Acquisition of Images

Computer Vision

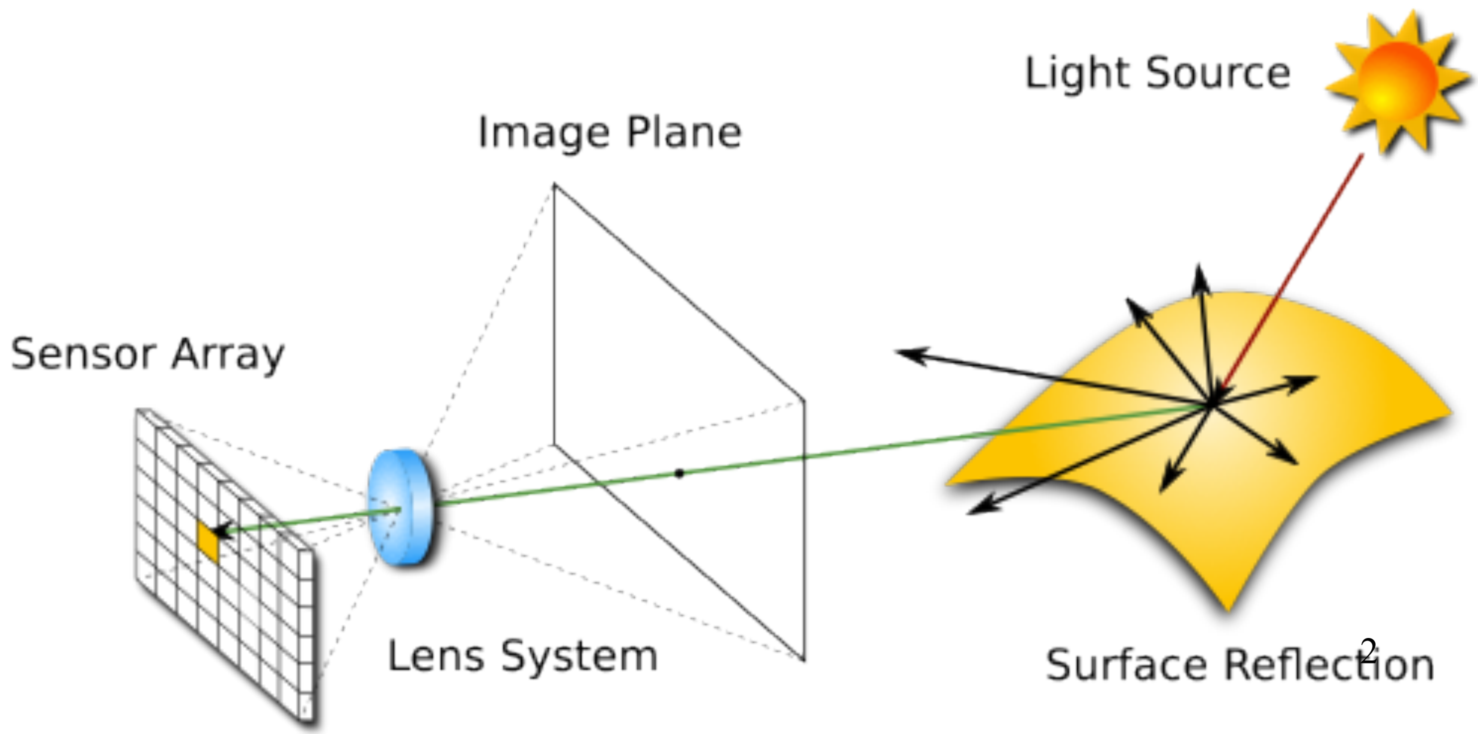
ACQUIS.

illumination
cameras

Acquisition of images

We focus on :

1. illumination
2. cameras



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Acquisition of images

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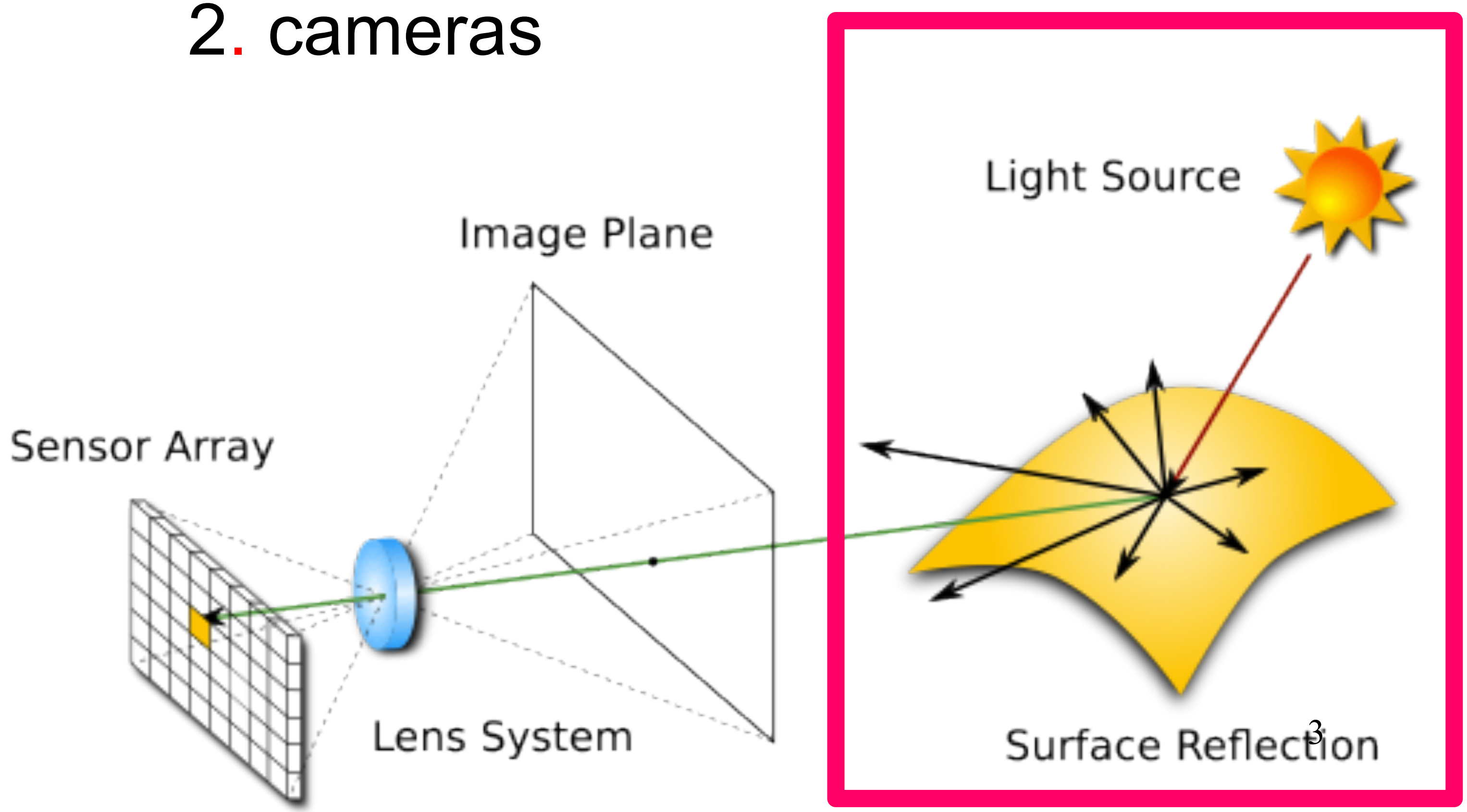

illumination

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Illumination

Well-designed illumination often is key in visual inspection

The light was good, but the hot wax was a problem...

Illumination techniques

Simplify the image processing by controlling the environment

An overview of illumination techniques:

1. back-lighting
2. directional-lighting
3. diffuse-lighting
4. polarized-lighting
5. coloured-lighting
6. structured-lighting
7. stroboscopic lighting

Back-lighting

lamps placed behind a transmitting diffuser plate, light source behind the object

generates high-contrast silhouette images, easy to handle with *binary vision*

often used in inspection

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Example backlighting

Directional and diffuse lighting

Directional-lighting

- generate sharp shadows
- generation of specular reflection (e.g. crack detection)
- shadows and shading yield information about shape

Diffuse-lighting

- illuminates uniformly from all directions
- prevents sharp shadows and large intensity variations over glossy surfaces:
- all directions contribute extra diffuse reflection, but contributions to the specular peak arise from directions close to the mirror one only

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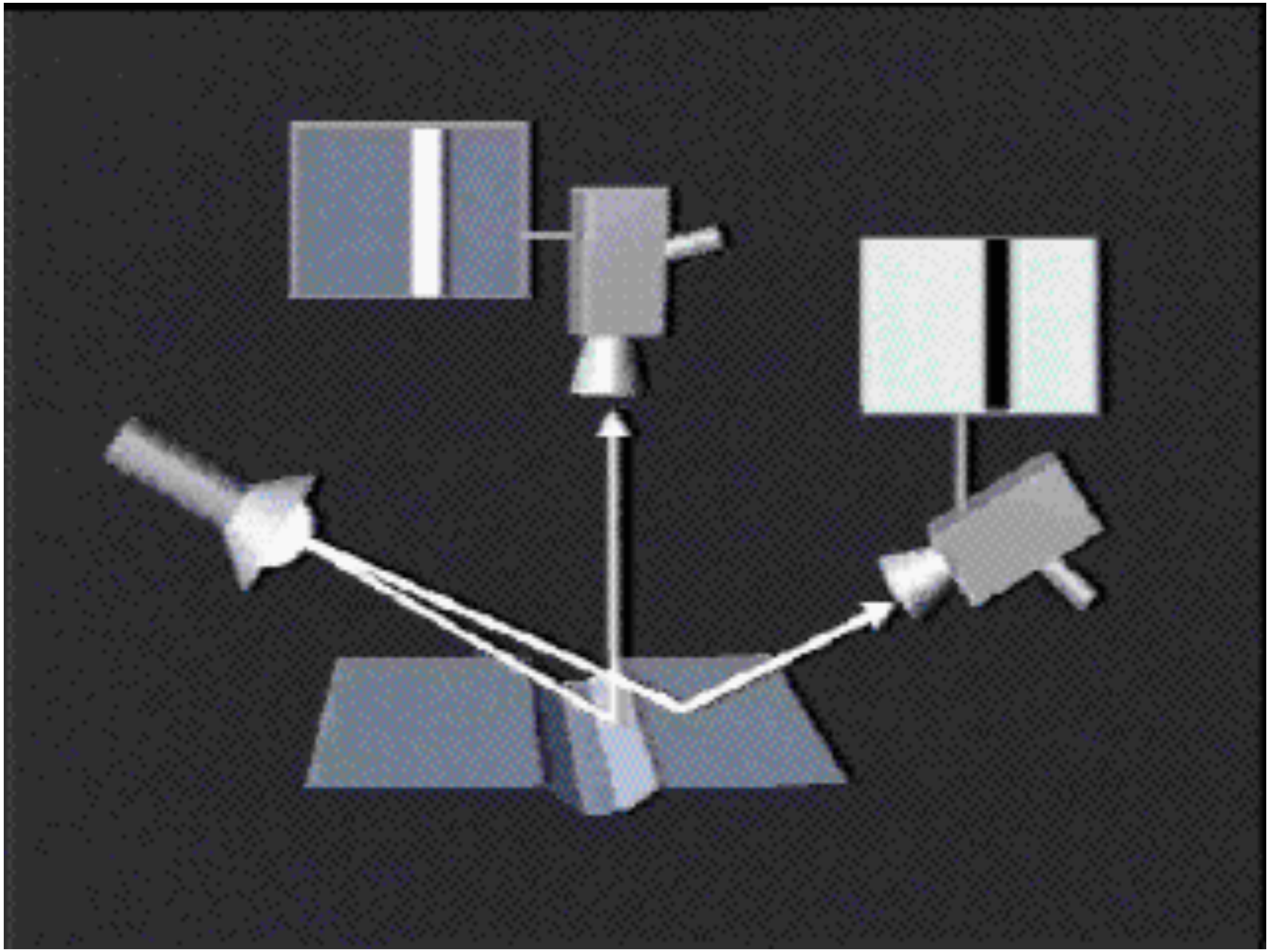
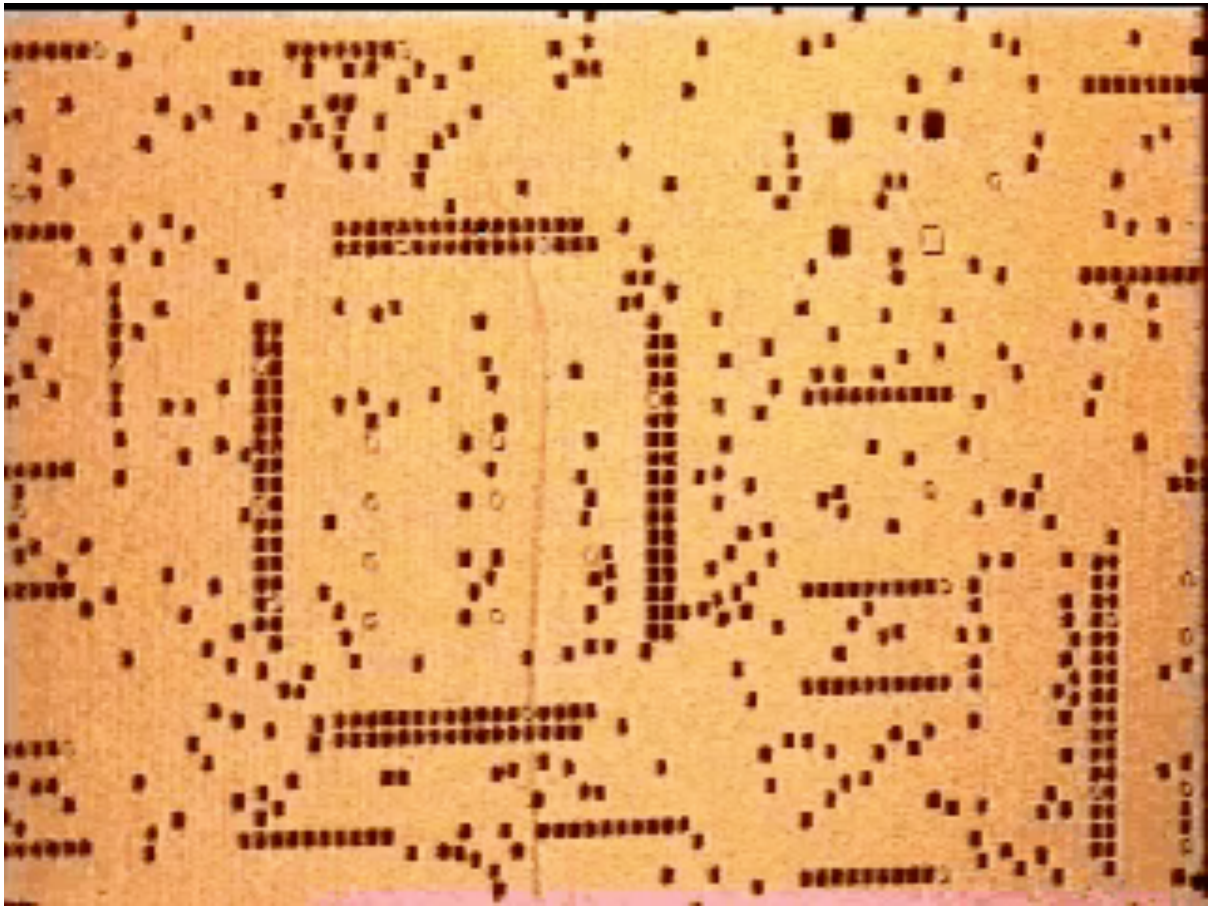
Crack detection



