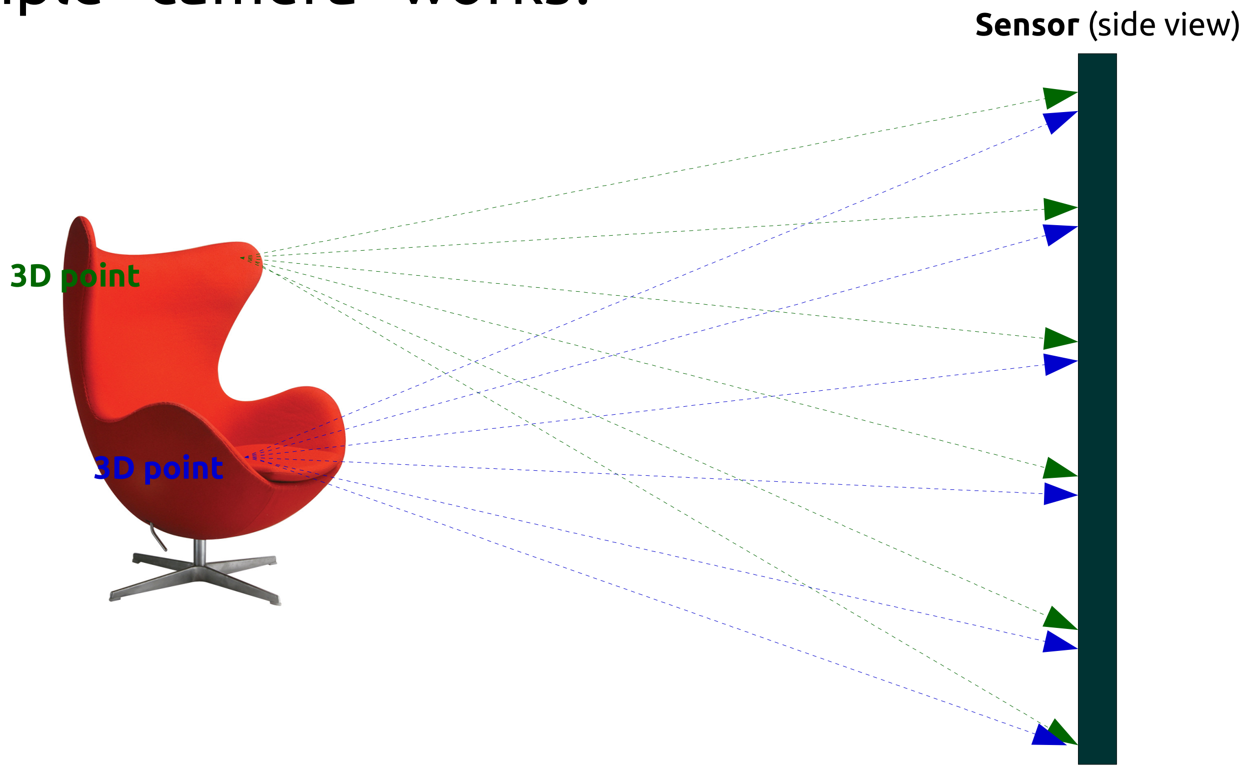


Three layer sensor



Camera model

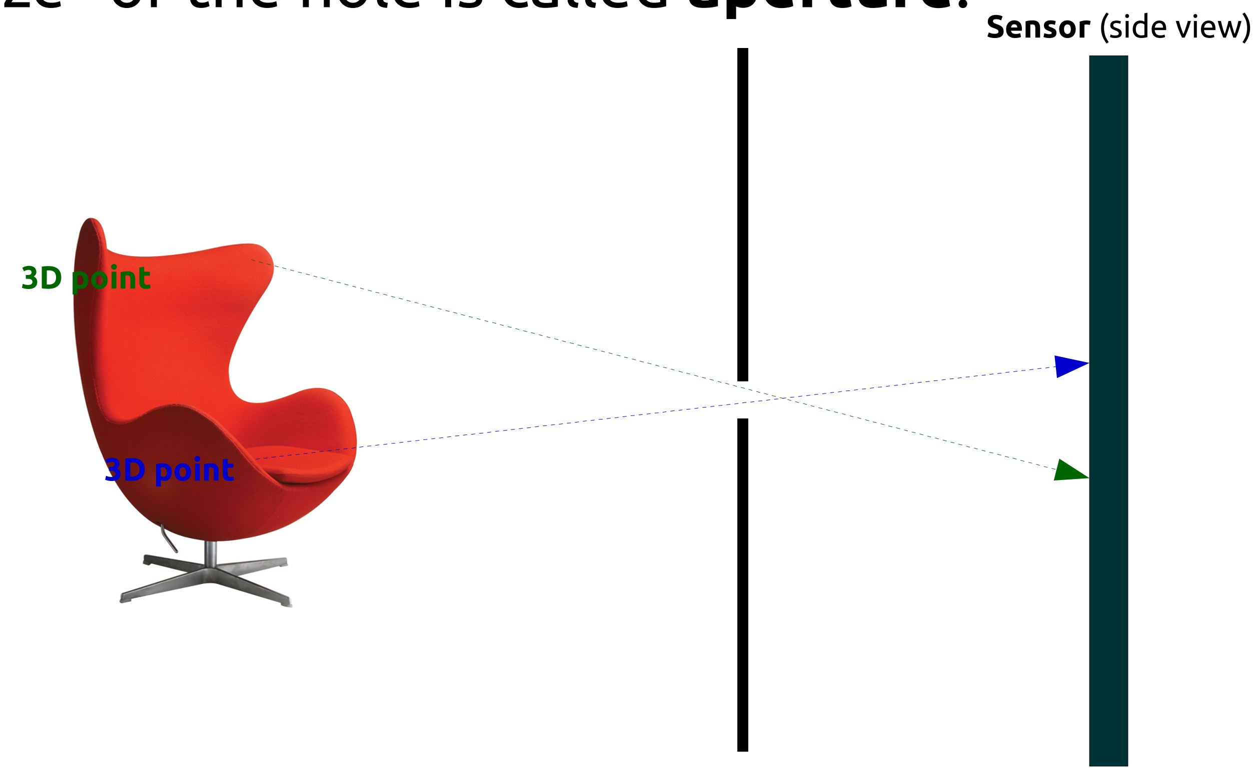
Put the sensor (e.g., the CMOS) in front of an object. Does this simple “camera” works?



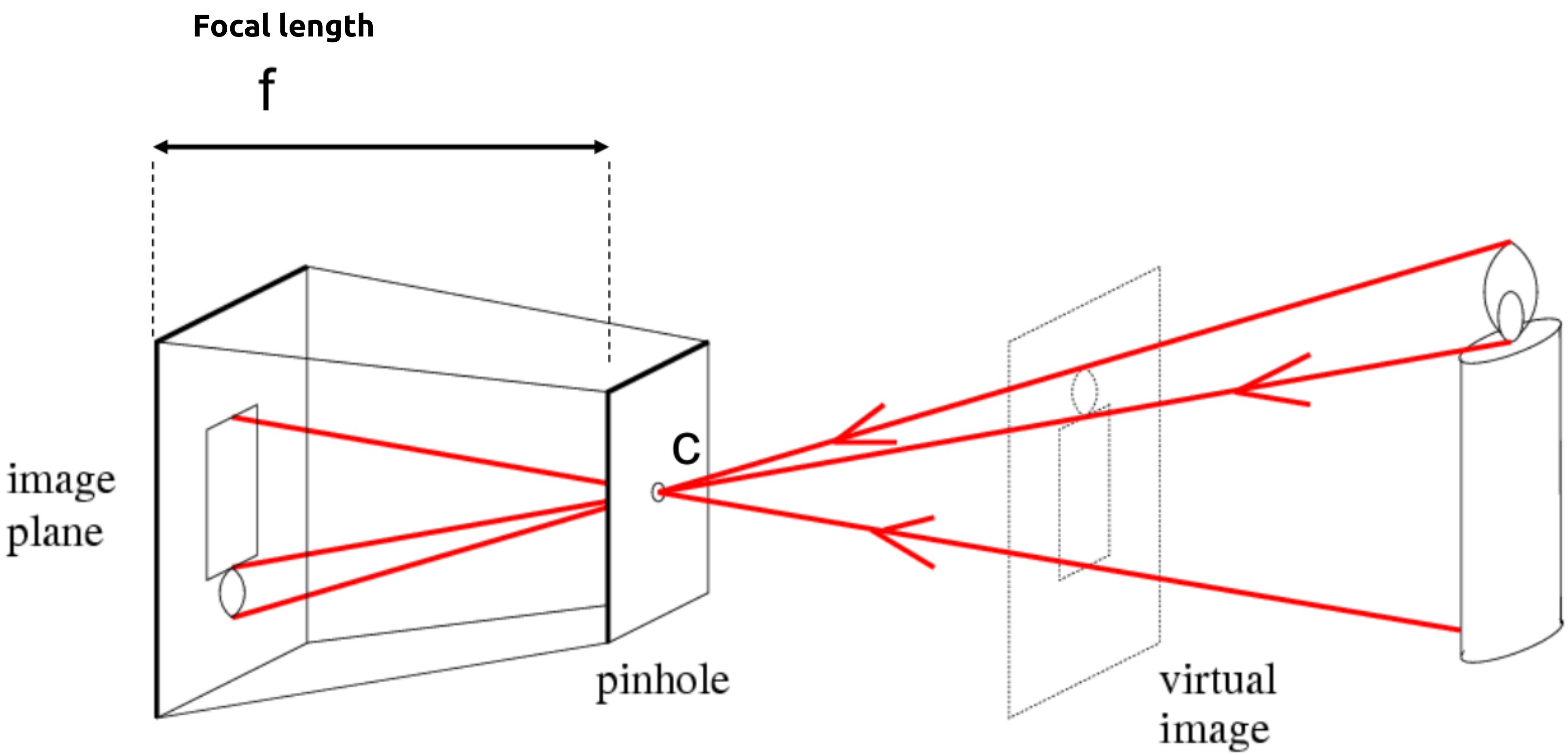
Pinhole camera model (1/2)

Idea: add a barrier to block off most of the rays!

The “size” of the hole is called **aperture**.