Example directional lighting



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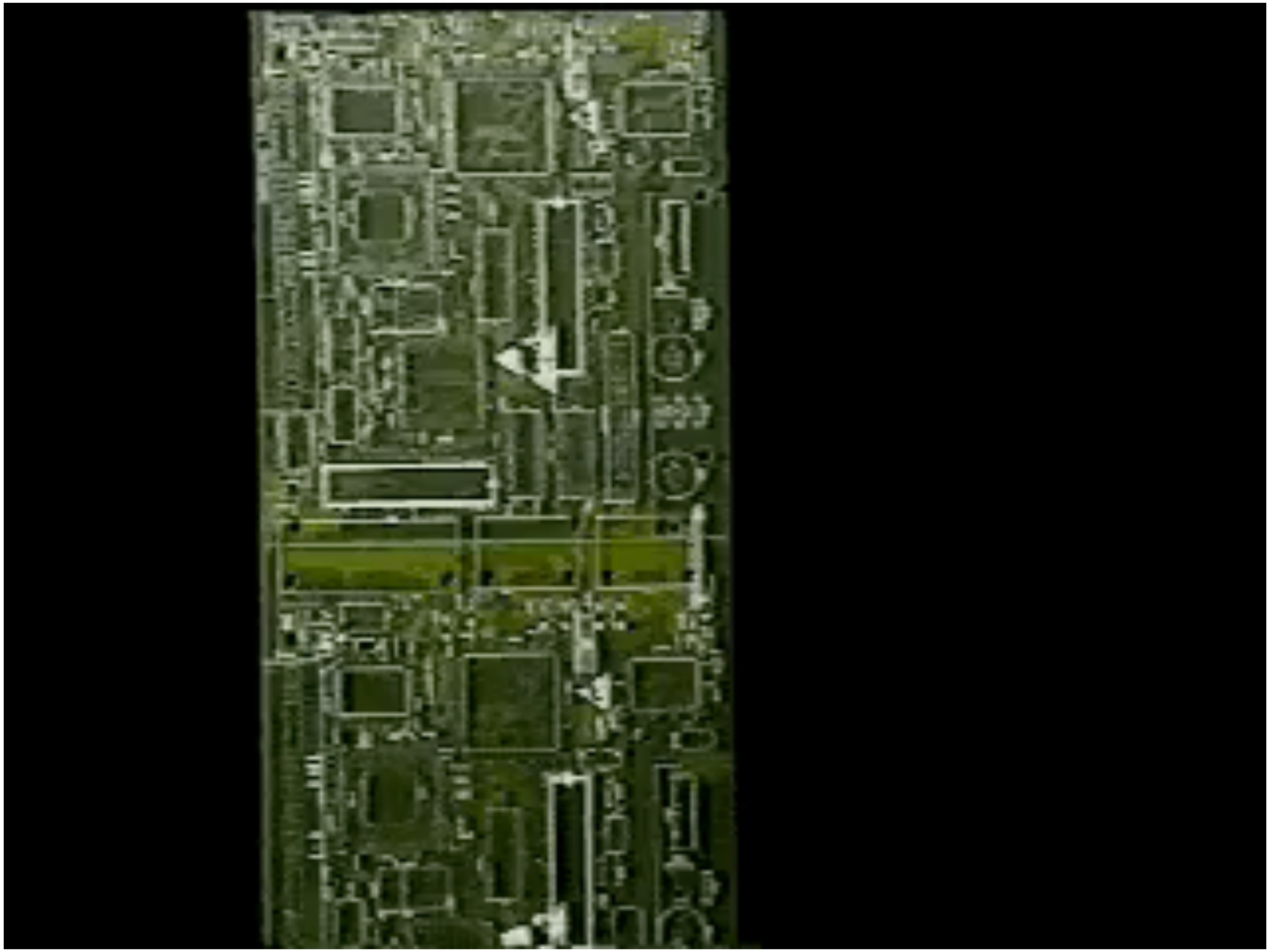
Example diffuse lighting



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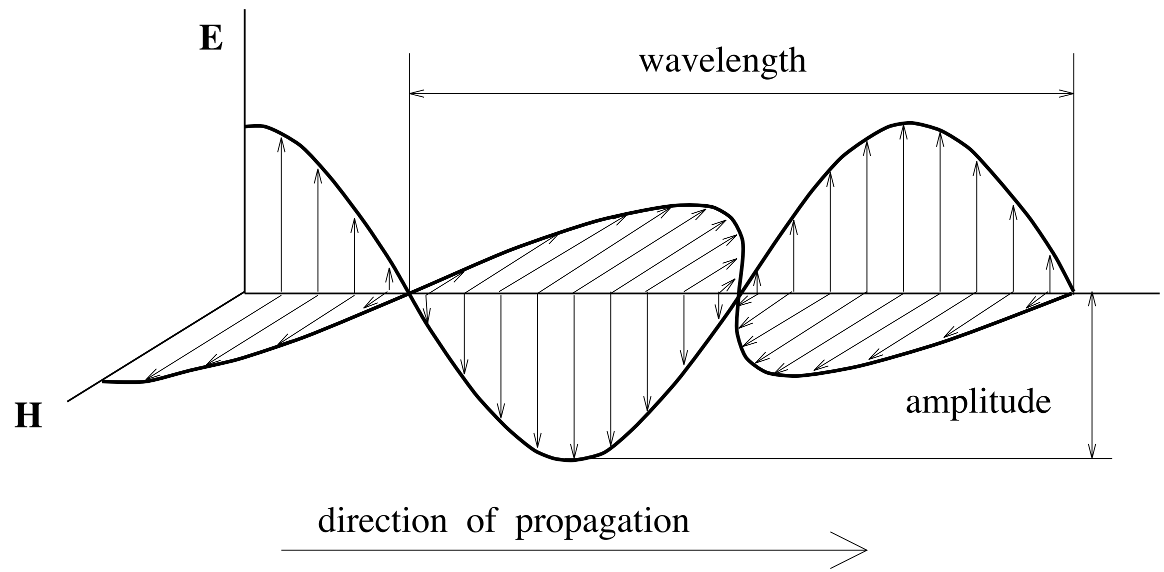
Polarized lighting

2 uses:

1. to improve contrast between Lambertian and specular reflections

2. to improve contrasts between dielectrics and metals, e.g. when inspecting electrical circuits

Polarized lighting



- Light as electro-magnetic wave.
- Polarization direction is the one of the E-wave.
- Normally, the light is composed of many waves with different polarizations

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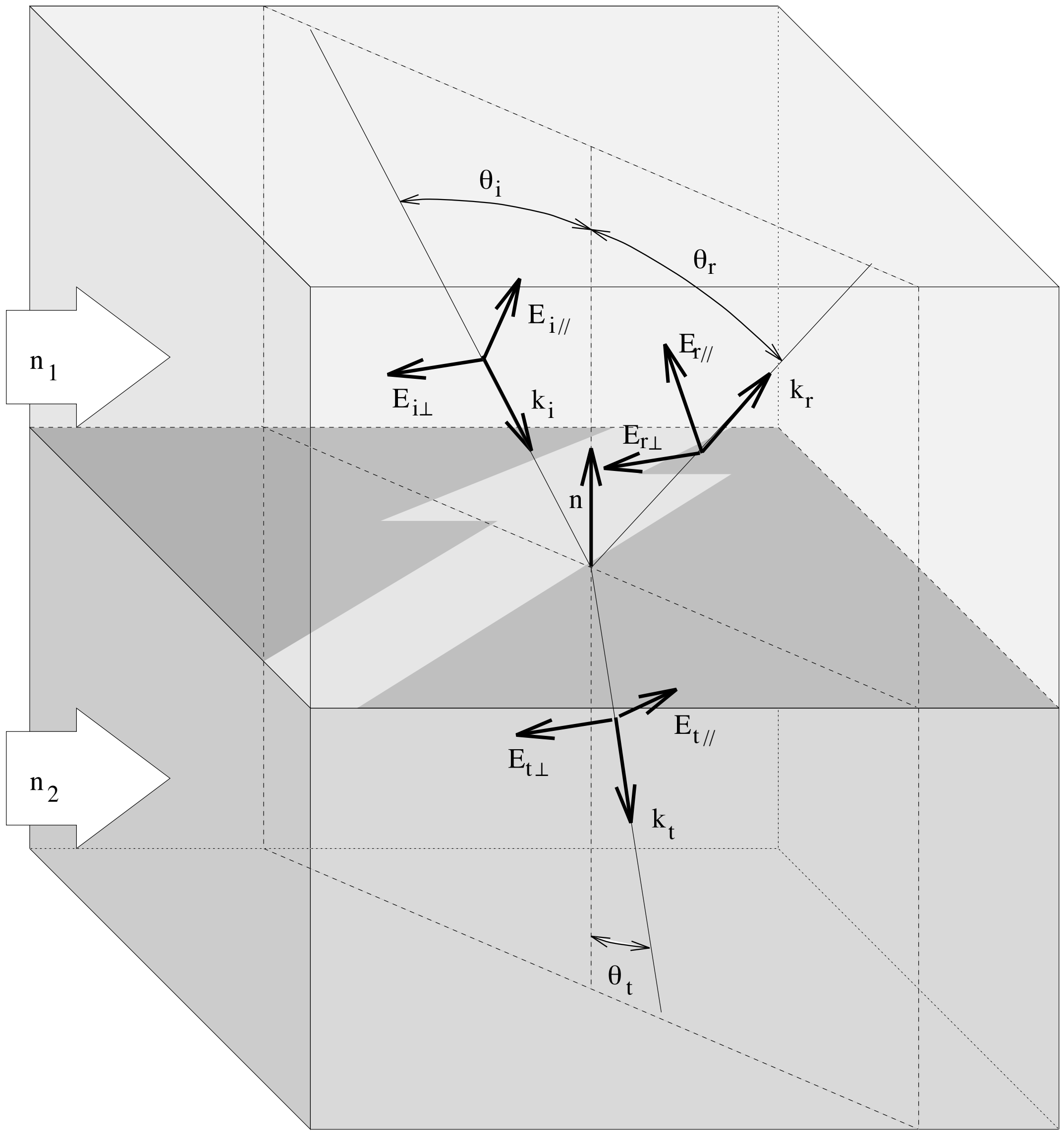
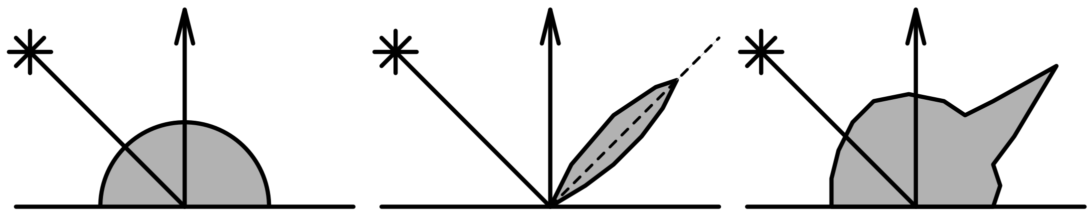


Basic models of reflection



- Purely diffused
- Lambertian

- Specular reflection

- Mixed reflection

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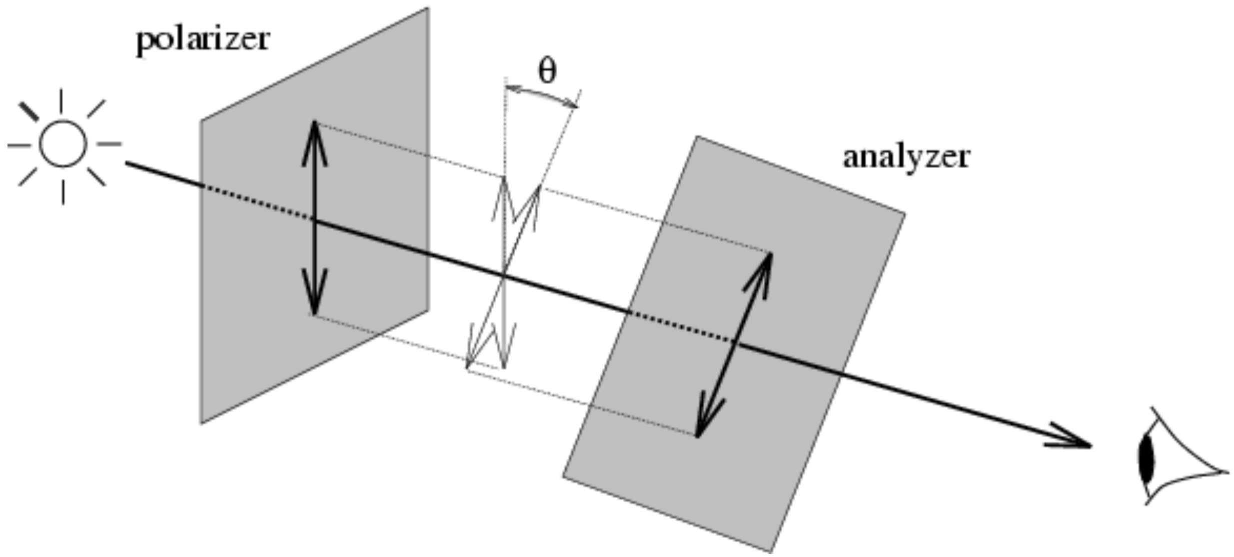
Polarised lighting

polarizer/analyzer configurations



law of Malus :

$$I(\theta) = I(0)\cos^2\theta$$

Polarized lighting

2 uses:

1. to improve contrast between Lambertian and specular reflections

2. to improve contrasts between dielectrics and metals

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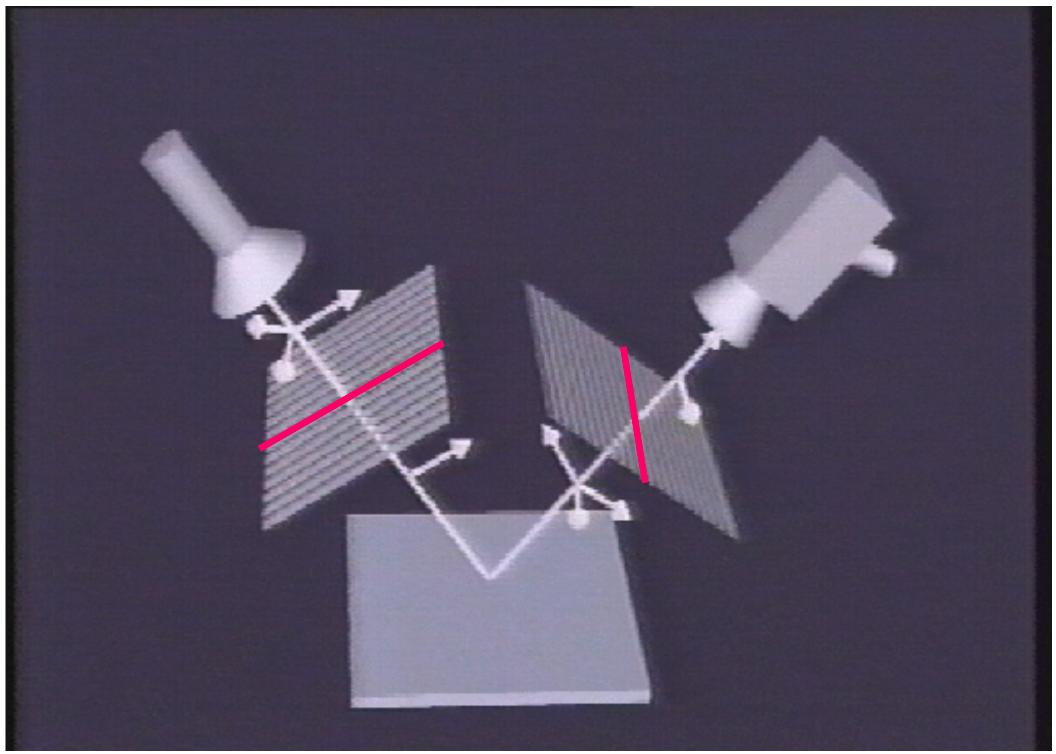
Polarized lighting

specular reflection keeps polarisation :
diffuse reflection depolarises

suppression of specular reflection :



polarizer/analyzer crossed
prevents the large dynamic range caused by glare

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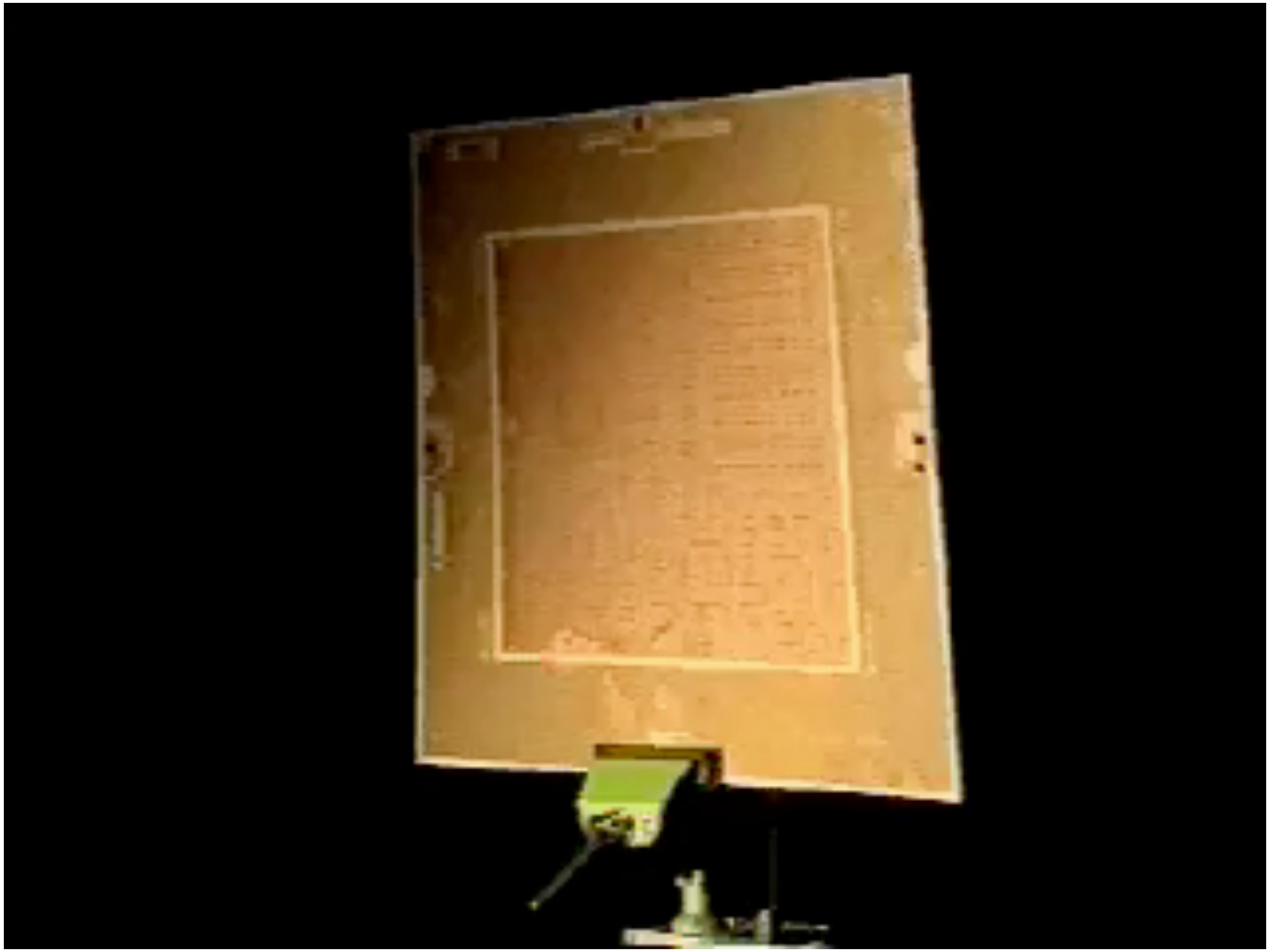
Example pol. lighting (pol./an.crossed)



Polarized lighting

2 uses:

1. to improve contrast between Lambertian and specular reflections

2. to improve contrasts between dielectrics and metals

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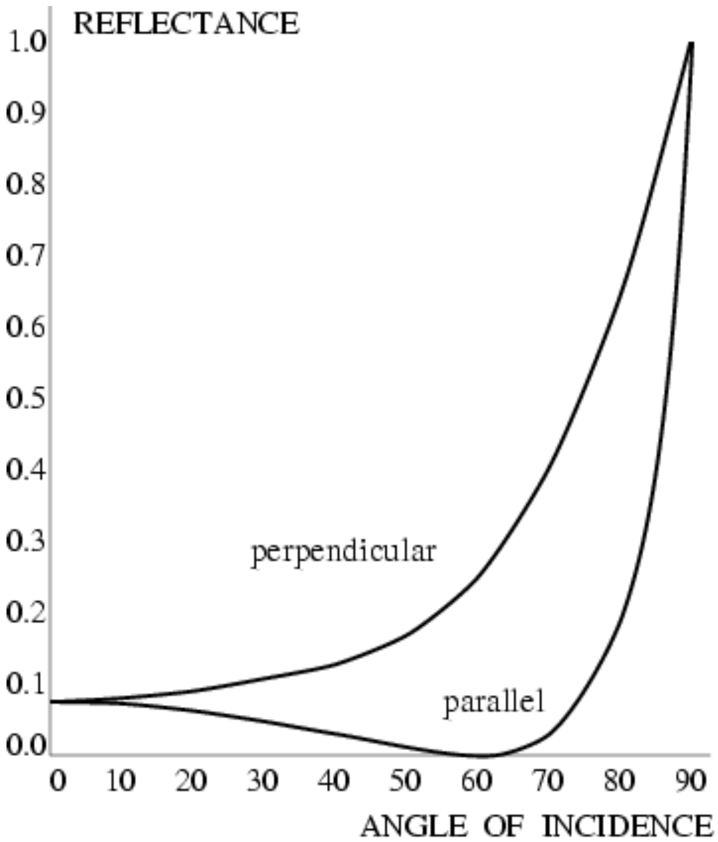
Reflection : dielectric



Polarizer at *Brewster angle*

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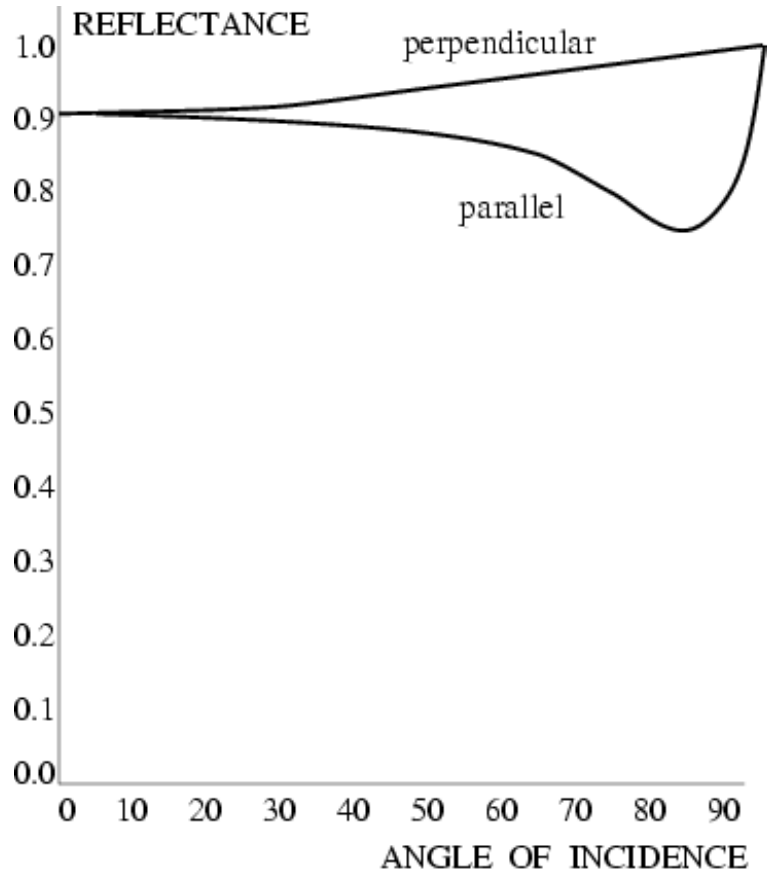
Reflection : conductor



strong reflectors

more or less preserve polarization

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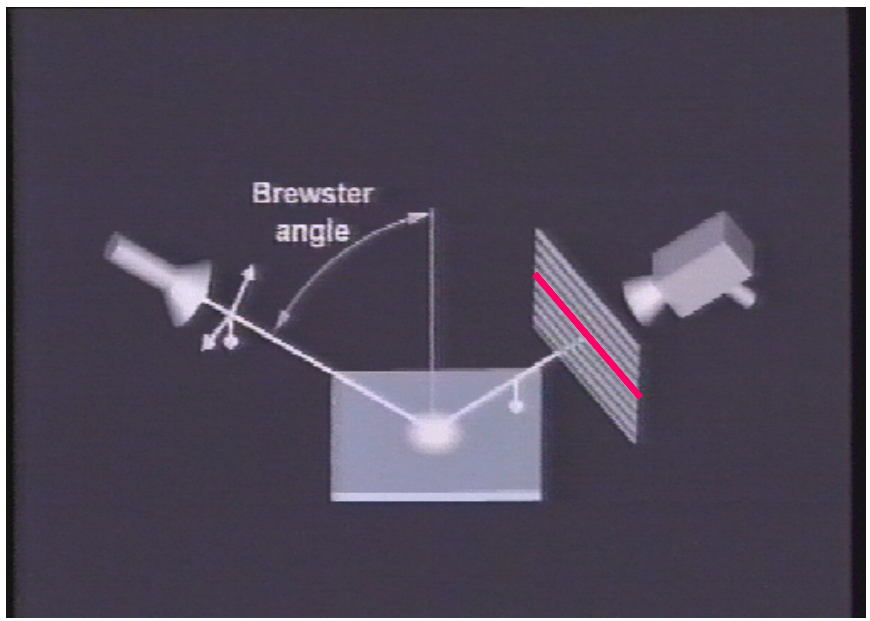
Polarised lighting

distinction between specular reflection from dielectrics and metals;
works under the Brewster angle for the dielectric
dielectric has no parallel comp. ; metal does

suppression of specular reflection from dielectrics :



polarizer/analyzer aligned
distinguished metals and dielectrics

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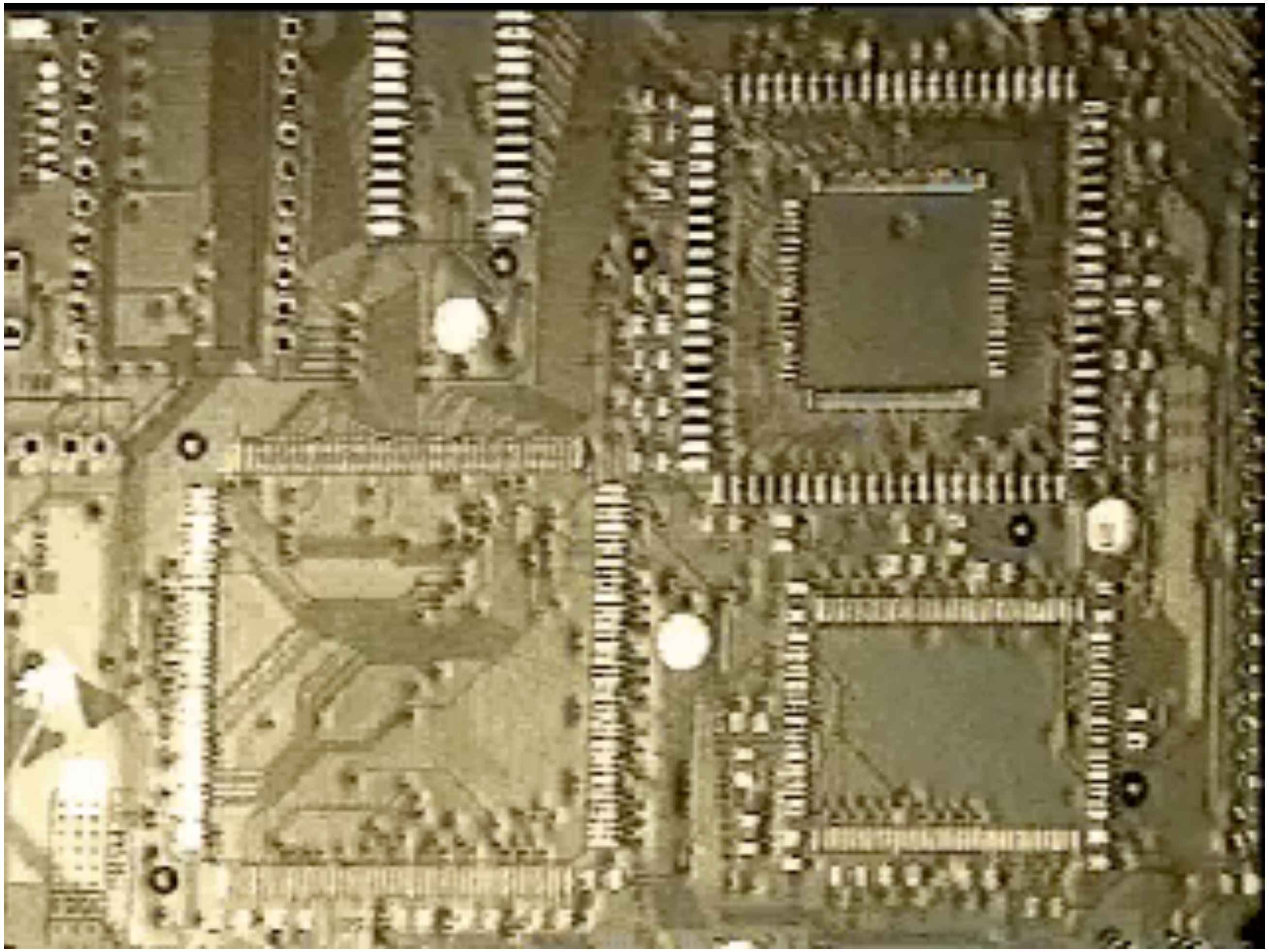
cameras

Example pol. lighting (pol./an. aligned)



Coloured lighting

highlight regions of a similar colour

with band-pass filter: only light from projected pattern (e.g. monochromatic light from a laser)

differentiation between specular and diffuse reflection

comparing colours ⇨ same spectral composition of sources!

spectral sensitivity function of the sensors!