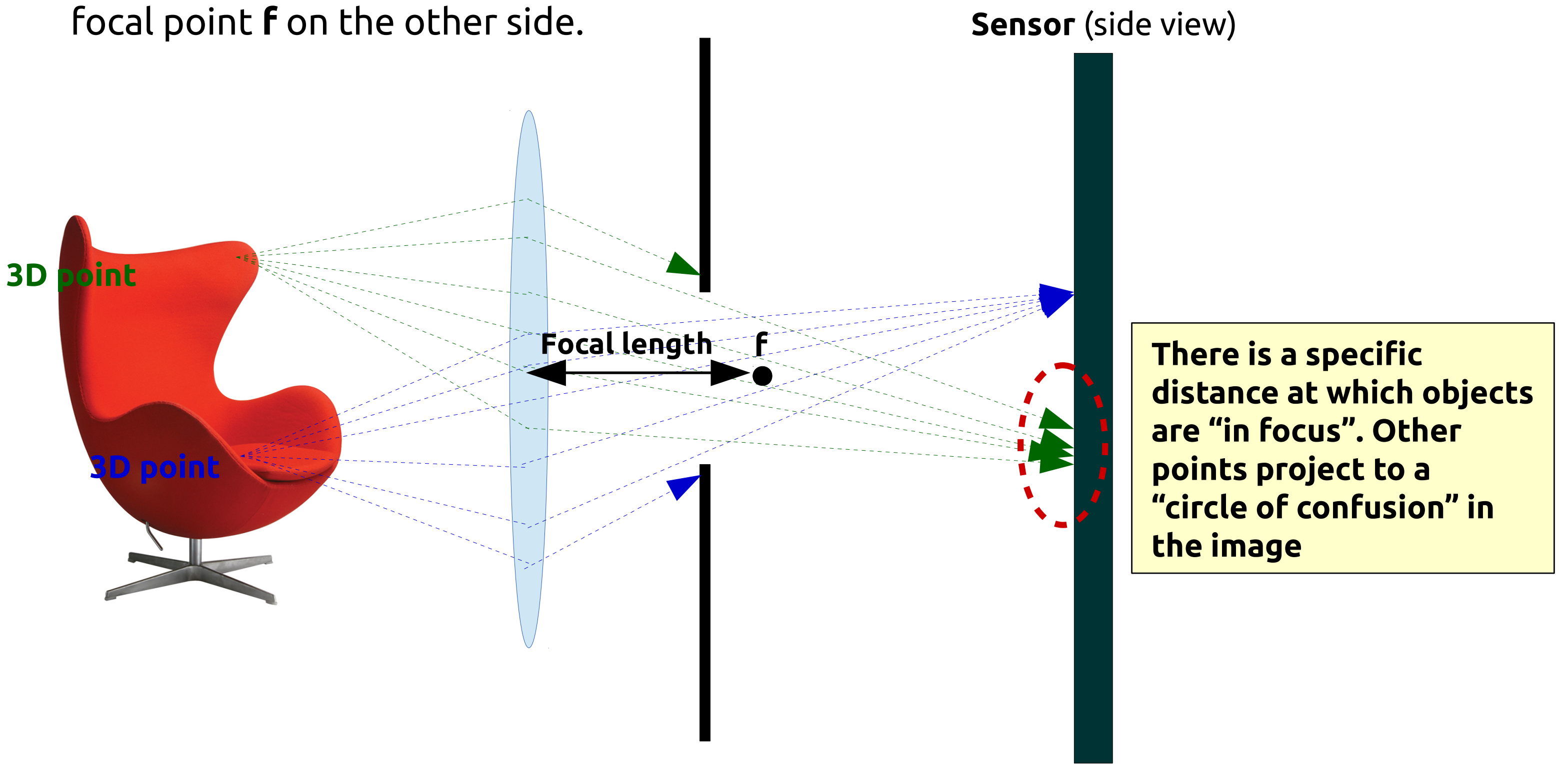
Pinhole camera model (2/2)



Adding a lens to the pinhole camera

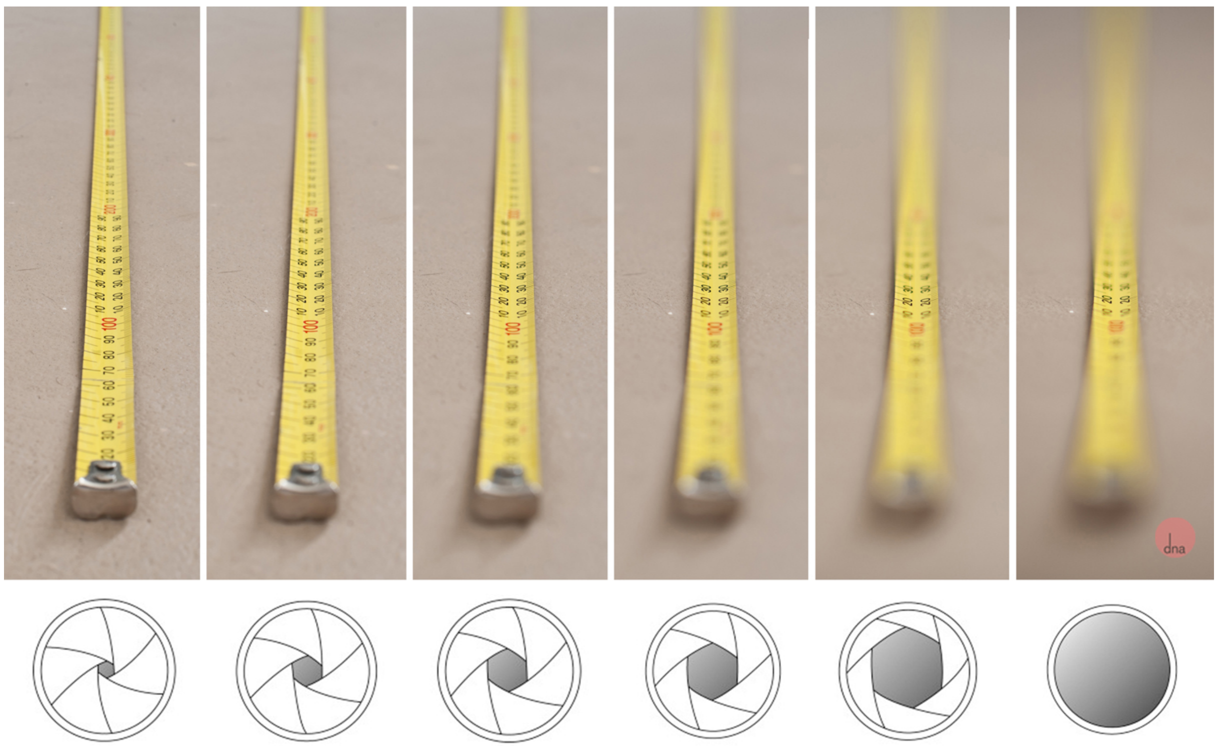
The lens redirect the rays in order to focuses light onto the sensor (**thin lens model**)

- Any ray that passes through the center of the lens will not change its direction
- Any ray that enters parallel to the axis on one side of the lens proceeds towards the focal point **f** on the other side.



Depth of field

DOF: distance between the nearest and farthest objects in a scene that appear acceptably sharp in an image



Decreasing the aperture we get a larger depth of field… but we get a less bright image (i.e., less light collide with the sensor)

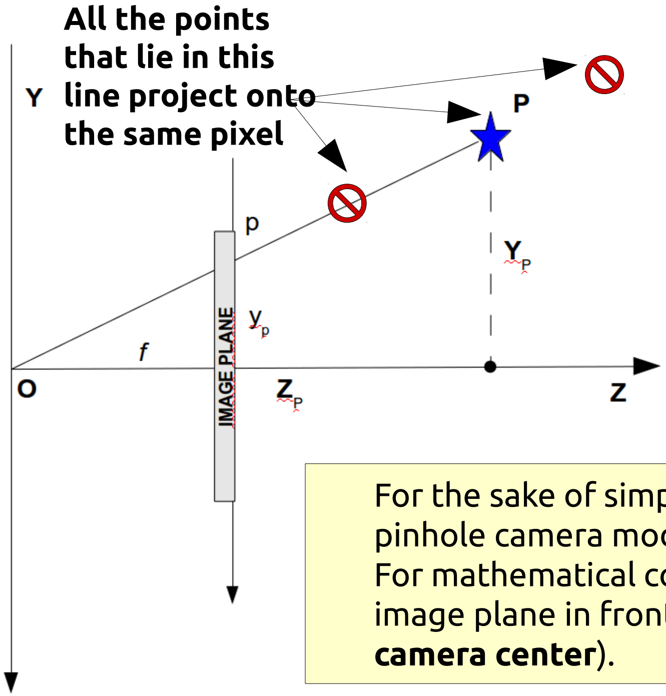
[Picture: www.drawmixpaint.com]

From 3D to 2D

A 3D scene is “projected” on the 2D the image plane

Dimensionality reduction → **the depth (i.e., the z cooridnate) of each point is lost!**

The standard coordinate system of the pinhole camera system seen from the X axis.

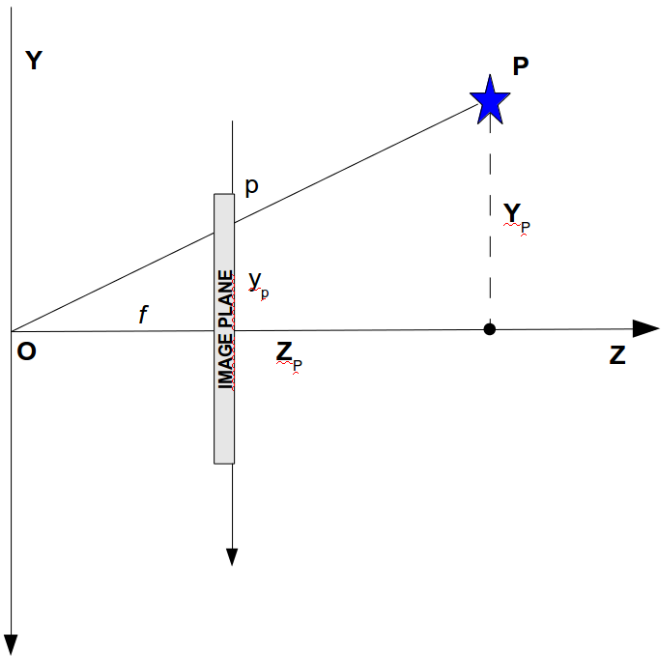


$$x_p = \frac{X_P f}{Z_P} \quad , \quad y_p = \frac{Y_P f}{Z_P}$$

For the sake of simplicity we will use the pinhole camera model.
For mathematical convenience, we put the image plane in front of the focal point (i.e., the **camera center**).

From 3D to 2D (cont.)

Use homogeneous coordinates!



$$x_p = \frac{X_P f}{Z_P} \quad , \quad y_p = \frac{Y_P f}{Z_P}$$

Converting to *homogeneous* coordinates

$$(x, y) \Rightarrow \begin{bmatrix} x \\ y \\ 1 \end{bmatrix}$$

homogeneous image coordinates

$$(x, y, z) \Rightarrow \begin{bmatrix} x \\ y \\ z \\ 1 \end{bmatrix}$$

homogeneous scene coordinates

Converting *from* homogeneous coordinates

$$\begin{bmatrix} x \\ y \\ w \end{bmatrix} \Rightarrow (x/w, y/w)$$

$$\begin{bmatrix} x \\ y \\ z \\ w \end{bmatrix} \Rightarrow (x/w, y/w, z/w)$$

$$\begin{bmatrix} sx \\ sy \\ s \end{bmatrix} = \begin{bmatrix} f & 0 & 0 & 0 \\ 0 & f & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} X_P \\ Y_P \\ Z_P \\ 1 \end{bmatrix}$$

Map to pixels (1/2)

We need to convert an image coordinates from meters to pixels.

Remember that the top left pixel has (0,0) coordinates (i.e., in pixel space, the origin is not the center of the image)

$$u = u_c + \frac{x}{w_p} \quad , \quad v = v_c + \frac{y}{h_p}$$

u_c and v_c are the coordinates of the principal point in pixels and w_p and

h_p are the pixel width and height, respectively.