Computer Vision

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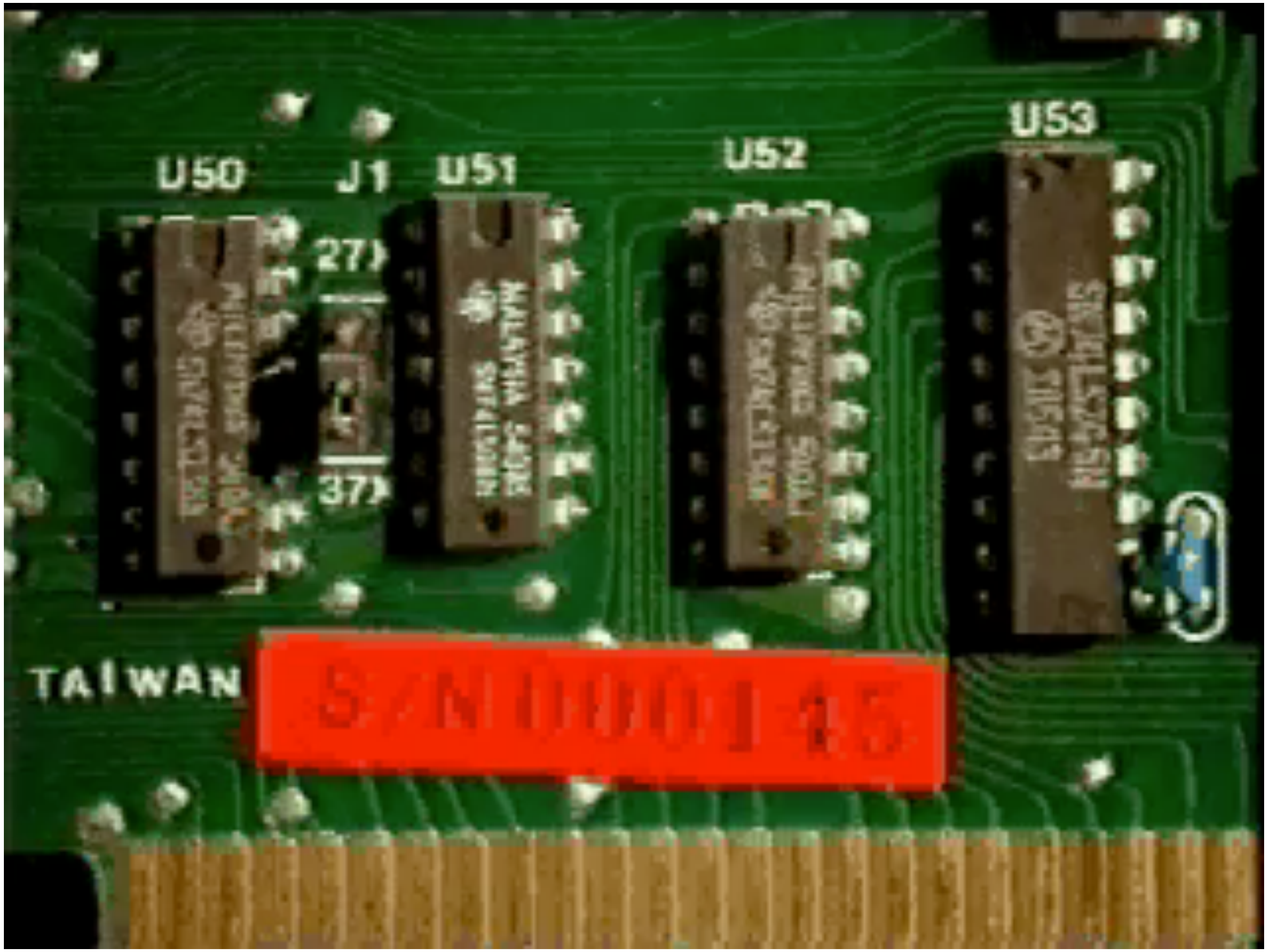
illumination
cameras

Example coloured lighting



Structured and stroboscopic lighting

spatially or temporally modulated light pattern

Structured lighting

e.g. : 3D shape : objects distort the projected pattern
(more on this later)

Stroboscopic lighting

high intensity light flash

to eliminate motion blur

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illumination
cameras

Stroboscopic lighting

Computer Vision

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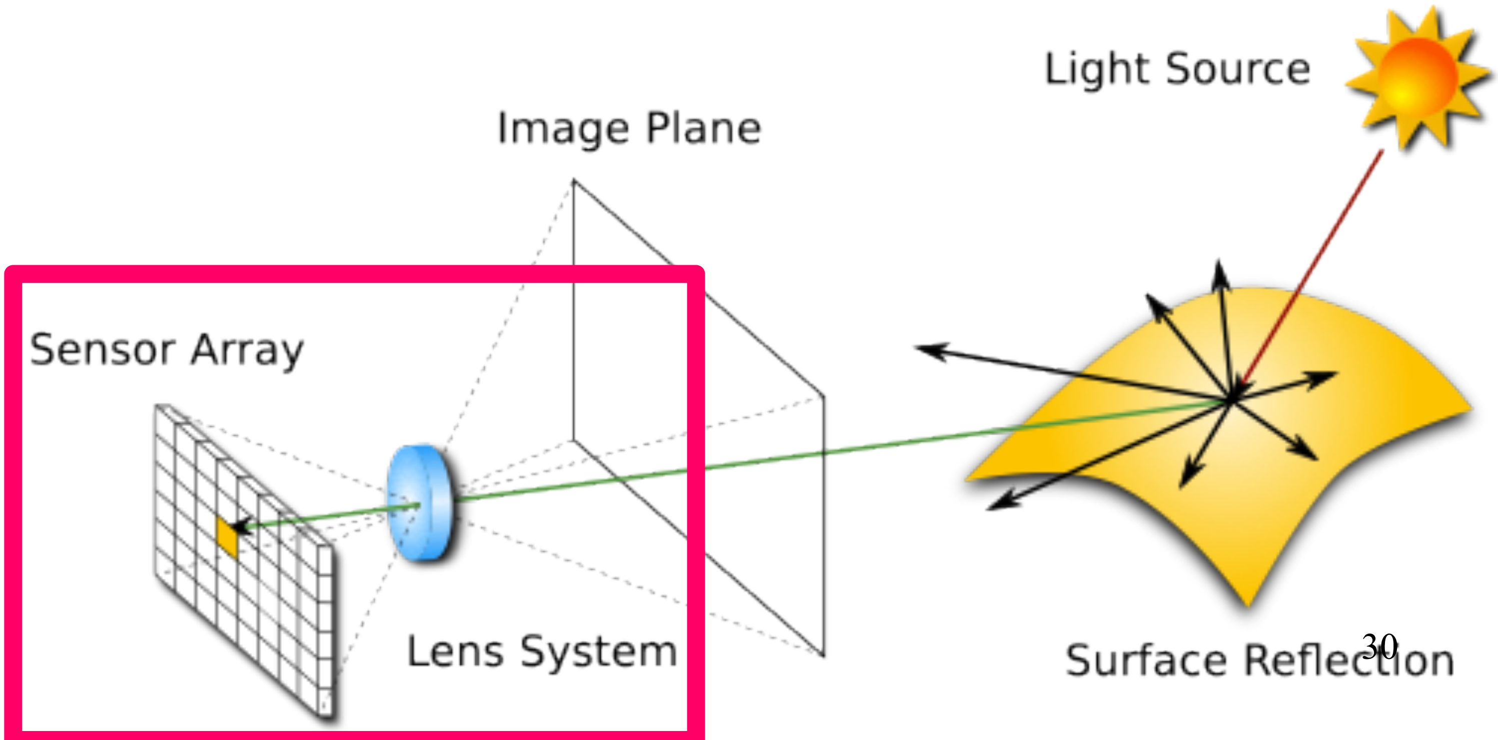
illumination
cameras

Acquisition of images

We focus on :

1. illumination
2. cameras

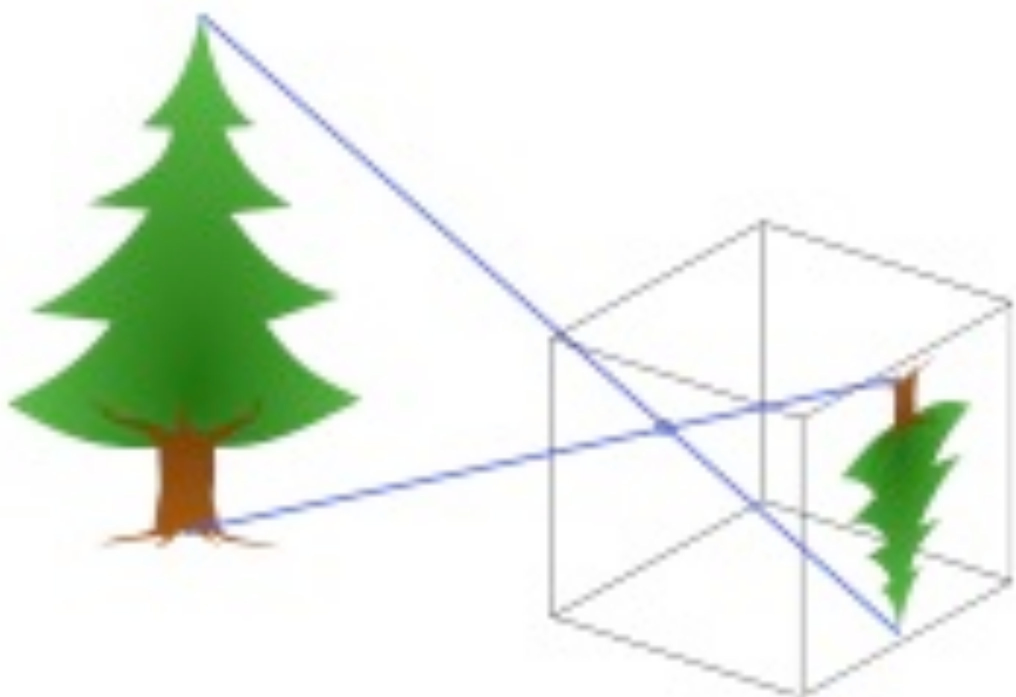


cameras

camera models

Optics for image formation

the pinhole model :



Computer Vision

Optics for image formation

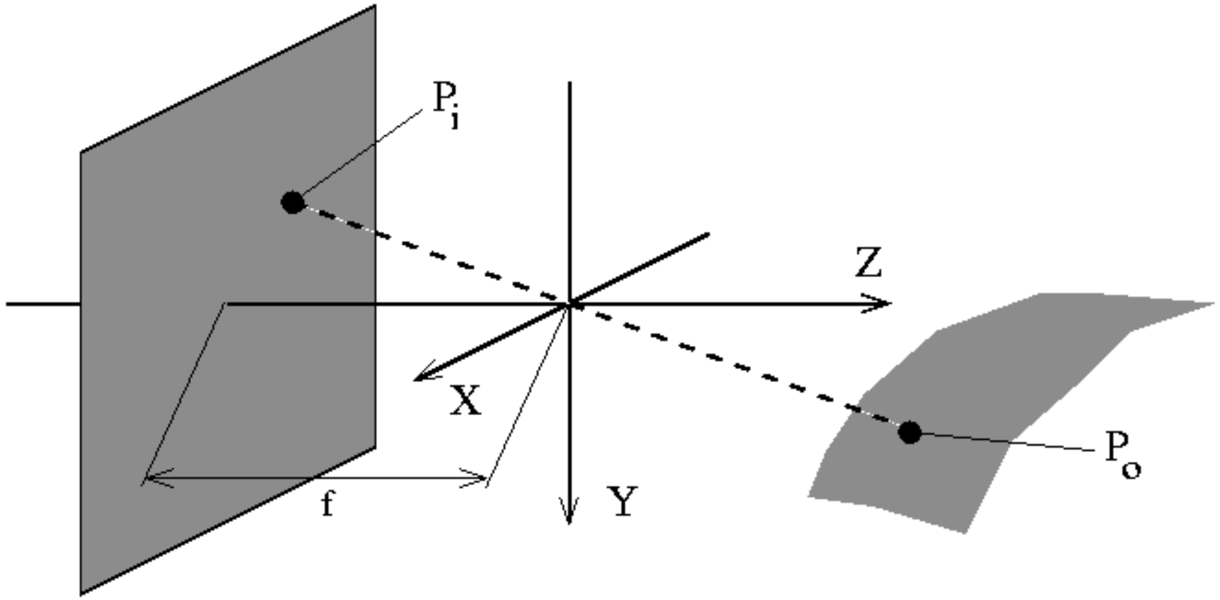
the pinhole model :

hence the name:
CAMERA
obscura

Computer Vision

Optics for image formation

the pinhole model :



$$\frac{X_i}{X_o} = \frac{Y_i}{Y_o} = \frac{f}{-Z_o} = -m$$

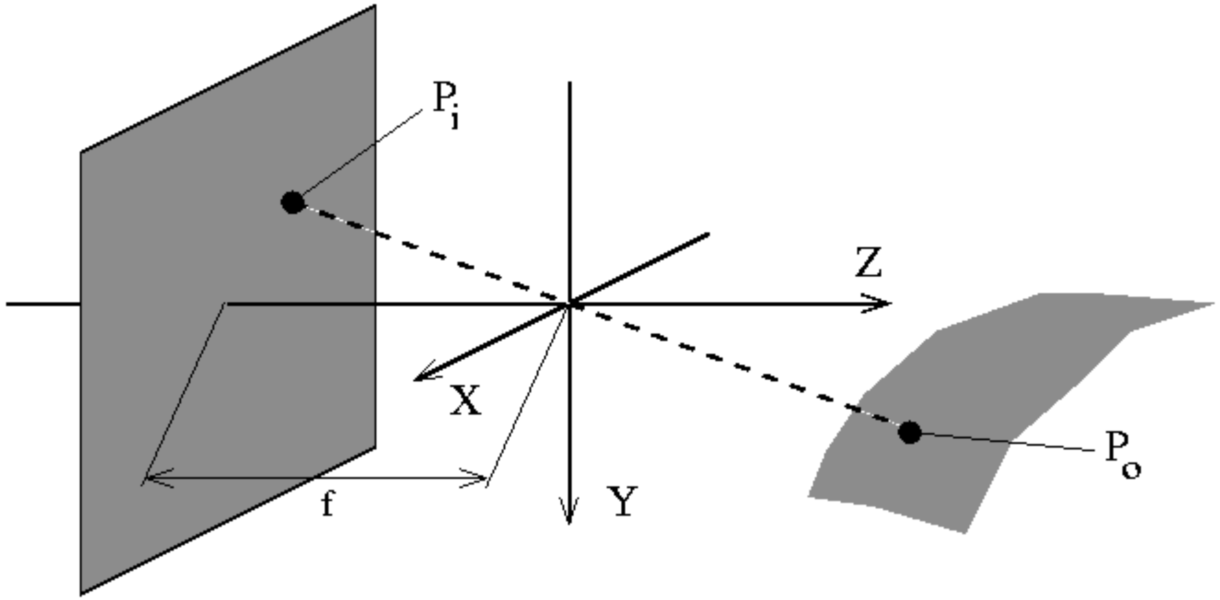
(m = linear magnification)

Camera obscura + lens

Computer Vision

Optics for image formation

the pinhole model :



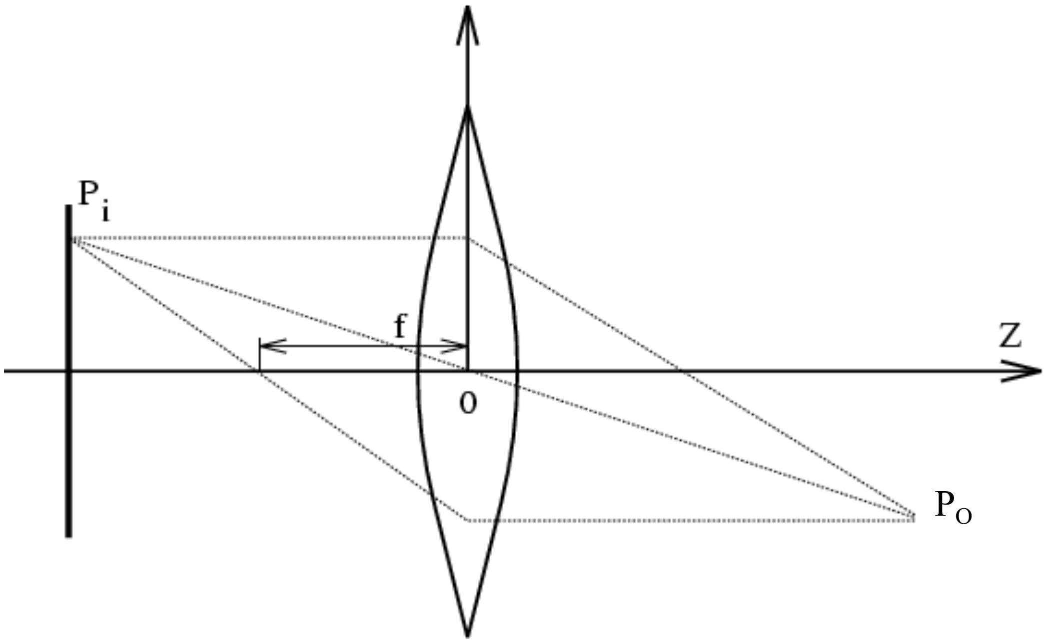
$$\frac{X_i}{X_o} = \frac{Y_i}{Y_o} = \frac{f}{-Z_o} = -m$$