Map to pixels (2/2)

Using homogeneous coordinates:

Perspective projection matrix

$$\begin{bmatrix} su \\ sv \\ s \end{bmatrix} = \begin{bmatrix} \alpha_u & 0 & u_c & 0 \\ 0 & \alpha_v & v_c & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} X_P \\ Y_P \\ Z_P \\ 1 \end{bmatrix}$$

where $\alpha_u = \frac{f}{w_p}$ and $\alpha_v = \frac{f}{h_p}$

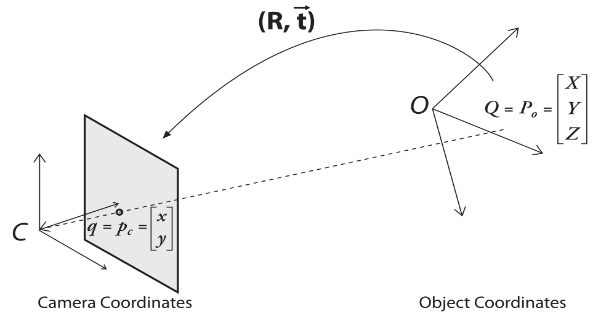
$$\tilde{\mathbf{u}} = \mathbf{A}\tilde{\mathbf{P}}$$

The perspective projection camera contains the **intrinsic parameters** of the camera (i.e., focal length, image sensor format, and principal point). These parameters are not are usually not known in advance, due the inaccuracies in camera assembly. The camera calibration process aims to estimate the intrinsic parameters.

Note: here we are not taking into account the skew factor.

From world to camera

In general, coordinates of a 3D point are not specified in current camera frame (remember that the drone with its camera is moving, while the ground is fixed): 3 points are often specified in a more convenient fixed frame we call here *world frame*.



Before projecting a point onto the image plane, we need to change its coordinates from the world frame to the current camera coordinate system.

3D point in camera coordinates

3D point in world coordinates

3x3 rotation matrix

3x1 translation vector

$$\tilde{\mathbf{P}} = \mathbf{T}\tilde{\mathbf{P}}' \quad , \quad \mathbf{T} = \begin{bmatrix} \mathbf{R} & \mathbf{t} \\ \mathbf{0}_3^T & 1 \end{bmatrix}$$

Putting all together

From world frame to pixels:

$$\tilde{\mathbf{u}} = \mathbf{A}\mathbf{T}\tilde{\mathbf{P}}' = \mathbf{C}\tilde{\mathbf{P}}'$$

Sometimes this equation is rewritten in an alternative way:

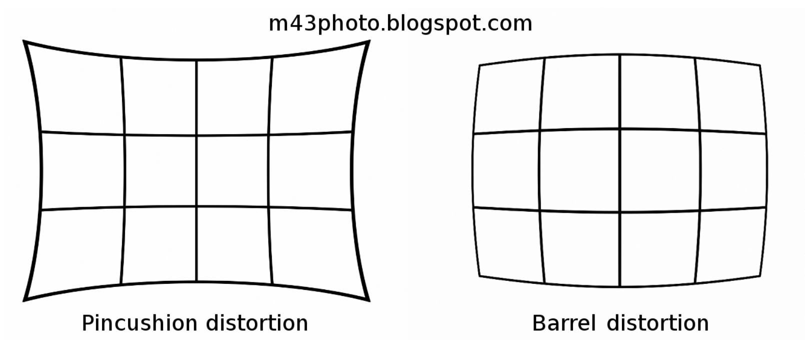
$$\tilde{\mathbf{u}} = \mathbf{K}[\mathbf{R}|\mathbf{t}]\tilde{\mathbf{P}}'$$

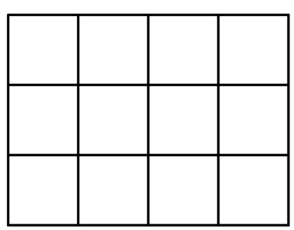
Where **[R|t]** is a 3x4 matrix composed by the rotation matrix followed by the translation vector, and K is a 3 × 3 matrix holding the intrinsic parameters:

$$\mathbf{K} = \begin{bmatrix} \alpha_u & 0 & u_c \\ 0 & \alpha_v & v_c \\ 0 & 0 & 1 \end{bmatrix}$$

Hints on radial distortion

In many cases, like in the wide-angles camera applications, the lens distortion should be taken into account in the perspective projection: distortion is modeled y nonlinear intrinsic parameters.

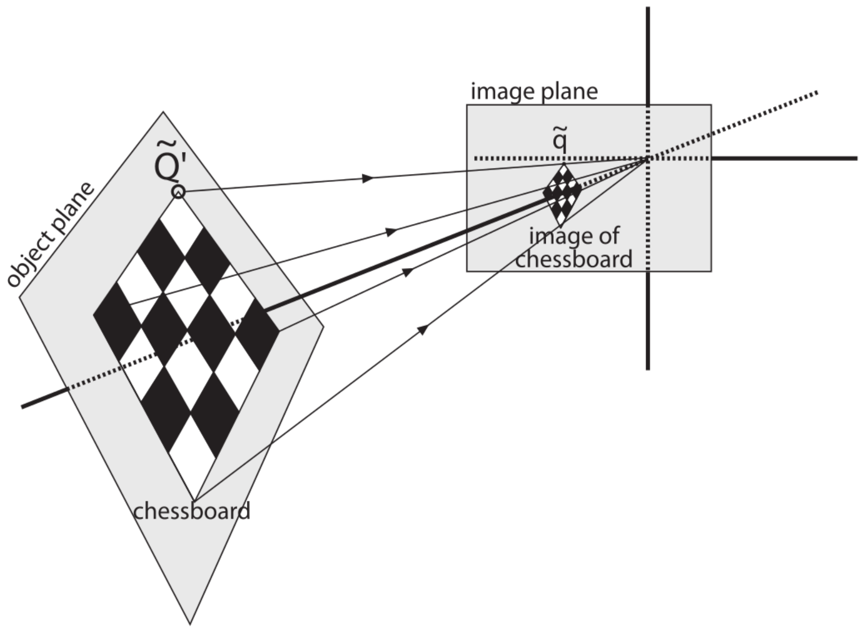




Rectilinear

Hints camera calibration (1/2)

The camera calibration process aims to estimate the camera intrinsic parameters and the radial distortion parameters.



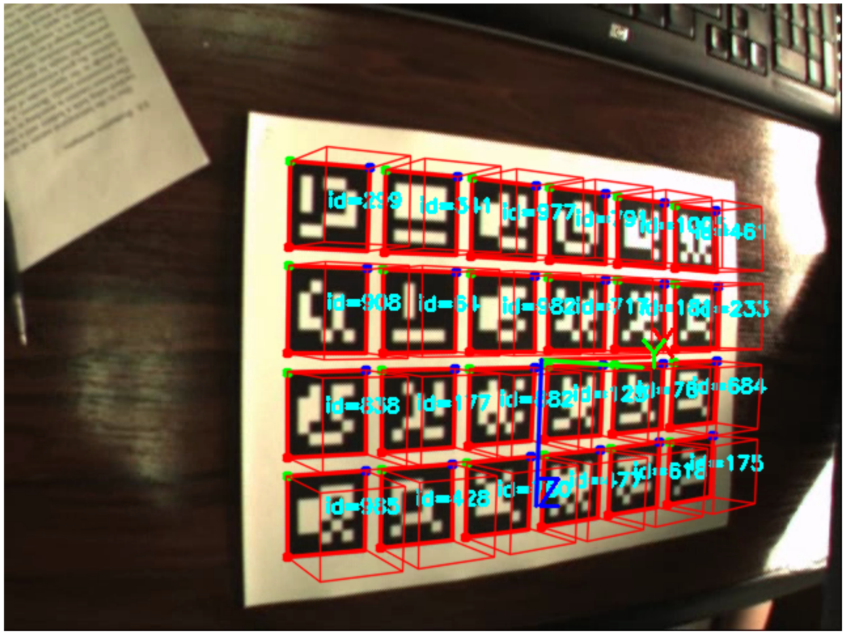
Basic idea of the most popular calibration technique [Zhang00], [Bouguet]:

-Use a known planar pattern (e.g., a cesser board)

-Collect a sequence of images of the pattern in several positions, and extract all corners

-Find the parameters set that minimize the squared distances in the image space, using conventional least square methods (e.g., Levenberg Marquardt)

Hints camera calibration (2/2)



An Augmented Reality (AR) board is a better calibration pattern compared with a checkerboard [Aruco]. An AR board is a marker composed by several markers arranged in a grid. Boards present two main advantages. First, since there have more than one markers, it is less likely to lose them all at the same time. Second, the more markers are detected, the more points are available.

References on calibration:

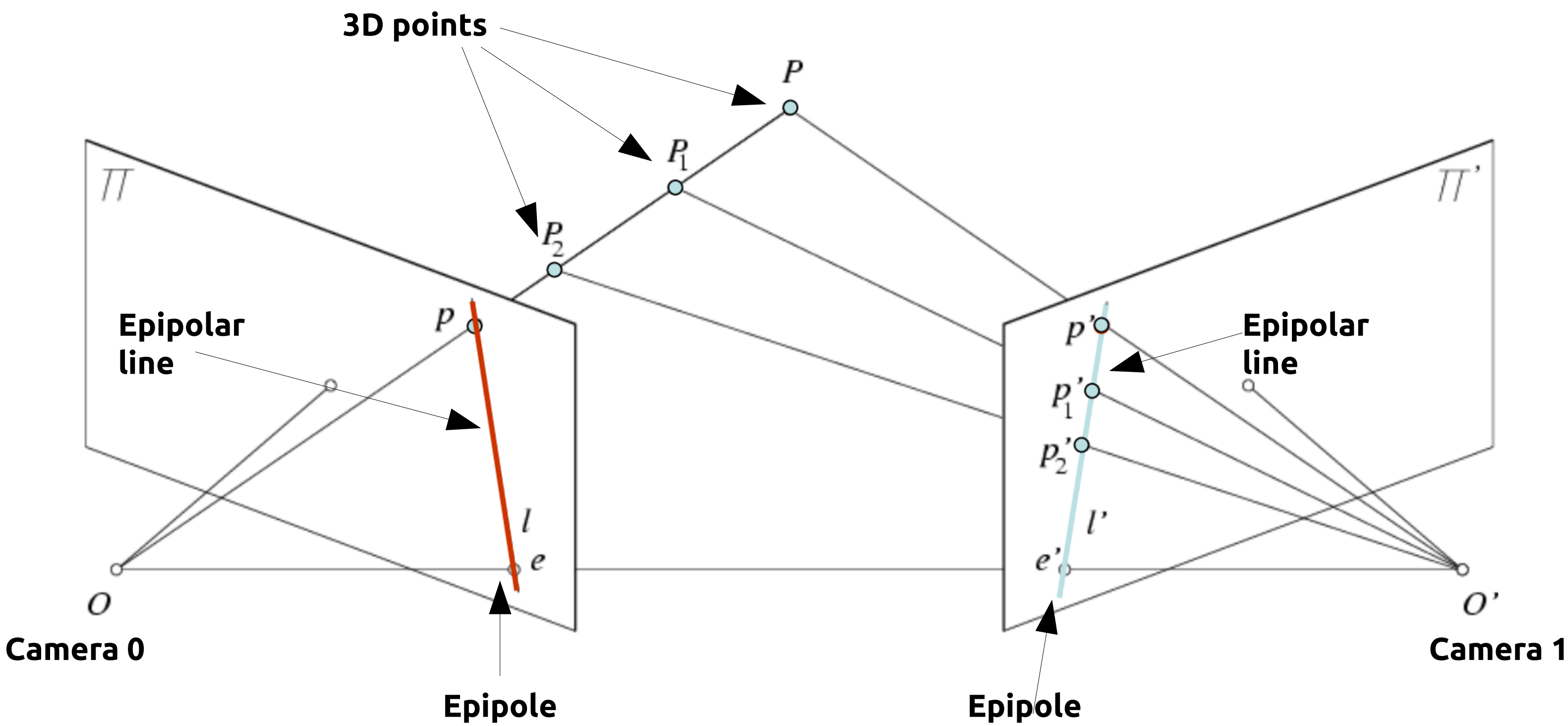
[Zhang00] Z. Zhang, “A flexible new technique for camera calibration,” IEEE Transactions on Pattern Analysis and Machine Intelligence 22 (2000): 1330–1334