(m = linear magnification)

Computer Vision

The thin-lens equation

lens to capture enough light :



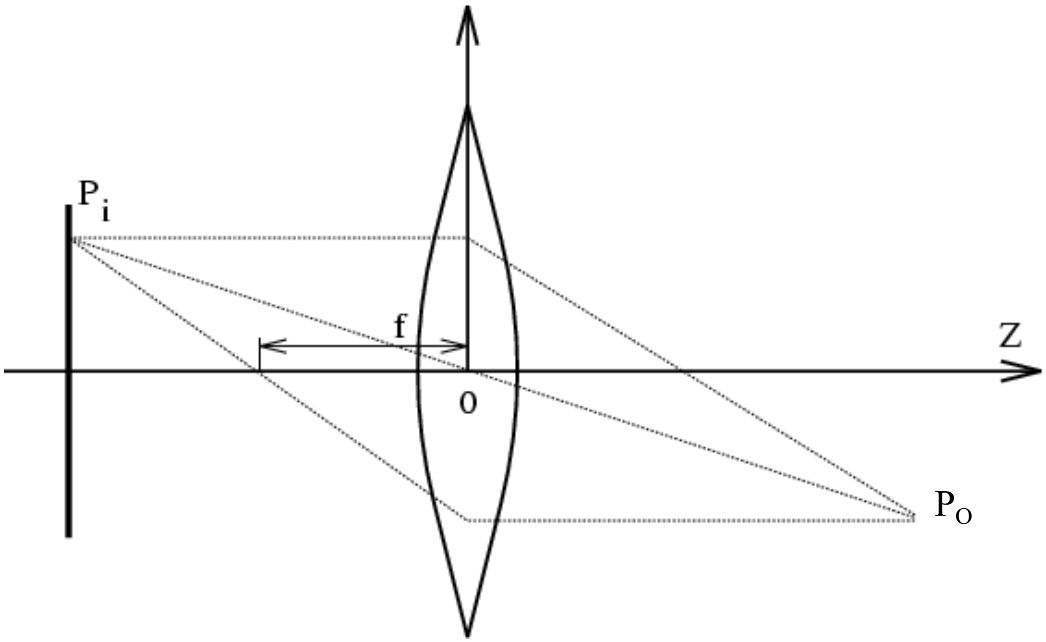
assuming

- spherical lens surfaces
- incoming light ± parallel to axis
- thickness << radii
- same refractive index on both sides

The thin-lens equation

lens to capture enough light :

$$\frac{1}{Z_O} - \frac{1}{Z_i} = \frac{1}{f}$$

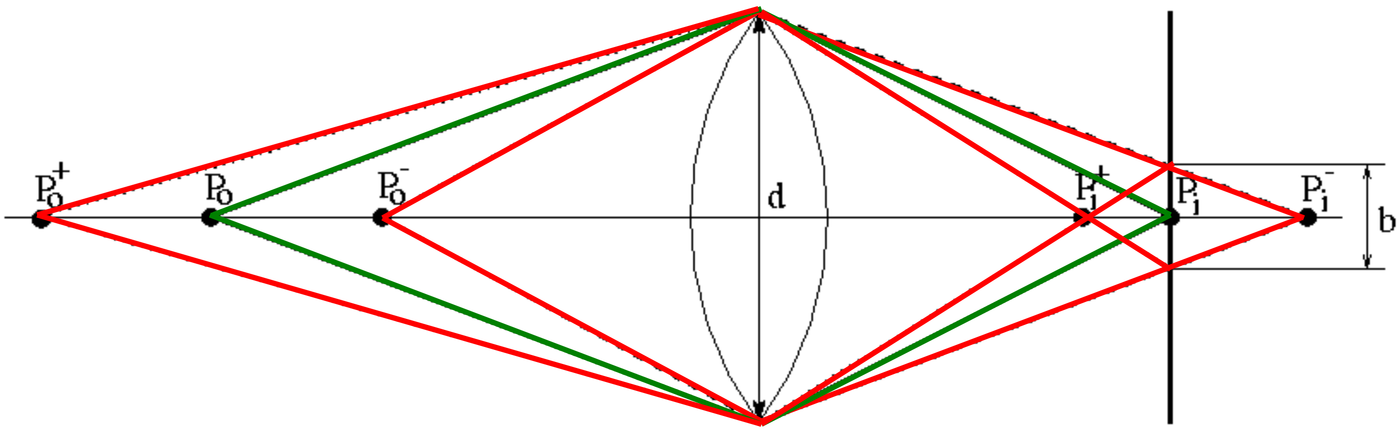


assuming

- spherical lens surfaces
- incoming light ± parallel to axis
- thickness << radii
- same refractive index on both sides

The depth-of-field

Only reasonable sharpness in Z-interval



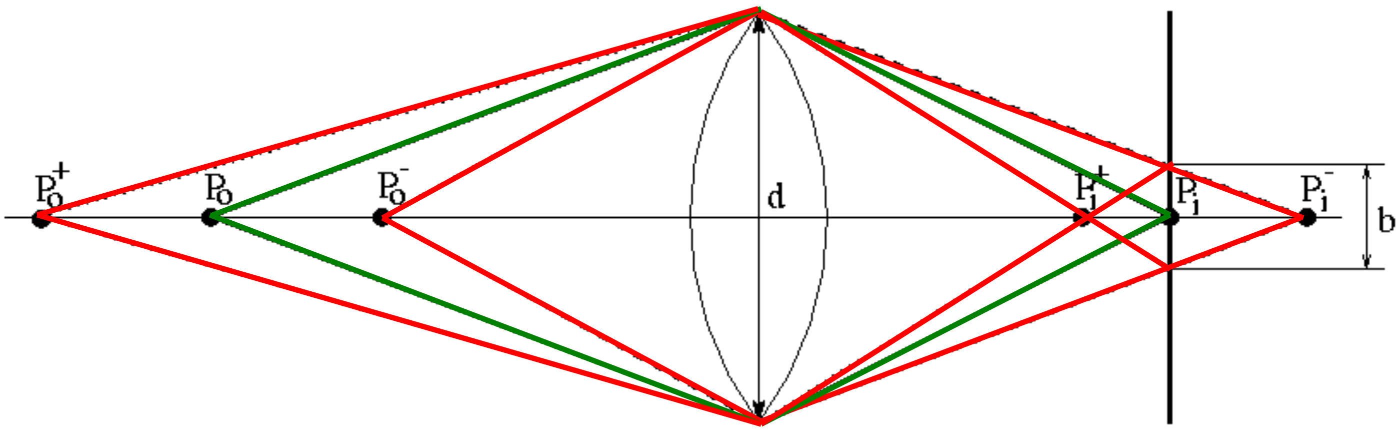
$$\Delta Z_0^- = Z_0 - Z_0^- = \frac{Z_0(Z_0 - f)}{Z_0 + f\, d / b - f}$$

decreases with d, increases with Z_0

strike a balance between incoming light (d) and large depth-of-field (usable depth range)

Computer Vision

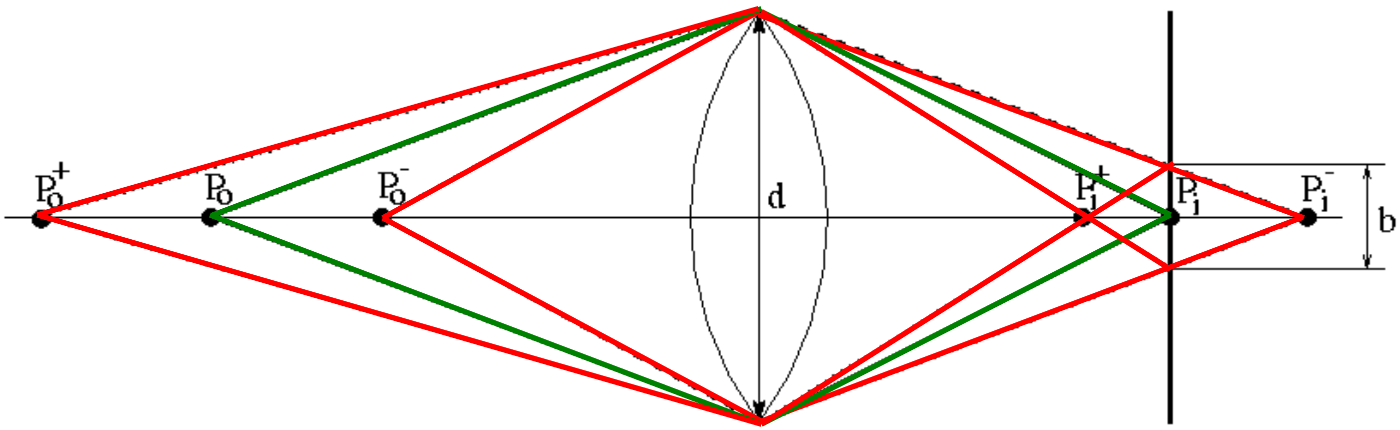
The depth-of-field



$$\Delta Z_0^- = Z_0 - Z_0^- = \frac{Z_0(Z_0 - f)}{Z_0 + f\, d/b - f}$$

Similar expression for $Z_O^+ - Z_O$

The depth-of-field



$$\Delta Z_0^- = Z_0 - Z_0^- = \frac{Z_0 (Z_0 - f)}{Z_0 + f\, d / b - f}$$

Ex 1: microscopes -> small DoF

Ex 2: special effects -> flood miniature scene with light

Deviations from the lens model

3 assumptions :

1. all rays from a point are focused onto 1 image point

2. all image points in a single plane

3. magnification is constant

deviations from this ideal are *aberrations*

Aberrations

2 types :

1. geometrical: visible as image distortions or degradation like blurring

2. chromatic: visible as different behavior for different wavelengths (e.g. colors)

geometrical : small for paraxial rays (rays close to the optical axis)

chromatic : refractive index function of wavelength (Snell's law !!)

Most common way to reduce severity:
Composite systems with multiple lenses.

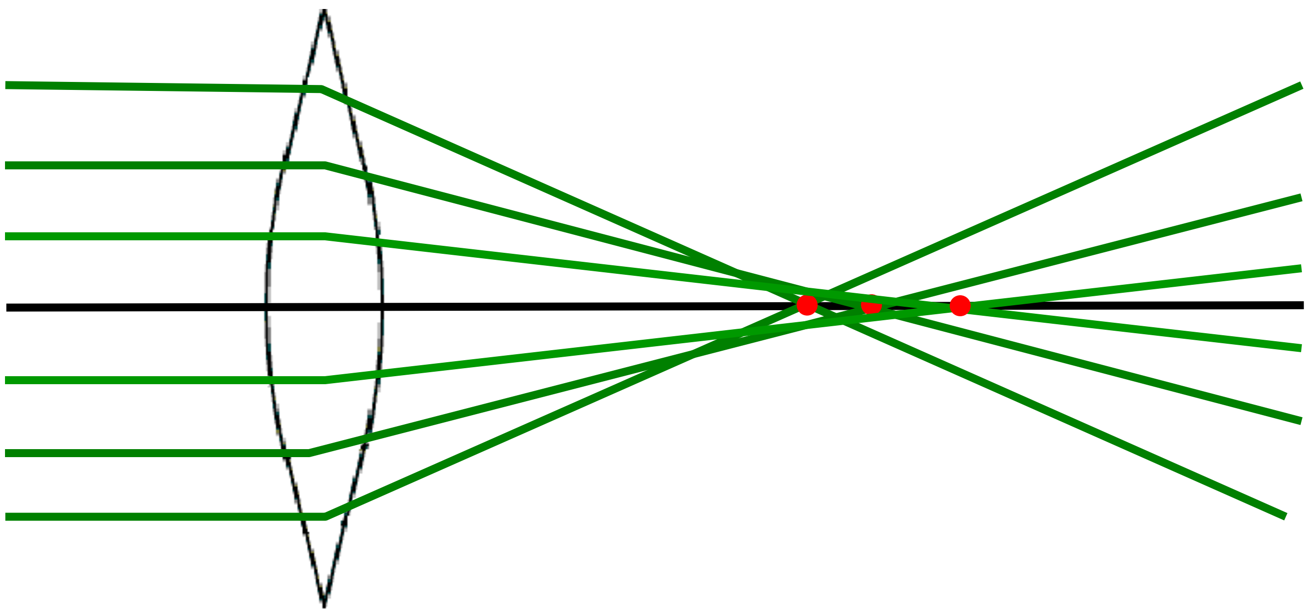
Geometrical aberrations

- spherical aberration
- astigmatism
- radial distortion ← the most important type
- coma

Spherical aberration

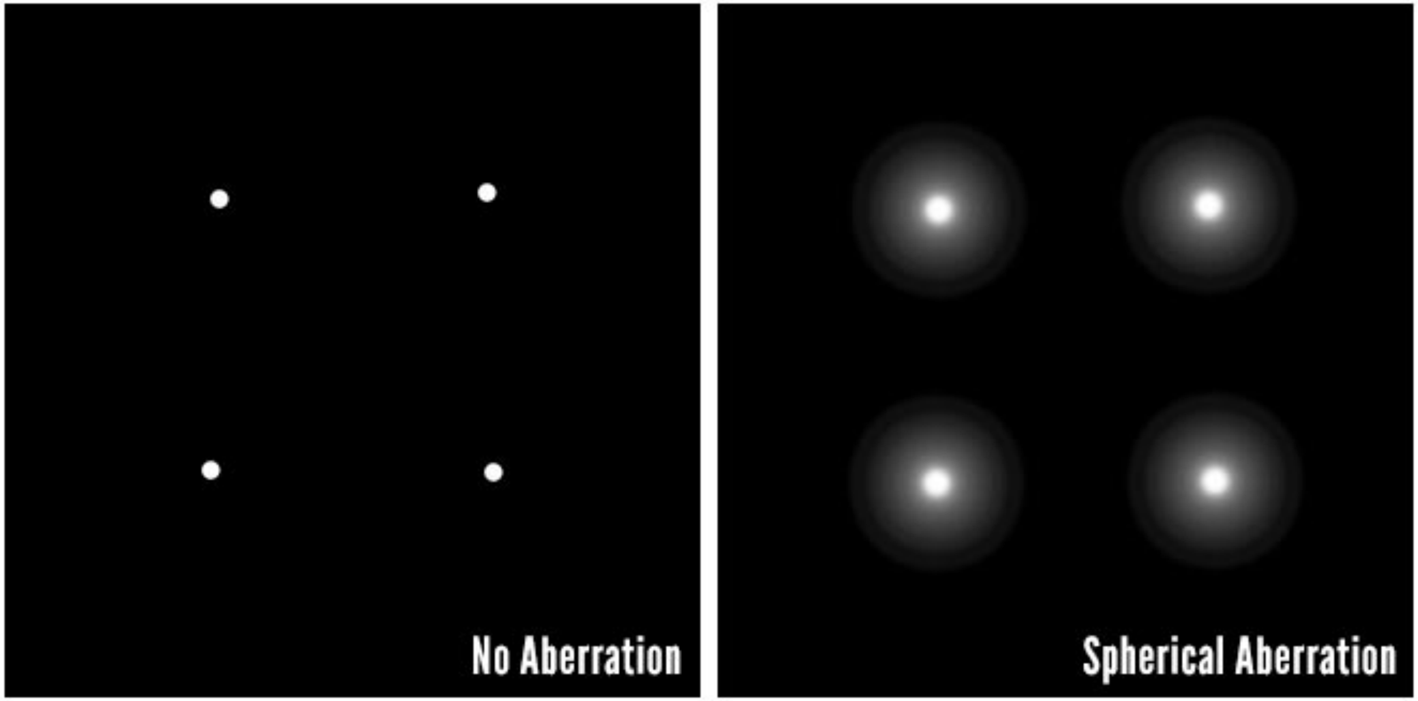
rays parallel to the axis do not converge

outer portions of the lens yield smaller focal lengths



Computer Vision

Spherical aberration



Radial distortion

different magnification for different angles of inclination

barrel

none

pincushion

Radial distortion

different magnification for different angles of inclination

barrel *none* *pincushion*

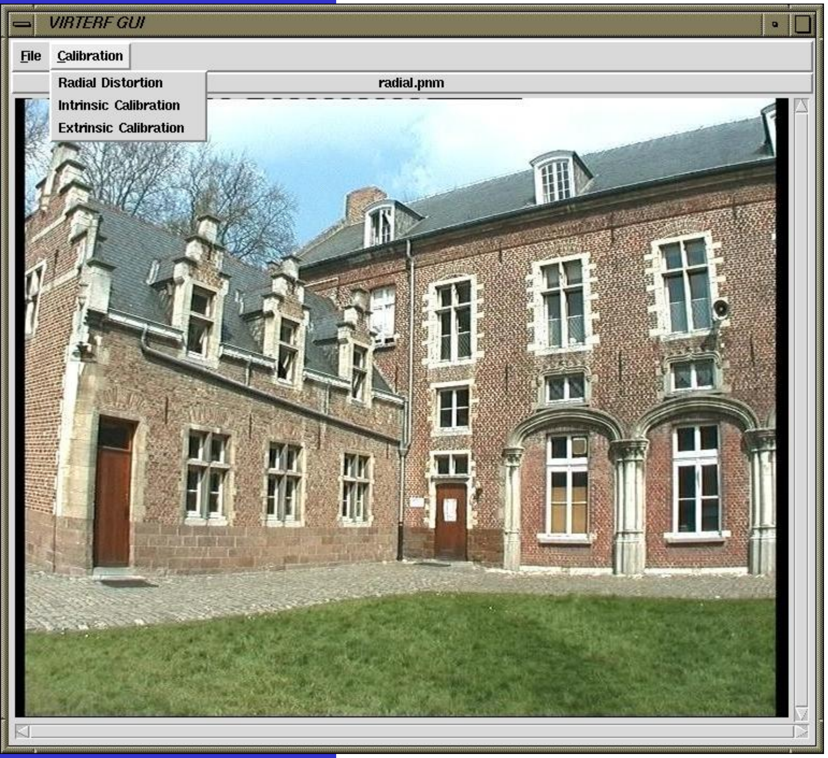
- The result is lines become curves.
- Curvature increases as you move away from the center of distortion.
- Models assume this is the image center. And there is a multiplicative factor on the pixel location depending on the pixels' distance r to the center

$$d = (1 + \kappa_1 r^2 + \kappa_2 r^4 + \dots)$$

- Even factors because effects are symmetric.

Computer Vision

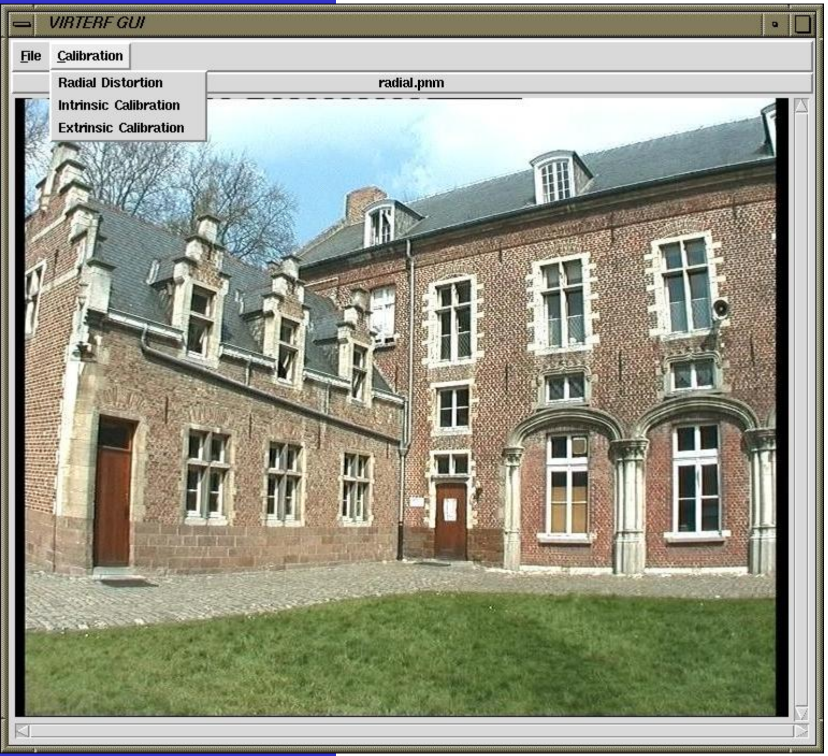
Radial distortion



This aberration type can be corrected by software if the parameters (κ_1 , κ_2 , …) are known

Computer Vision

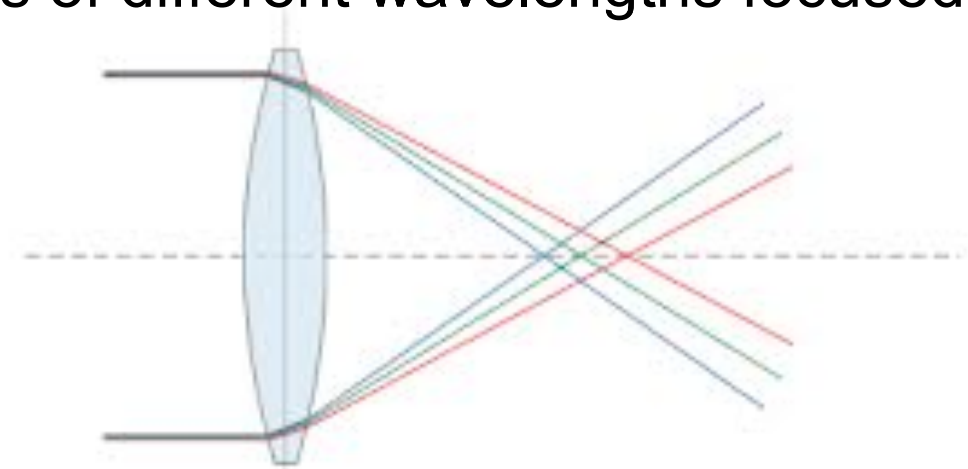
Radial distortion



Some methods do this by looking how straight lines curve instead of being straight

Chromatic aberration

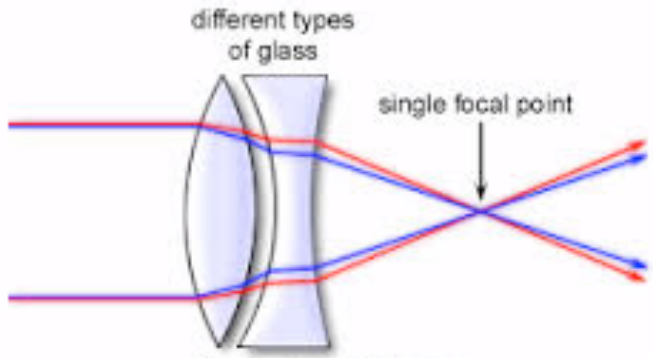
rays of different wavelengths focused in different planes



The image is blurred and appears colored at the fringe.

cannot be removed completely

but *achromatization* can be achieved at some well chosen wavelength pair, by combining lenses made of different glasses



Achromatic Lens

sometimes *achromatization* is achieved for more than 2 wavelengths

device technologies: brief overview

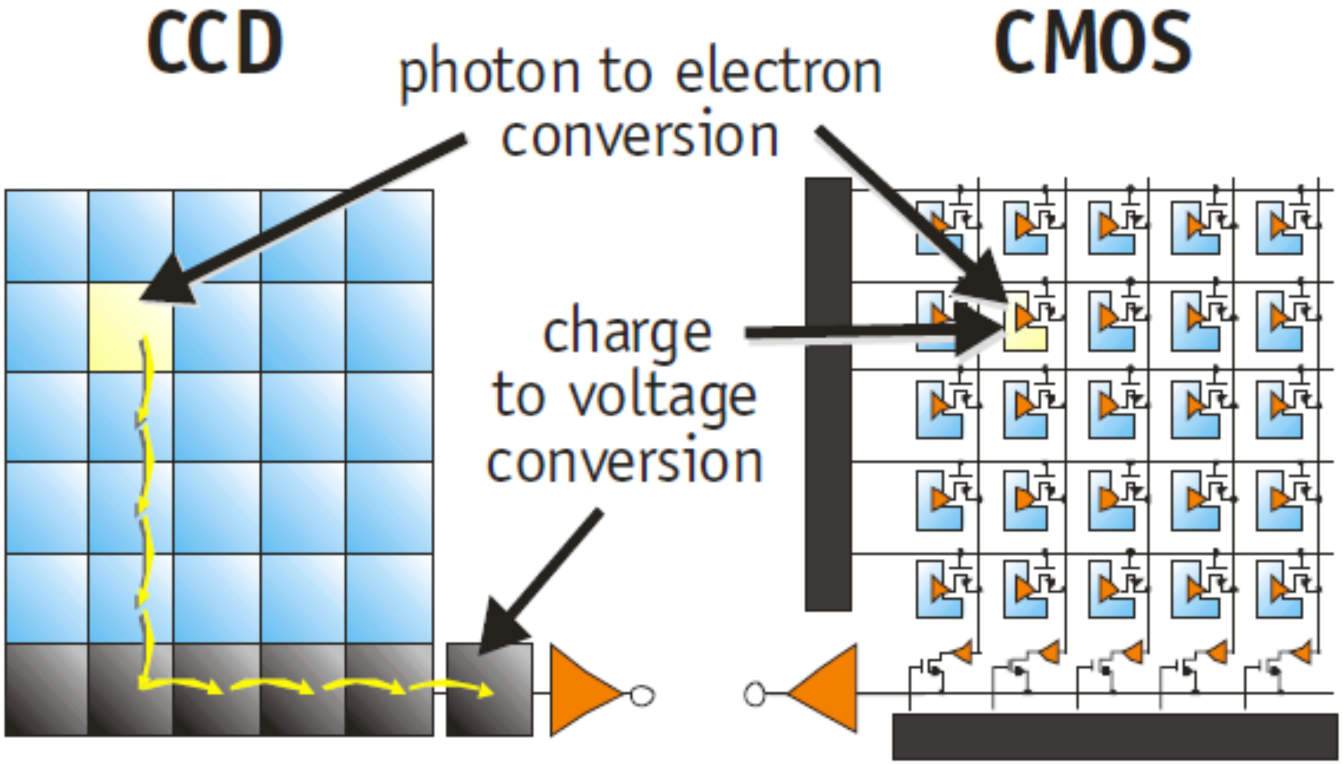
Cameras

we consider 2 types :

1. CCD

2. CMOS

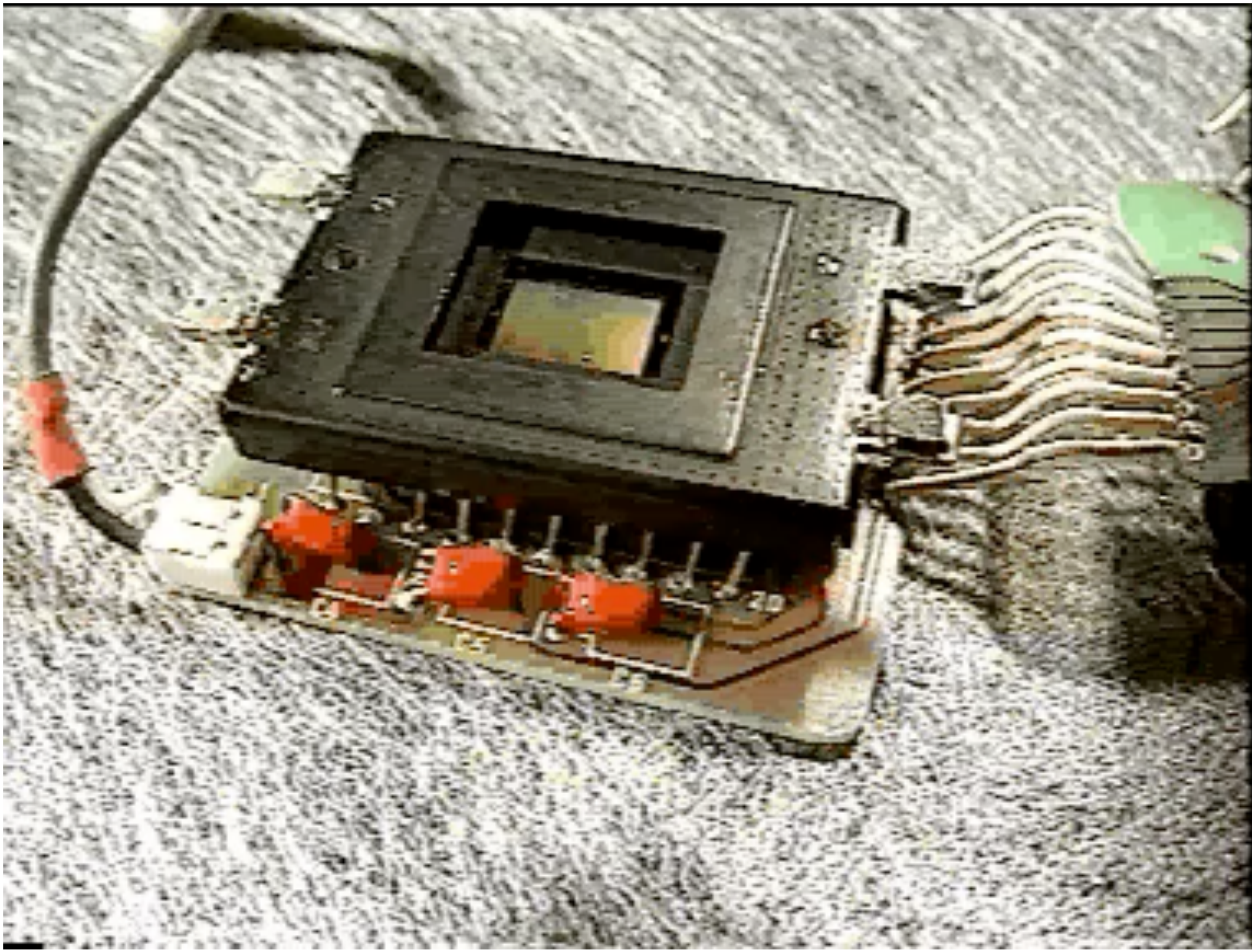
Cameras



CCD = Charge-coupled device
CMOS = Complementary Metal Oxide Semiconductor

Computer Vision

CCD Interline camera



Computer Vision

CMOS

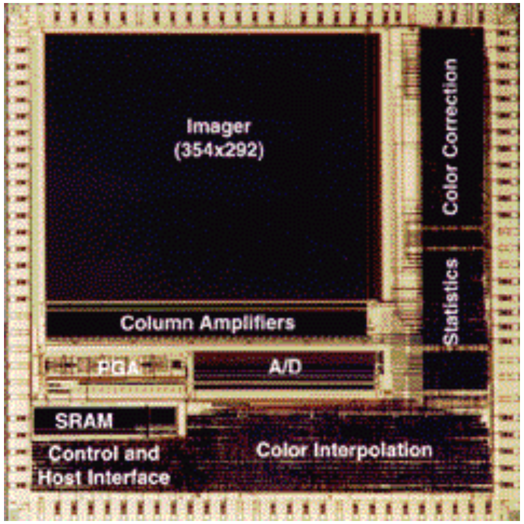
Same sensor elements as CCD

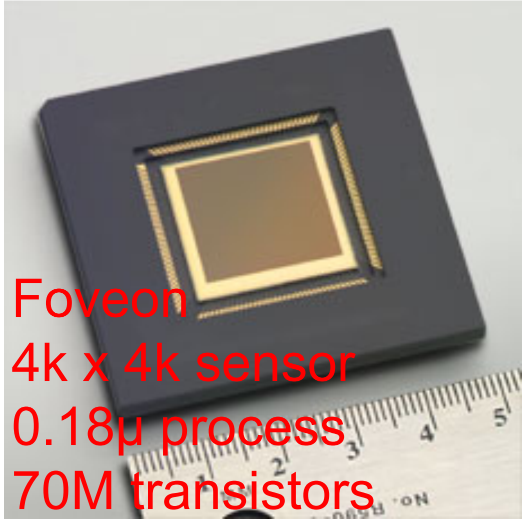
Each photo sensor has its own amplifier (Active Pixel Sensor)