[Bouguet] http://www.vision.caltech.edu/bouguetj/calib_doc/

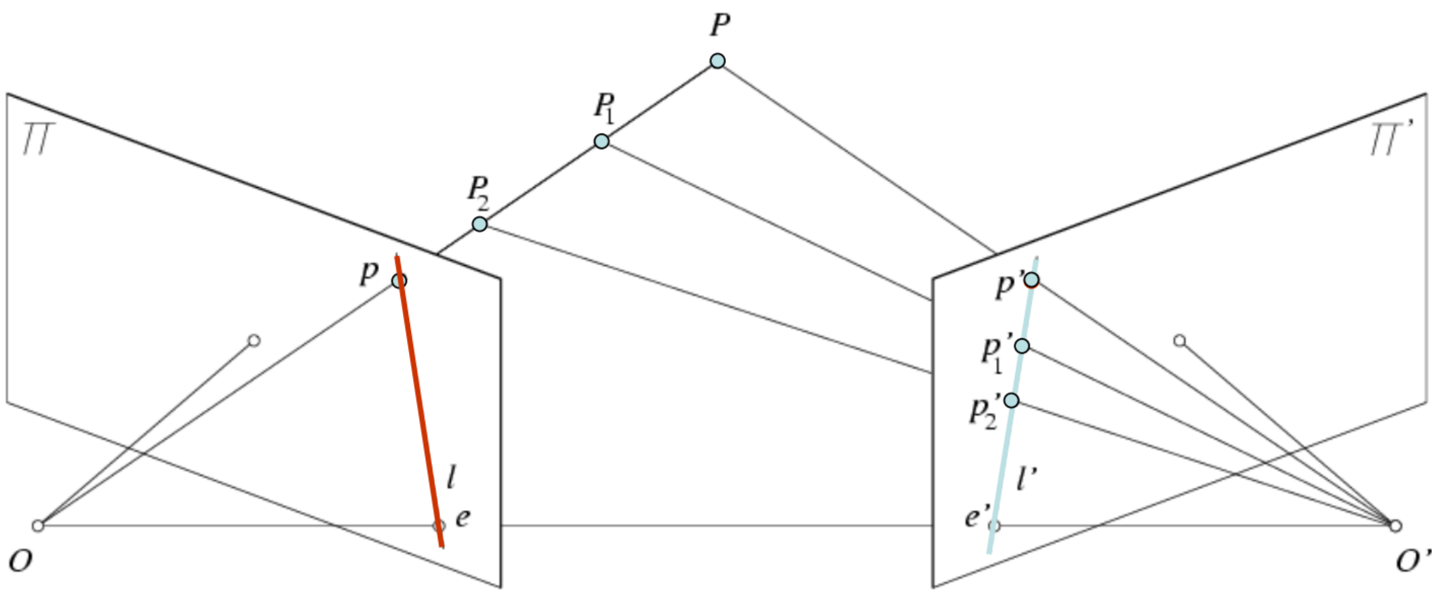
[Aruco] http://www.uco.es/investiga/grupos/ava/node/26

Epipolar constraint (1/3)

When using more than one camera:



Epipolar constraint (2/3)



Mapping from p’ to l: $$l = t \times Rp' = [t]_\times R \cdot p' = E \cdot p'$$

E is a 3x3, 5 DOF matrix

Epipolar constraint $\Rightarrow$ $$p^T E p' = 0$$

Epipolar constraint (3/3)

Reduces the correspondence problem to a 1D search in the second image along an epipolar line

[Source: Andrew Zisserman]

Image filtering

Compute function of local neighborhood at each position

Really important:

- Enhance images (de-noise, resize, increase contrast, etc...)
- Extract information from images (texture, edges, distinctive points, etc...)
- Detect patterns

Image filters in spatial domain: modify the pixels in an image based on some function of a local neighborhood of the pixels

- Filter is a mathematical operation of a grid of numbers
- Smoothing, sharpening, measuring texture

Linear filtering

Linear case is simplest and most useful

- Replace each pixel with a linear combination of its neighbors.

The prescription for the linear combination is sometimes called the “convolution kernel” (even if linear filtering uses correlation).

For symmetrical kernel, there's no difference between correlation and convolution.

10	5	3
4	5	1
1	1	7

$\otimes$

0	0	0
0	0.5	0
0	1.0	0.5

kernel

$=$

	7	

Example: box (mean) filter

Simple method for reducing noise in an image

Convolution kernel

$$g[\cdot,\cdot] = \frac{1}{9}\begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix}$$

Filtered image

Input image

$$h[m,n] = \sum_{k,l} g[k,l]\, f[m+k, n+l]$$

Example: box (mean) filter

$f[.,.]$

0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	90	0	90	90	90	0	0
0	0	0	90	90	90	90	90	0	0
0	0	0	0	0	0	0	0	0	0
0	0	90	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0

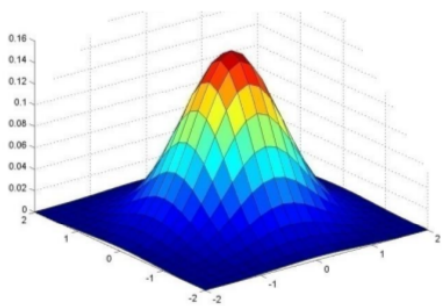
$h[.,.]$

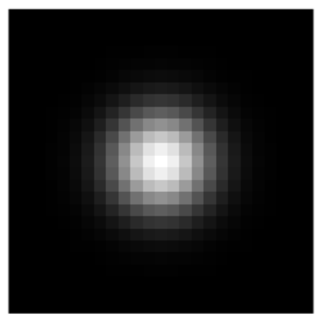
	0	10	20	30	30	30	20	10	
	0	20	40	60	60	60	40	20	
	0	30	60	90	90	90	60	30	
	0	30	50	80	80	90	60	30	
	0	30	50	80	80	90	60	30	
	0	20	30	50	50	60	40	20	
	10	20	30	30	30	30	20	10	
	10	10	10	0	0	0	0	0	

Gaussian Smoothing (1/2)

A better way to reduce noise and details from an image is to employ a Gaussian filter → **it removes the "high-frequency" components from the image** (low-pass filter)

Weight contributions of neighboring pixels by nearness:



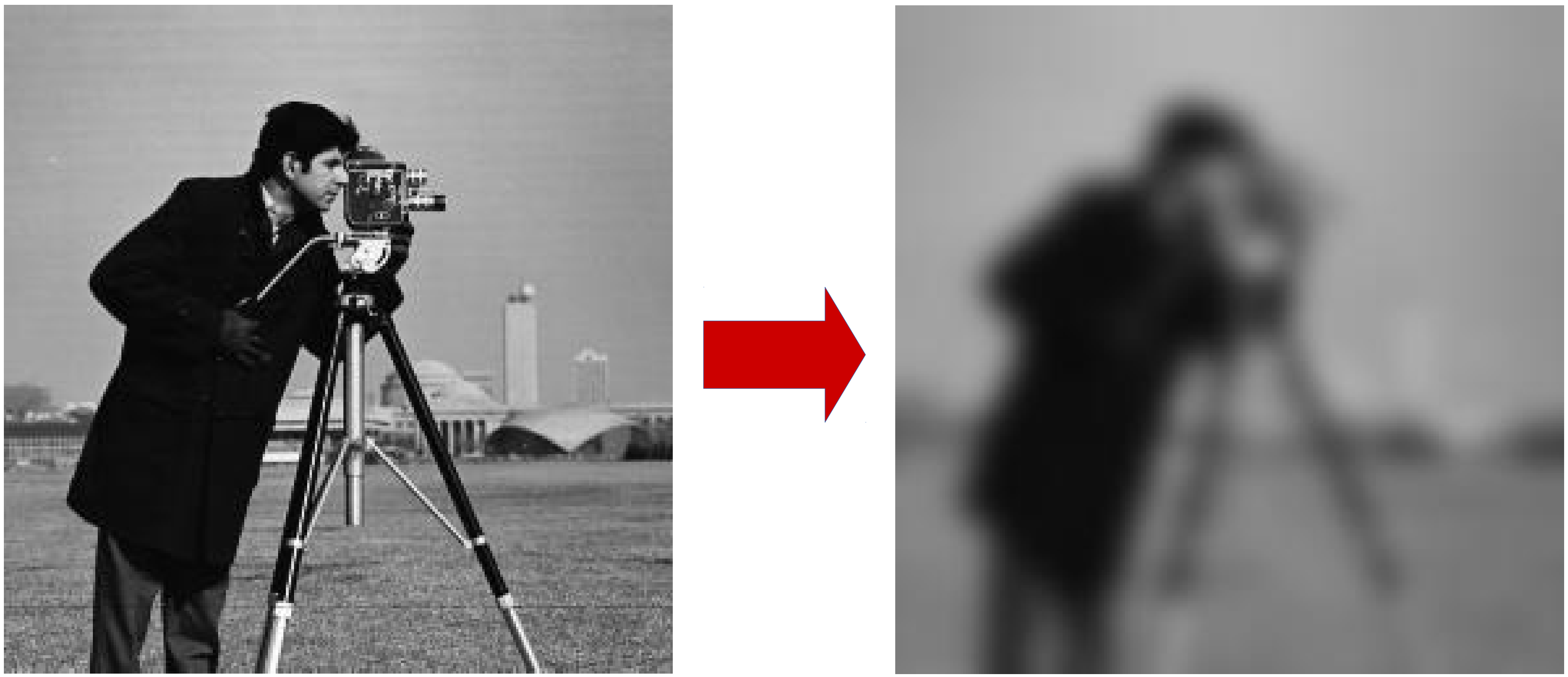


0.003	0.013	0.022	0.013	0.003
0.013	0.059	0.097	0.059	0.013
0.022	0.097	0.159	0.097	0.022
0.013	0.059	0.097	0.059	0.013
0.003	0.013	0.022	0.013	0.003

5 x 5, $\sigma = 1$

$$G_\sigma = \frac{1}{2\pi\sigma^2} e^{-\frac{(x^2+y^2)}{2\sigma^2}}$$

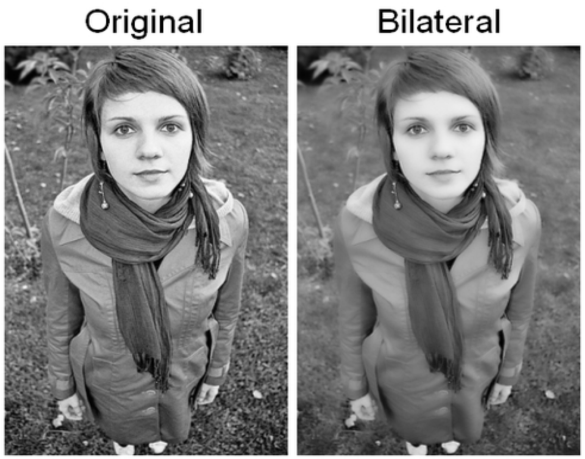
Gaussian Smoothing (2/2)



Bilateral Filter (1/2)

Non-linear, edge-preserving and noise-reducing filter

Is basically a modified Gaussian filter that takes into account also the difference in the intensity domain.



[Tomasi98] Carlo Tomasi, Roberto Manduchi, "Bilateral Filtering for Gray and Color Images", Proceedings of the ICCV 1998

Bilateral Filter (2/2)

Gaussian Blur

$$I^{\mathrm{b}}_{\mathbf{p}} = \sum_{\mathbf{q}\in\mathcal{S}} \boxed{G_{\sigma_{\mathrm{s}}}(\|\mathbf{p}-\mathbf{q}\|)}\, I_{\mathbf{q}}$$

space

Bilateral filter

$$I^{\mathrm{bf}}_{\mathbf{p}} = \boxed{\frac{1}{W^{\mathrm{bf}}_{\mathbf{p}}}} \sum_{\mathbf{q}\in\mathcal{S}} \boxed{G_{\sigma_{\mathrm{s}}}(\|\mathbf{p}-\mathbf{q}\|)}\, \boxed{G_{\sigma_{\mathrm{r}}}(|I_{\mathbf{p}}-I_{\mathbf{q}}|)}\, I_{\mathbf{q}}$$

space **intensity**

normalization

Edge detection

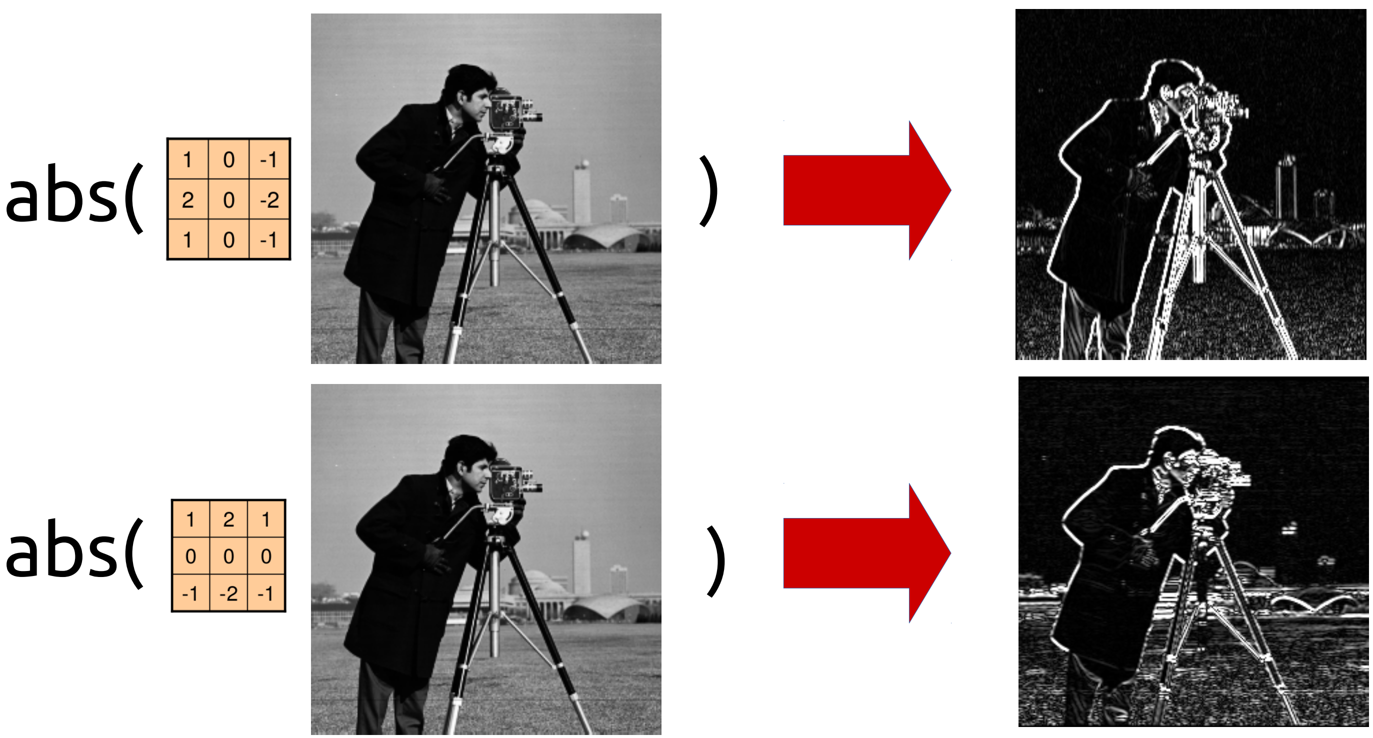
Edges are very simple but informative part of the image

Replace image with a binary "edge map"that highlights all the borders in the image

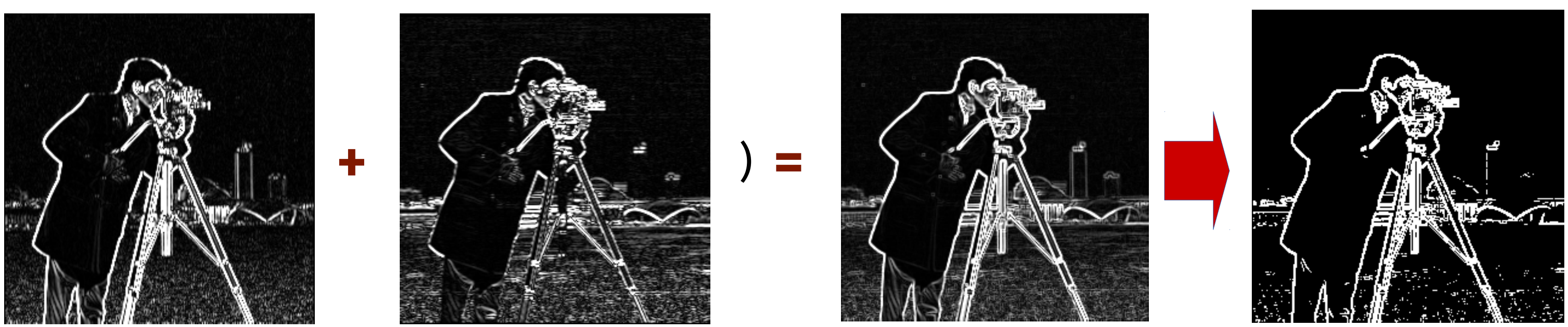
Sobel Operator

The Sobel operator is used to compute the 2D spatial derivatives of an image: higher gradient measurement emphasizes regions of high spatial frequency that correspond to edges.



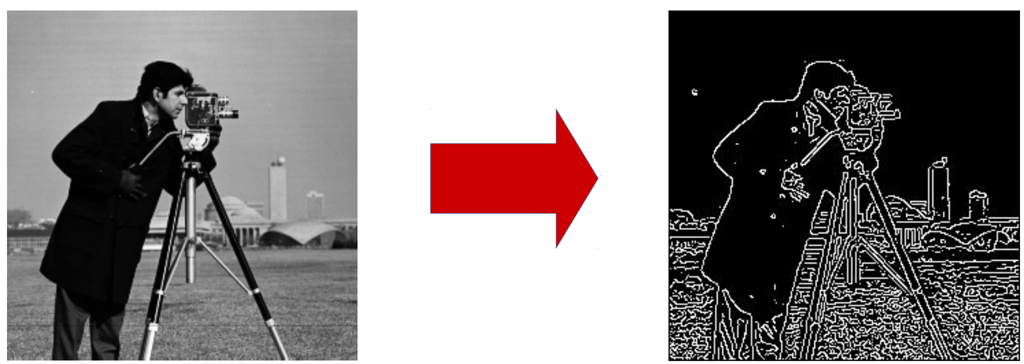
Sobel Operator

Typically it is used to find the approximate absolute gradient magnitude at each point → **edges**



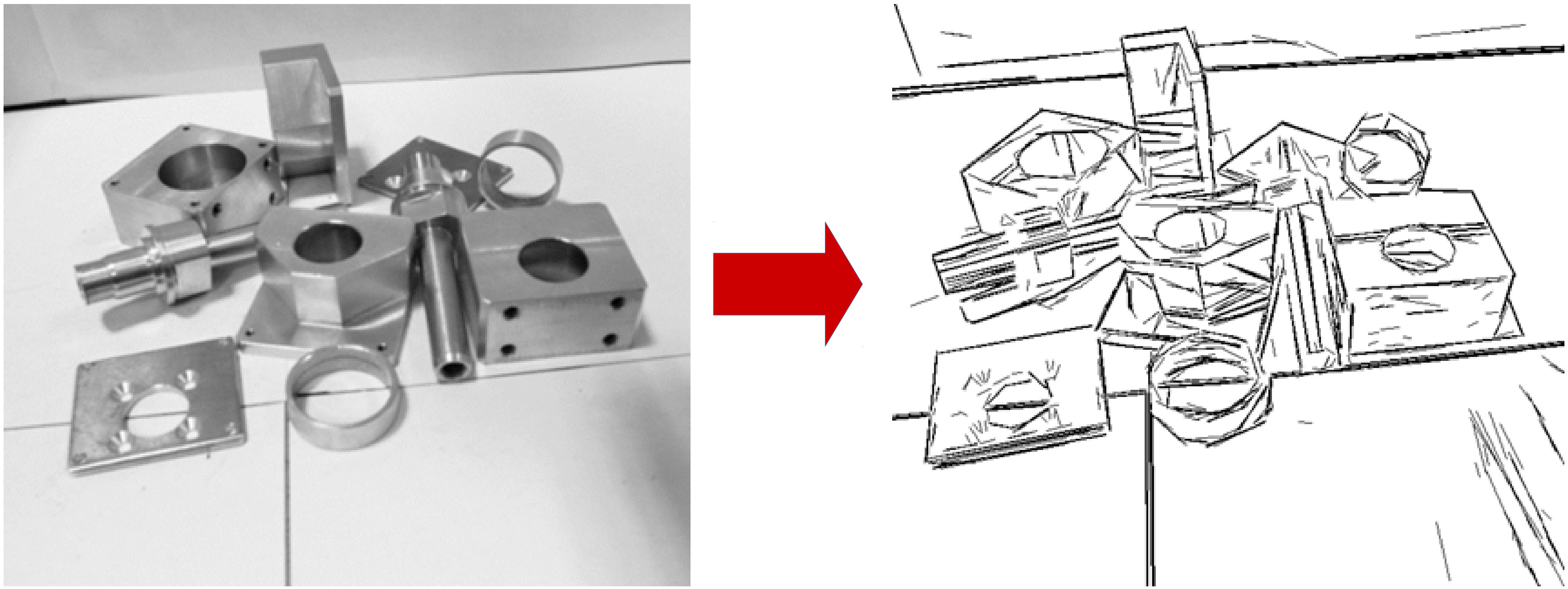
Hints on the Canny edge detector

- Edge localized using an operator very similar to the derivative of a Gaussian
- Non-maximum suppression - remove edges orthogonal to a maxima
- Hysteresis thresholding - Improved recovery of long image contours



[Canny86] J Canny, “A computational approach to edge detection”, Pattern Analysis and Machine Intelligence, IEEE Transactions on, 679-698

LSD - Line Segments Detector



[VonGioi2010] Von Gioi, R. Grompone, et al. LSD: A fast line segment detector with a false detection control, IEEE Transactions on Pattern Analysis and Machine Intelligence 32.4 (2010): 722-732.