- More noise (reduced by subtracting 'black' image)
- Lower sensitivity (lower fill rate)

Uses standard CMOS technology

- Allows to put other components on chip
- 'Smart' pixels

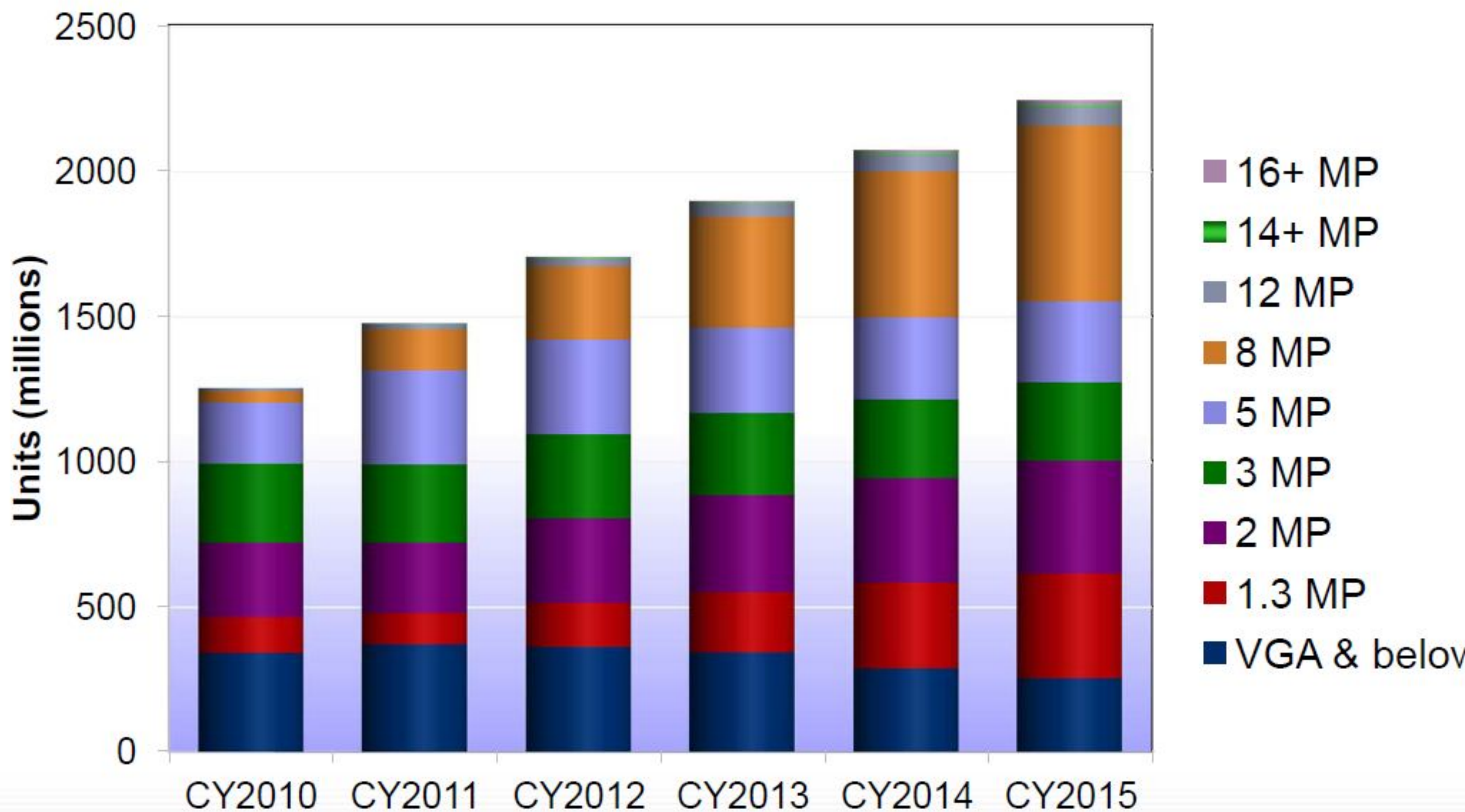




CMOS

Resolution trend in mobile phones

Volume and revenue opportunity for high resolution sensors



Source: TSR, CCD/CMOS Area Image Sensor Market Analysis, dated June 2011

CCD vs. CMOS

- Niche applications
- Specific technology
- High production cost
- High power consumption
- Higher fill rate
- Blooming
- Sequential readout

- Consumer cameras
- Standard IC technology
- Cheap
- Low power
- Less sensitive
- Per pixel amplification
- Random pixel access
- Smart pixels
- On chip integration with other components

2006 was year of sales cross-over

Computer Vision

CCD vs. CMOS

- Niche applications
- Specific technology
- High production cost
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- Blooming
- Sequential readout

- Consumer cameras
- Standard IC technology
- Cheap
- Low power
- Less sensitive
- Per pixel amplification
- Random pixel access
- Smart pixels
- On chip integration with other components

In 2015 Sony said to stop CCD chip production

Color cameras

- We consider 3 concepts:

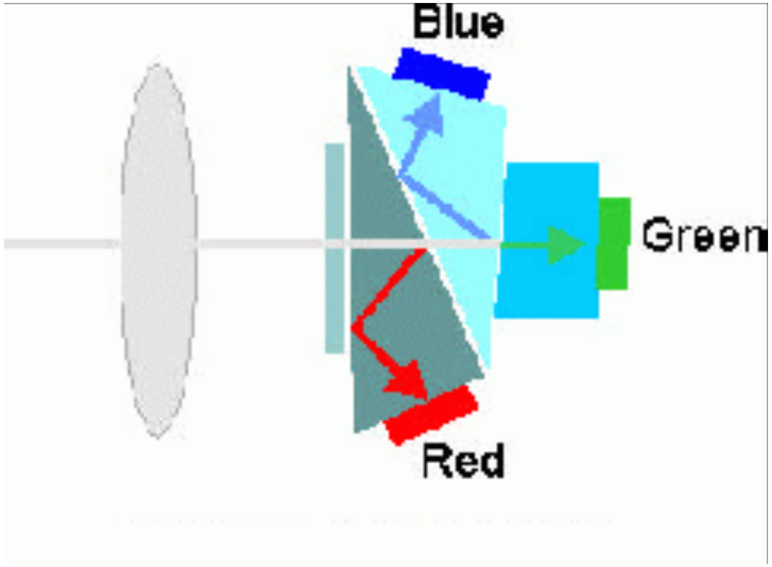
1. Prism (with 3 sensors)
2. Filter mosaic
3. Filter wheel

Prism color camera

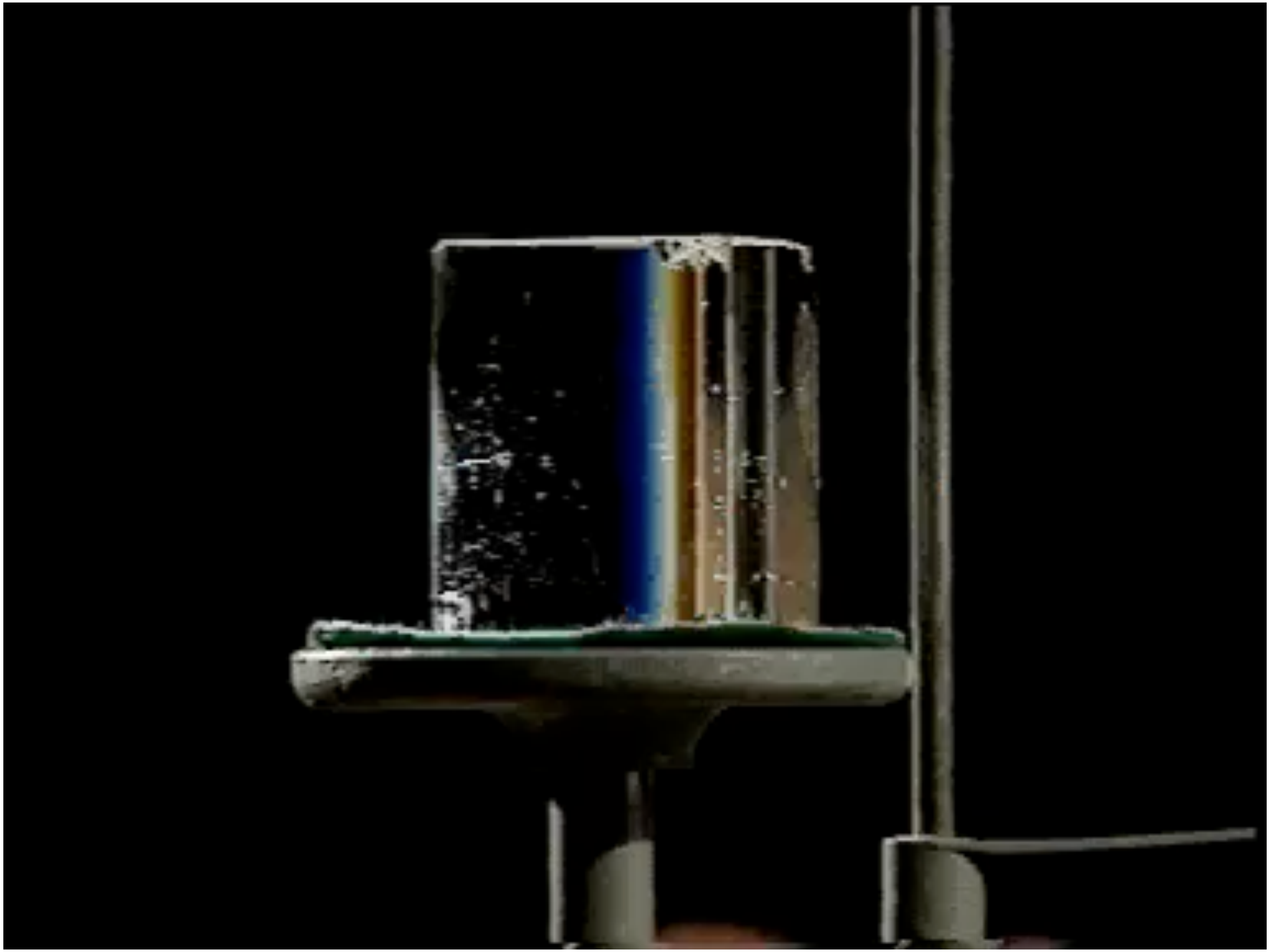
Separate light in 3 beams using dichroic prism

Requires 3 sensors & precise alignment

Good color separation

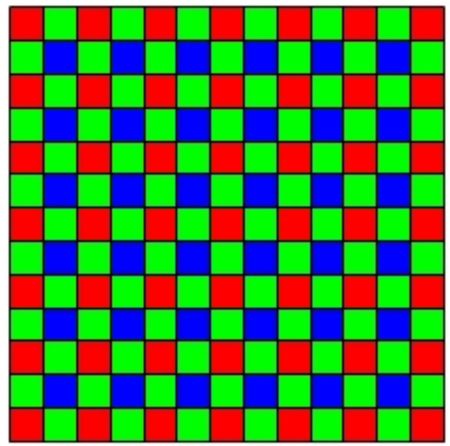


Prism color camera

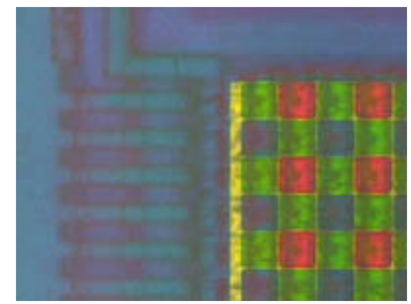


Filter mosaic

Coat filter directly on sensor

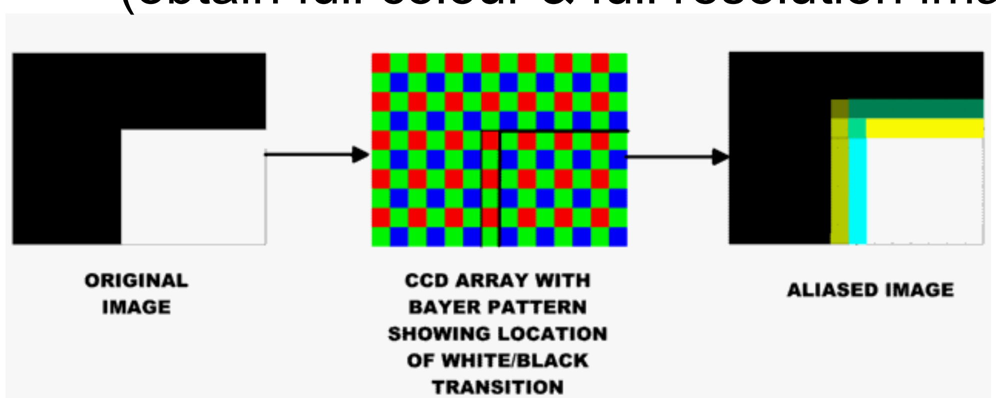


Bayer filter

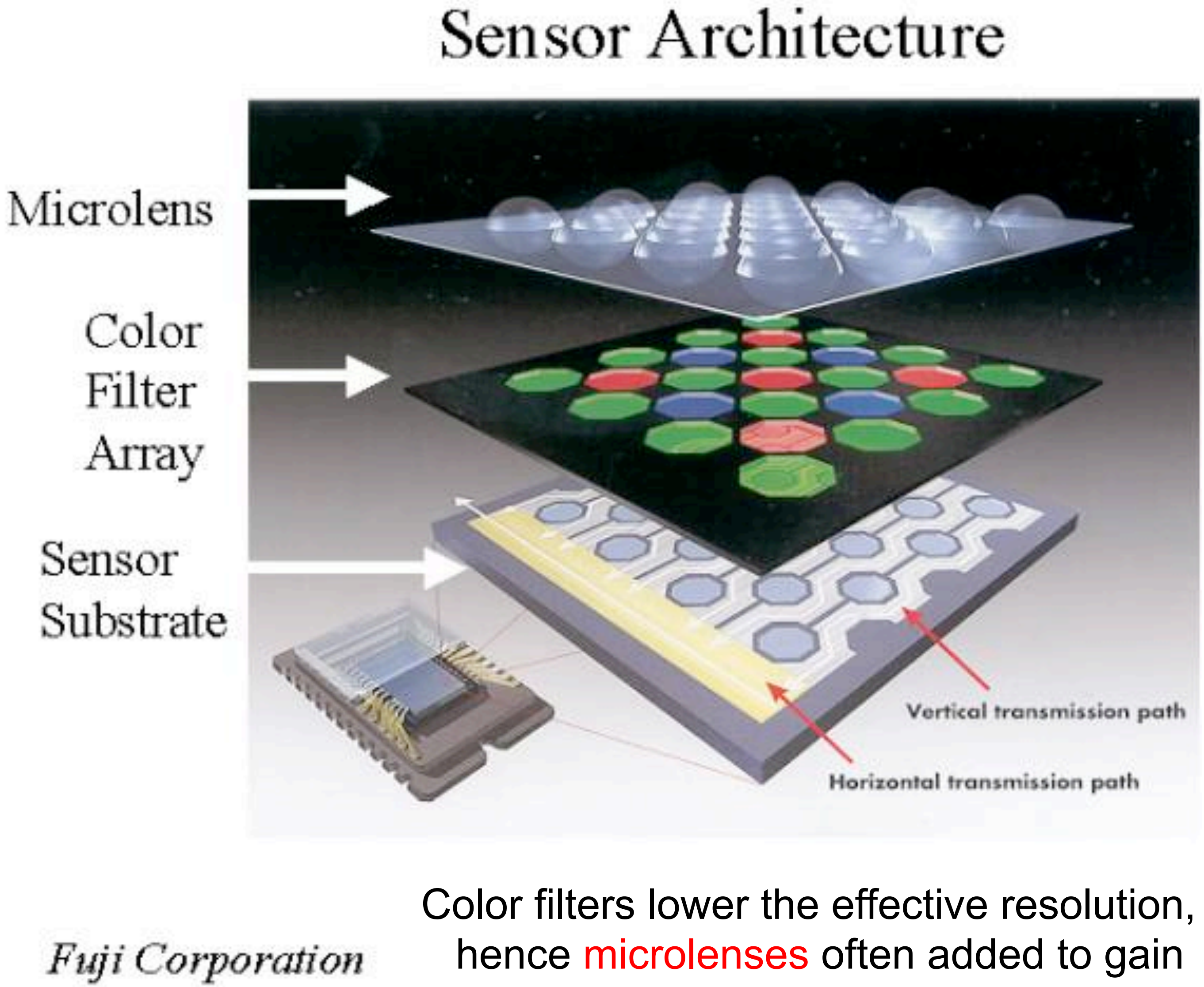


Demosaicing / Interpolation

(obtain full colour & full resolution image)