Feature Detection

A feature (also called keypoint) can be defined as a meaningful, detectable parts of the image

- Corners, blobs, stable regions

Used to match points in different images

Feature should be repeatable and distinctive

- **Distinctive** : features should be easily matched between them
- **Robust** to noise, blur, discretization, compression
- **Repeatable**

SIFT – Scale Invariant Features

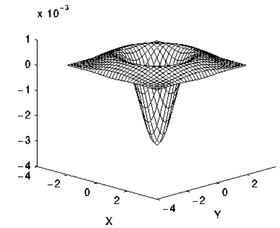
Scale-invariant feature transform (SIFT) is a very popular method to **detect** and to **describe** visual features (i.e., provide also a *signature* for each feature).

Enable very robust **features matching** also in presence of changing in scale (i.e., depth) and rotation around the optical axis (the x-axis).

[SIFT] Lowe, D. G., “Distinctive Image Features from Scale-Invariant Keypoints”, International Journal of Computer Vision, 60, 2, pp. 91-110, 2004.

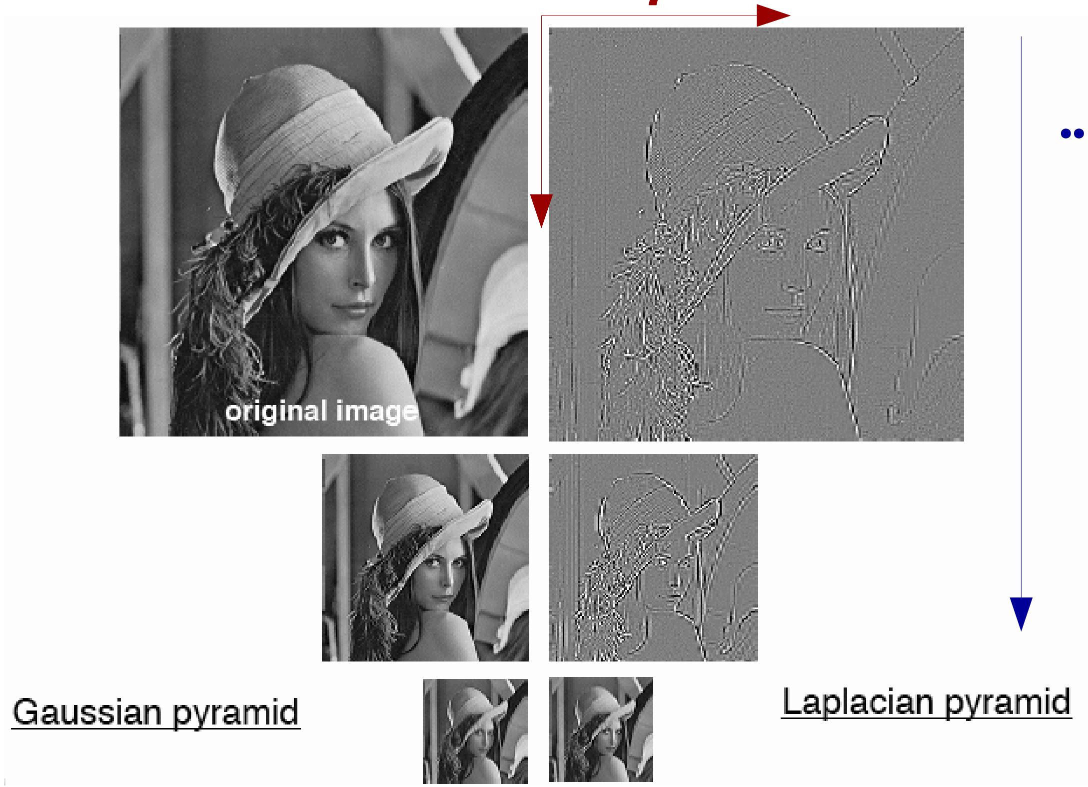
Hints on SIFT (1/3)

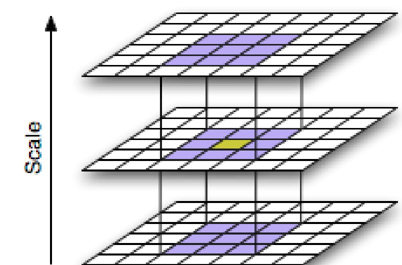
Detect features using a Laplacian of Gaussian fiter



In *space* ...

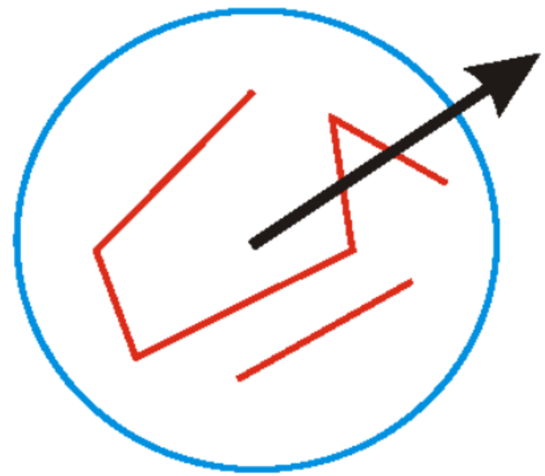
.. but also in *scale*





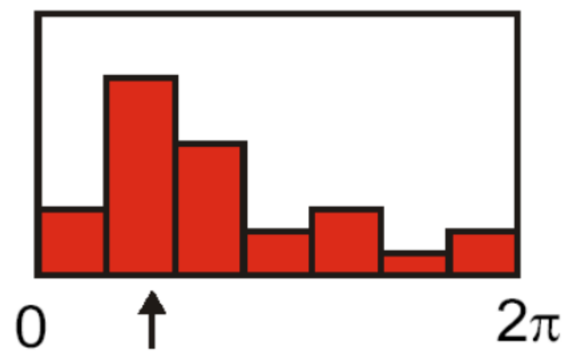
Hints on SIFT (2/3)

Assign an orientation to each detected point:



Compute gradient magnitude and gradient orientation of the image at each scale.

For each point, create a histogram of local (i.e., inside a patch surrounding the point) **quantized** gradient directions at selected scale

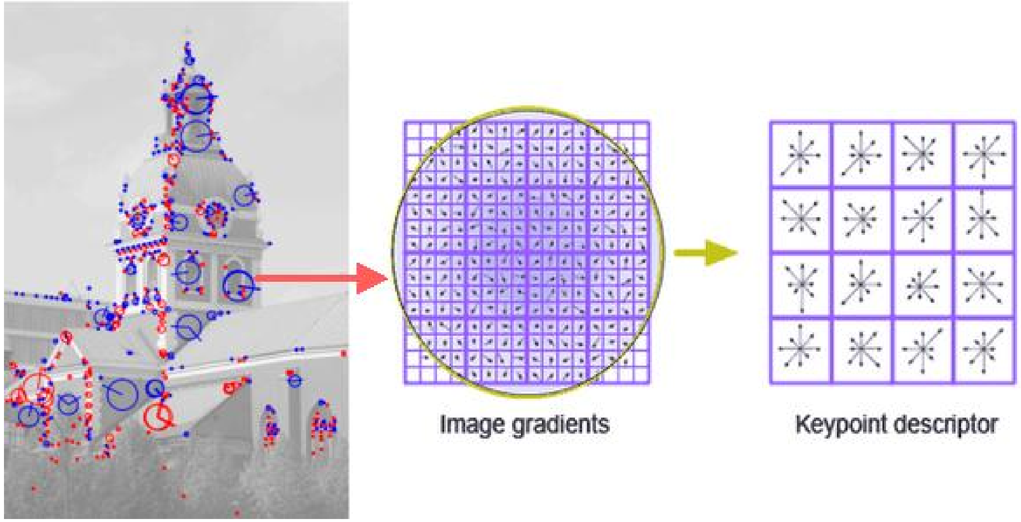


Hints on SIFT (3/3)

For each point, define a patch that is rotated to the estimated orientation orientation.

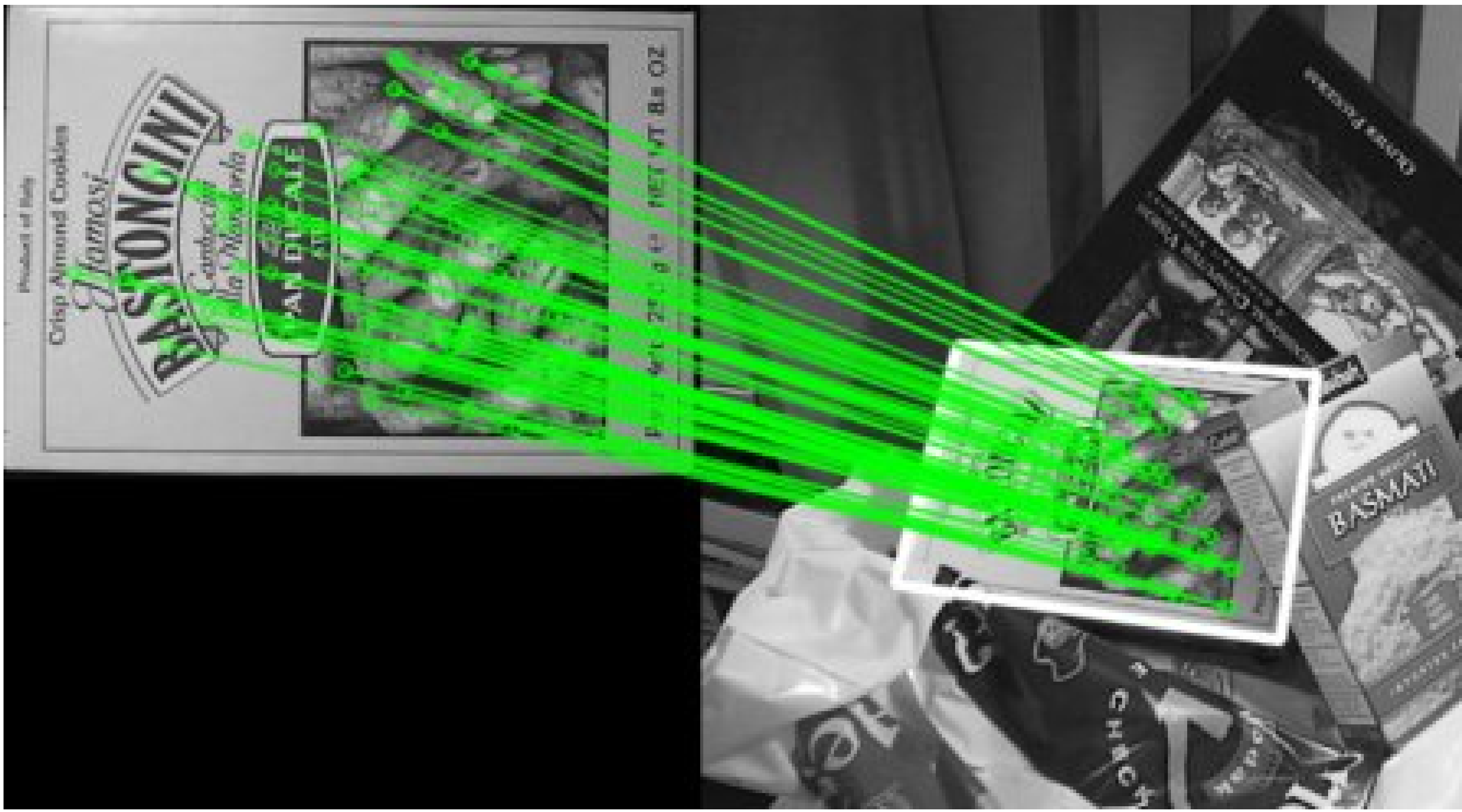
Compute gradient magnitude and orientation at each point in the patch.

Create a normalized orientation histogram over the 4 X 4 subregions of the window → the SIFT descriptor



Feaures matching with SIFT

Simply use a nearest neighbor search



Other Features

FAST detector

E. Rosten, T. Drummond "Machine Learning for High-speed Corner Detection", ECCV 2006

SURF - Speeded Up Robust Feature

Herbert Bay, Tinne Tuytelaars, Luc Van Gool, "SURF: Speeded Up Robust Features", ECCV 2006

BRISK - Binary Robust Invariant Scalable Keypoints

Stefan Leutenegger, Margarita Chli and Roland Siegwart: BRISK: Binary Robust Invariant Scalable Keypoints. ICCV 2011: 2548-2555.

ORB - oriented BRIEF

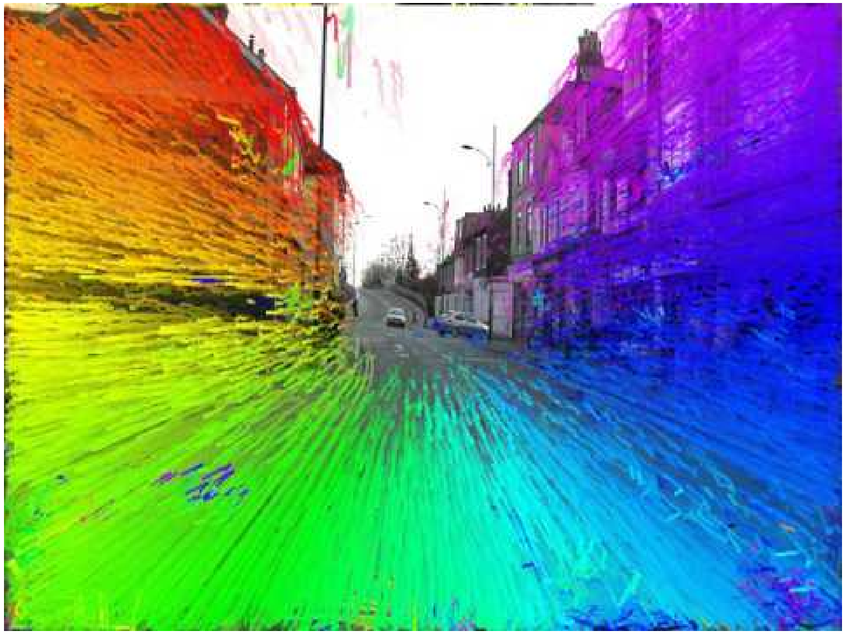
Ethan Rublee, Vincent Rabaud, Kurt Konolige, Gary R. Bradski: ORB: An efficient alternative to SIFT or SURF. ICCV 2011: 2564-2571.

...

Optical flow

Optical flow: two-dimensional apparent motion field of two consecutive images in an image sequence.

Whenever a camera records a scene over time, the resulting image sequence can be considered as a function I (x, y, t) of the gray value at image pixel position x = (x, y) and time t.



Brightness Constancy Equation

$$I(x,y,t-1) = I(x+u(x,y), y+v(x,y), t)$$

Linearizing right hand side using Taylor expansion:

$$I(x+u, y+v, t) \approx I(x, y, t-1) + I_x \cdot u(x,y) + I_y \cdot v(x,y) + I_t$$

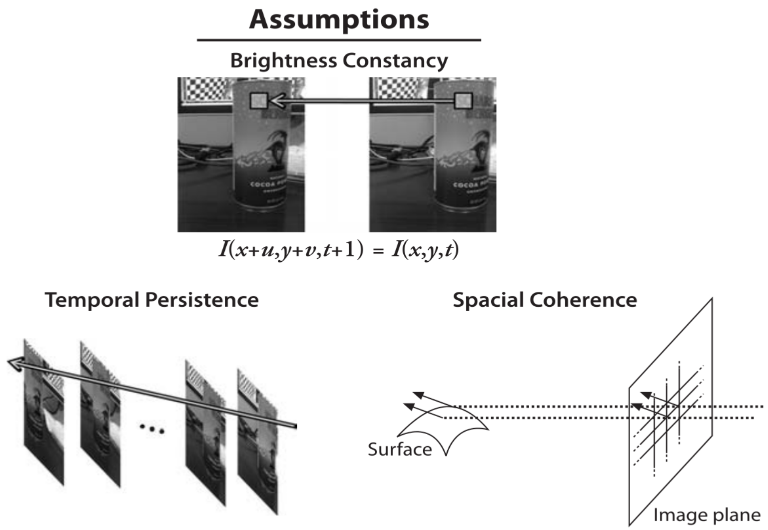
$$I(x+u, y+v, t) - I(x, y, t-1) = I_x \cdot u(x,y) + I_y \cdot v(x,y) + I_t$$

$$\Rightarrow \quad I_x \cdot u + I_y \cdot v + I_t \approx 0$$

Hints on L-K Method (1/2)

Lucas–Kanade is a *local* method: selected features are tracked over time and their movement is converted into velocity vectors.

The **Lucas-Kanade** (**LK**) algorithm is usually used to perform **sparse** optical-flow.



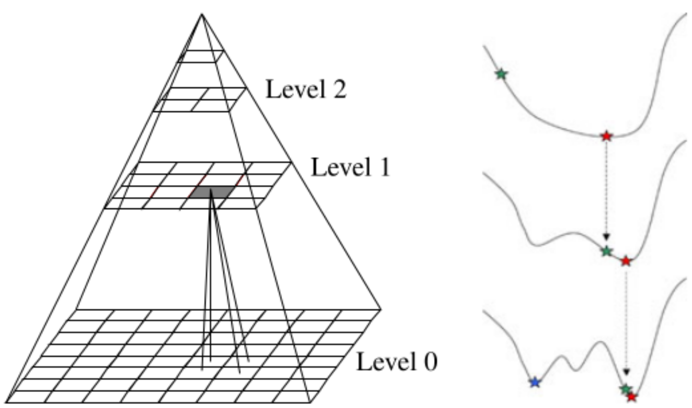
[LK] B. D. Lucas and T. Kanade (1981), An iterative image registration technique with an application to stereo vision. Proceedings of Imaging Understanding Workshop, pages 121--130

Hints on L-K Method (2/2)

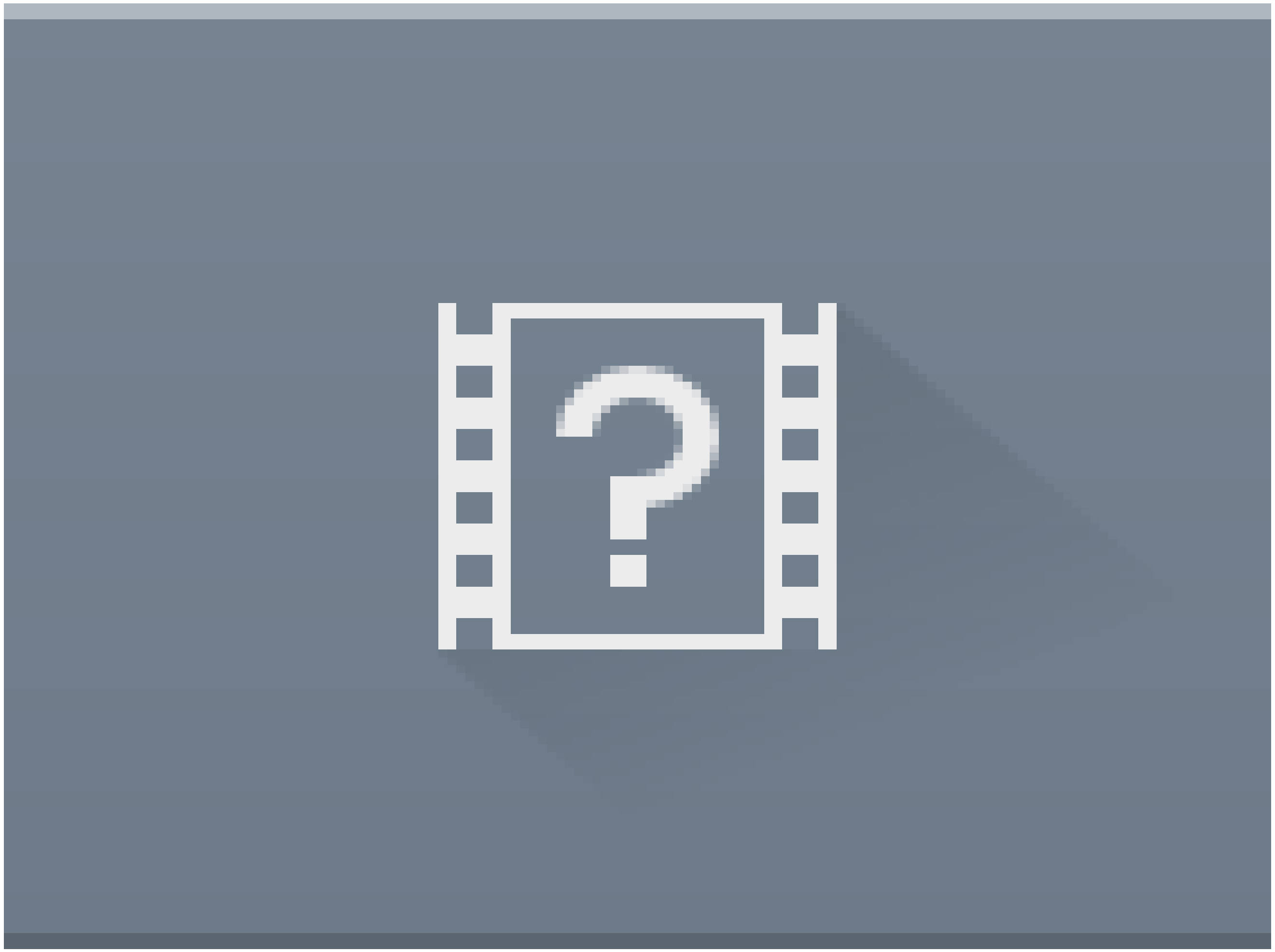
L-K method minimize the sum of quadratic deviations of the brightness constancy equation in a neighborhood *N* of each feature x

$$\min_{u,v} \left\{ \sum_{\mathbf{x}' \in \mathcal{N}(\mathbf{x})} \left(I_t(\mathbf{x}') + I_x(\mathbf{x}')u + I_y(\mathbf{x}')v \right)^2 \right\}.$$

In order to deal with large displacement optical flow, image pyramids are usually used by solving for low frequency structures in low resolution images first and refining the search on higher resolved images.



Pyramid L-K example



The real frame rate is 4X

Dense optical flow (1/2)

Variational method [Horn and Schunck, 1981]: variational approaches → penalizing the derivative of the optical flow field.

$$\min_{u(\mathbf{x}),v(\mathbf{x})} \left\{ \int_{\Omega} \left(|\nabla u(\mathbf{x})|^2 + |\nabla v(\mathbf{x})|^2 \right) \mathrm{d}\Omega + \lambda \int_{\Omega} \left(I_t + I_x u(\mathbf{x}) + I_y v(\mathbf{x}) \right)^2 \mathrm{d}\Omega \right\}.$$

Regularization term

Variational optical flow approaches compute the optical flow field for all pixels within the image.

[Horn and Schunck, 1981] B.K.P. Horn and B.G. Schunck, "Determining optical flow." Artificial Intelligence, vol 17, pp 185–203, 1981.

Dense optical flow (2/2)

The became only recently more popular as processor speed has increased.

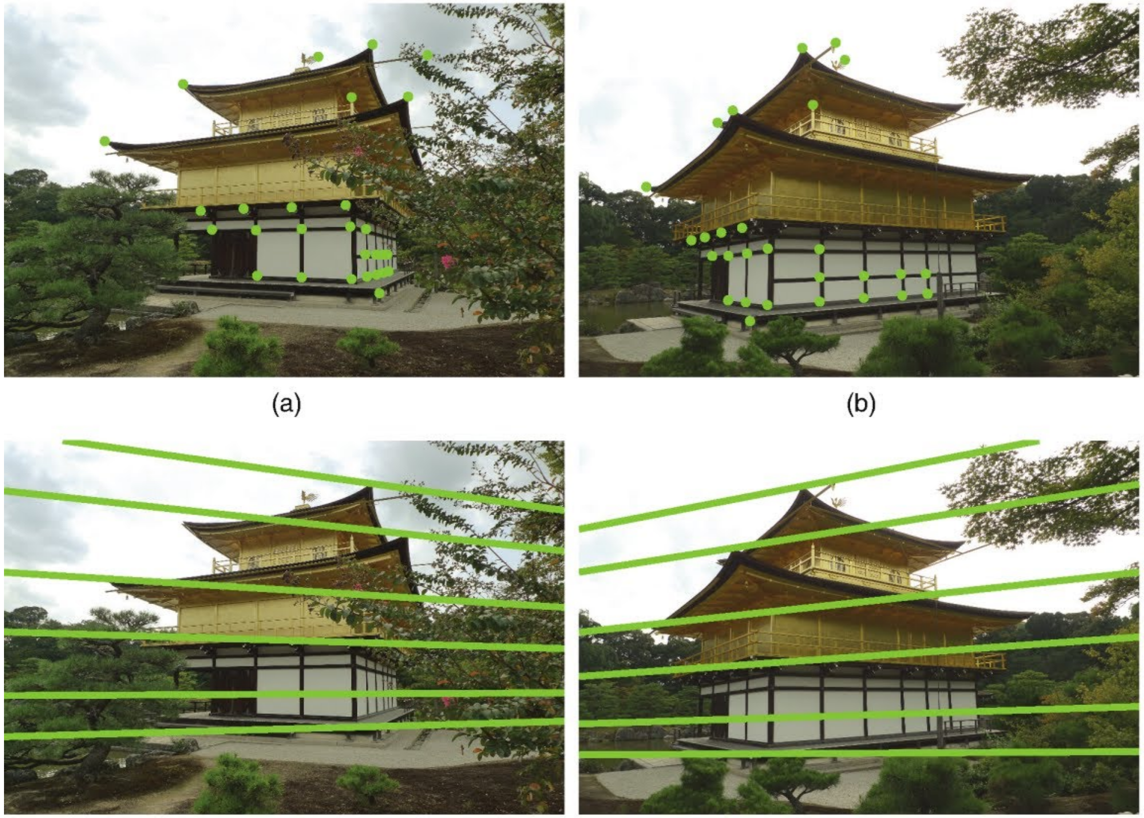
- Smoothing and fixed point iterations [Brox et al. ’04]
- Primal-dual optimization [Chambolle, Pock, ’10]
- ...

[Brox et al. ’04] Brox, Thomas, et al. "High accuracy optical flow estimation based on a theory for warping." Computer Vision-ECCV 2004. Springer Berlin Heidelberg, 2004.

[Chambolle, Pock, ’10] Chambolle, A. & Pock, T. “A First-Order Primal-Dual Algorithm for Convex Problems with Applications to Imaging” J Math Imaging Vis (2011) 40: 120.

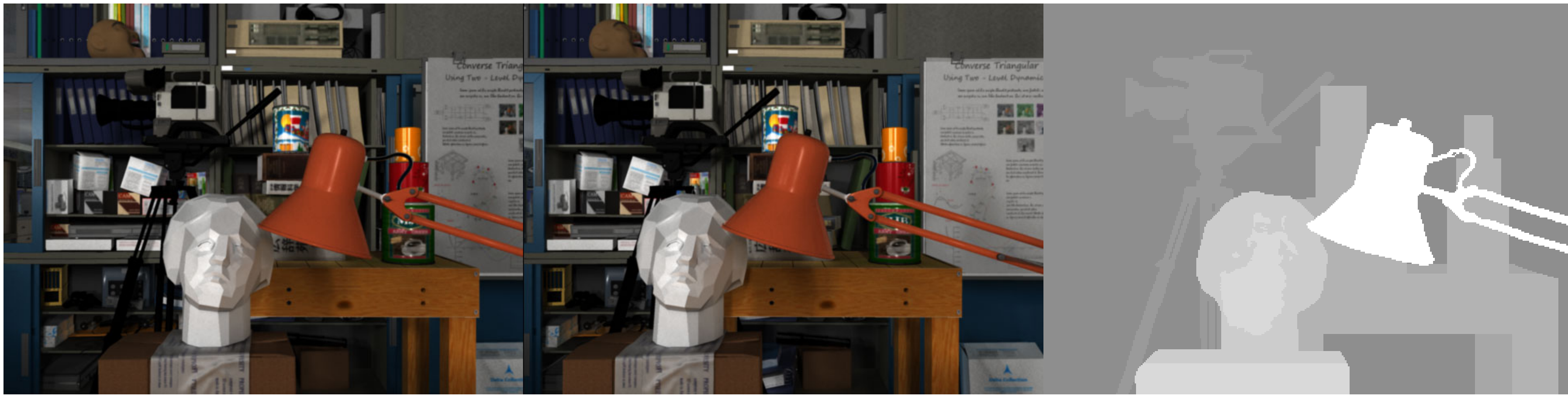
Stereo vs Optical Flow

Why don't we typically use epipolar constraints for optical flow?

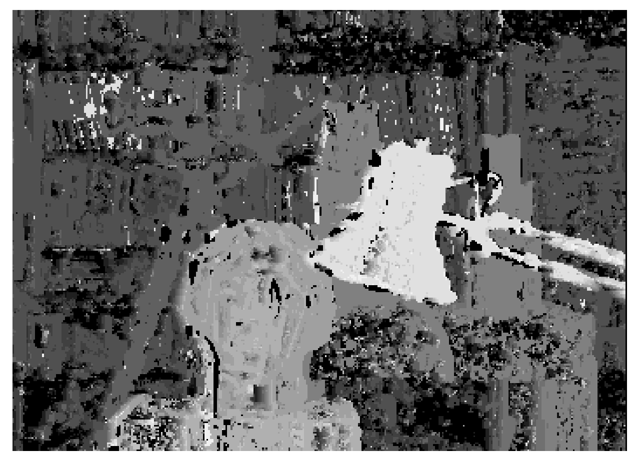


(a) (b) (c) (d)

Dense stereo matching



Dense stereo using a block matching algorithm: **pixelwise cost calculation is generally ambiguous!**



Hints on Semi-global matchnig (1/2)

As in variational optical flow, ad regularization terms:

sum of all pixel matching costs for the disparity map D

Penalty term for small changes

$$E(D) = \sum_{\mathbf{p}} \Big(C(\mathbf{p}, D_{\mathbf{p}}) + \sum_{\mathbf{q} \in N_{\mathbf{p}}} P_1 \, \mathrm{T}[|D_{\mathbf{p}} - D_{\mathbf{q}}| = 1] + \sum_{\mathbf{q} \in N_{\mathbf{p}}} P_2 \, \mathrm{T}[|D_{\mathbf{p}} - D_{\mathbf{q}}| > 1] \Big)$$

Penalty term for small changes

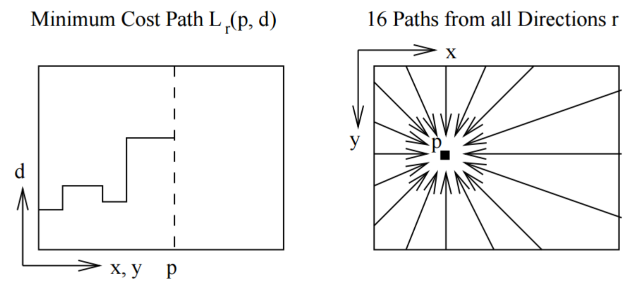
NP-complete problem!

– Aggregate costs for a number of directions

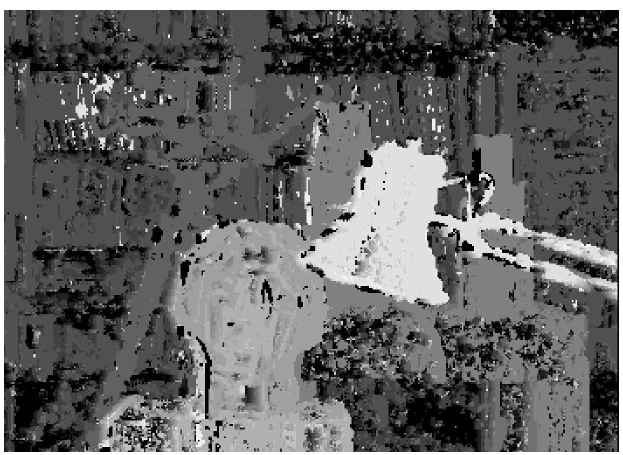
[Hirschmuller 2010] H Hirschmuller “Stereo processing by semiglobal matching and mutual information”, Pattern Analysis and Machine Intelligence, IEEE Transactions on 30 (2), 328-341

Hints on Semi-global matchnig (2/2)

$$
\begin{aligned}
L'_{\mathbf{r}}(\mathbf{p}, d) = & C(\mathbf{p}, d) + \min(L'_{\mathbf{r}}(\mathbf{p} - \mathbf{r}, d), \\
& L'_{\mathbf{r}}(\mathbf{p} - \mathbf{r}, d - 1) + P_1, \\
& L'_{\mathbf{r}}(\mathbf{p} - \mathbf{r}, d + 1) + P_1, \\
& \min_i L'_{\mathbf{r}}(\mathbf{p} - \mathbf{r}, i) + P_2).
\end{aligned}
$$



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



Using SGM

Seminars in Artificial Intelligence and Robotics

Computer Vision for Intelligent Robotics

Basics and hints on low level vision

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