Filter mosaic

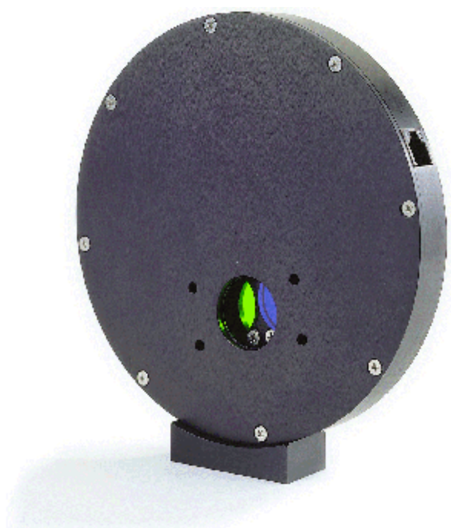


Color filters lower the effective resolution, hence microlenses often added to gain more light on the small pixels

Filter wheel

Rotate multiple filters in front of lens

Allows more than 3 colour bands



Only suitable for static scenes

Prism vs. Mosaic vs. Wheel

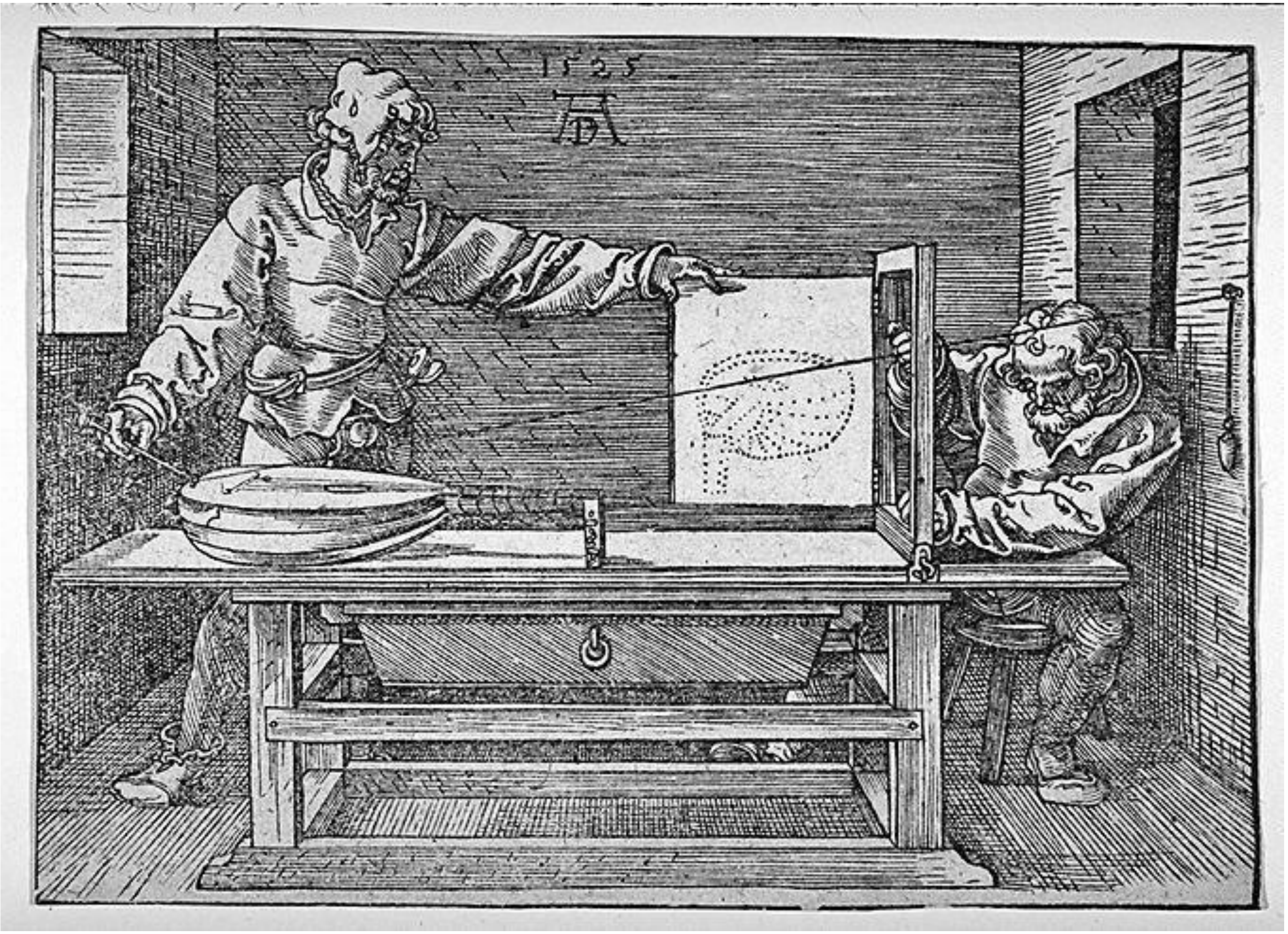
approach	Prism	Mosaic	Wheel
# sensors	3	1	1
Resolution	High	Average	Good
Cost	High	Low	Average
Framerate	High	High	Low
Artefacts	Low	Aliasing	Motion
Bands	3	3	3 or more
	High-end cameras	Low-end cameras	Scientific applications

geometric models

Computer Vision

Geometric camera model

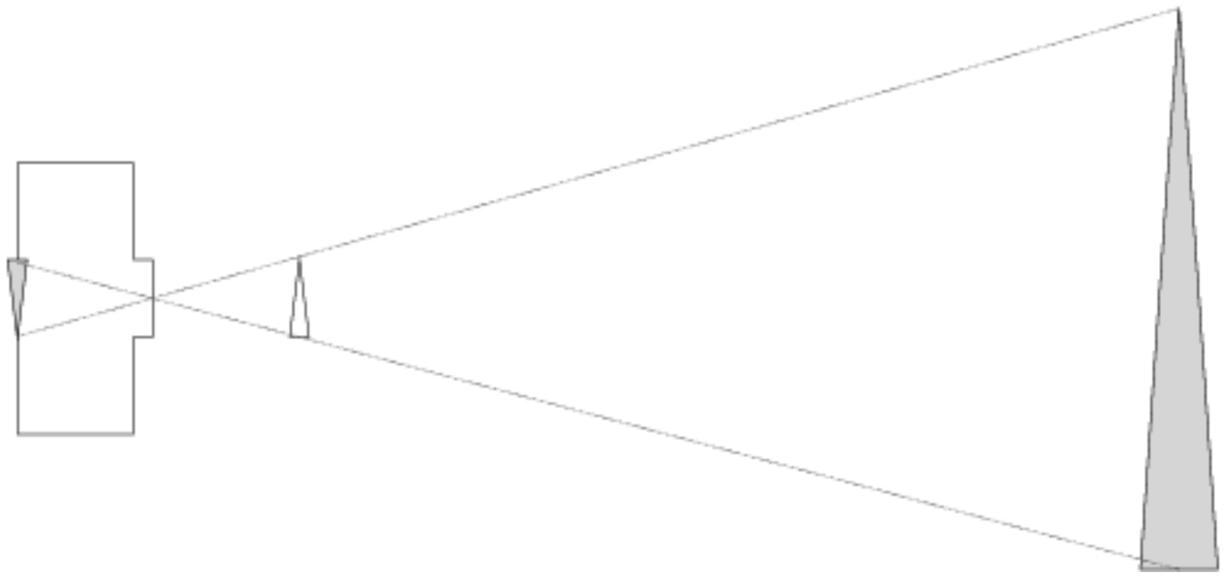
perspective projection



(Man Drawing a Lute, woodcut, 1525, Albrecht Dürer)

Models for camera projection

the pinhole model revisited :



center of the lens = center of projection

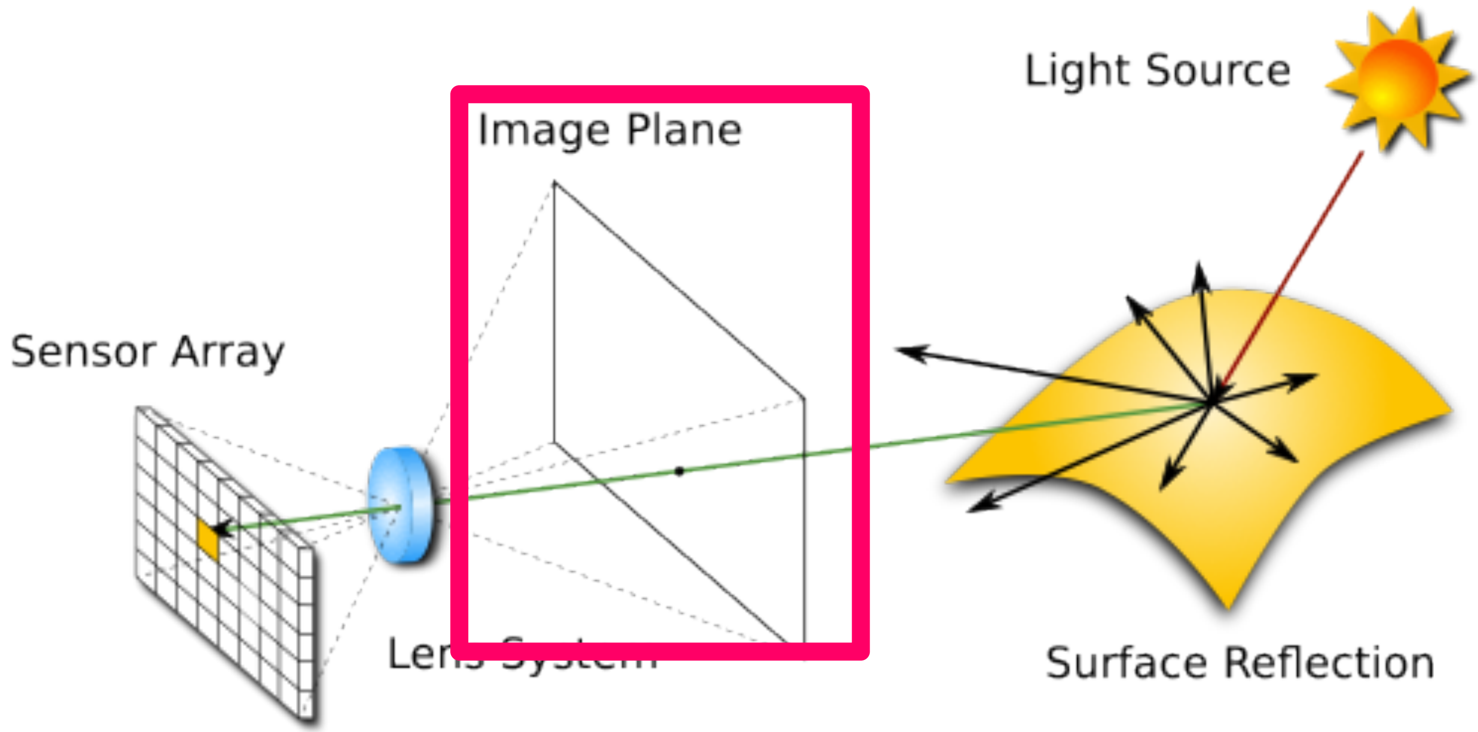
notice the virtual image plane

this is called *perspective* projection

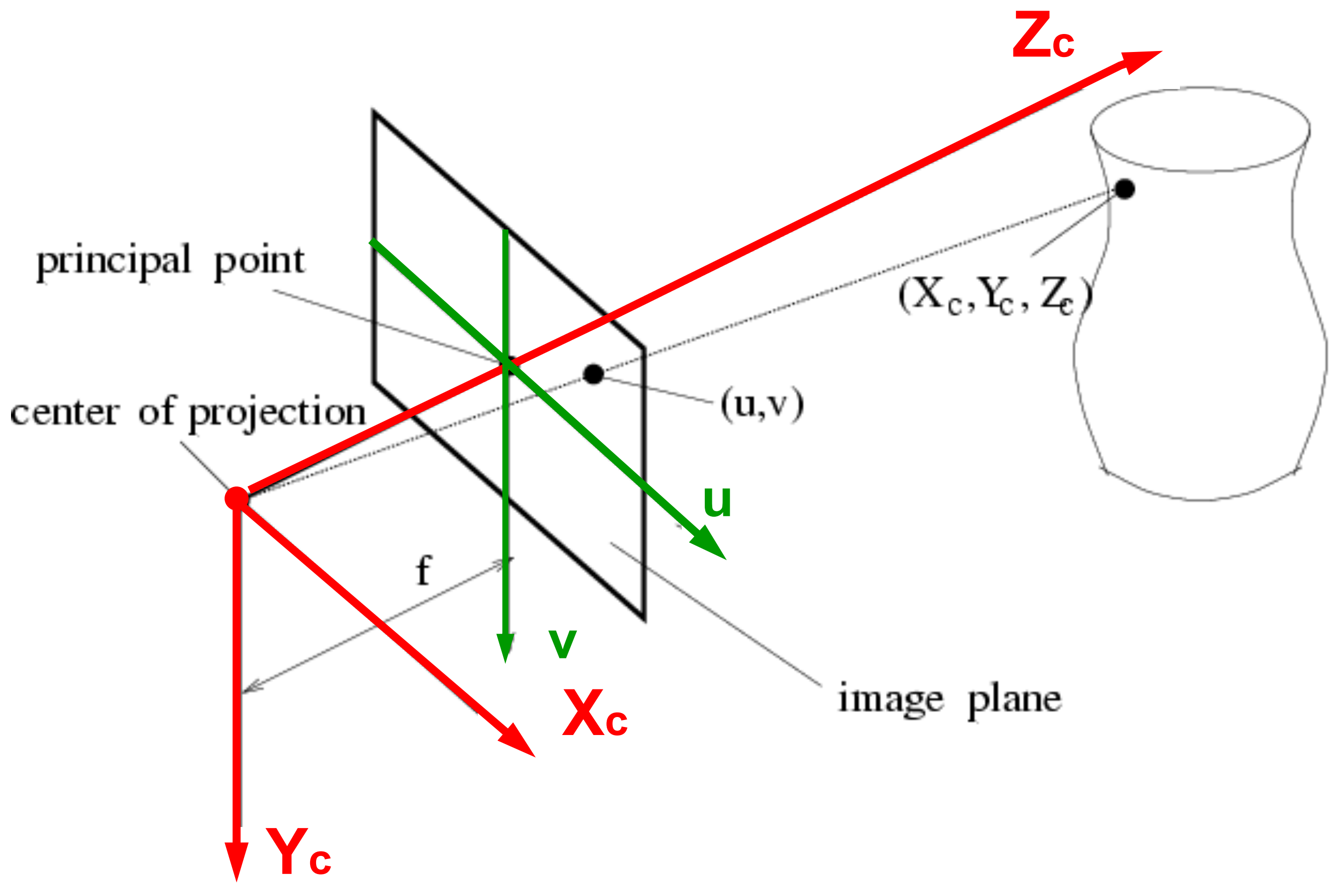
Computer Vision

Models for camera projection

We had the virtual plane also in the original reference sketch:



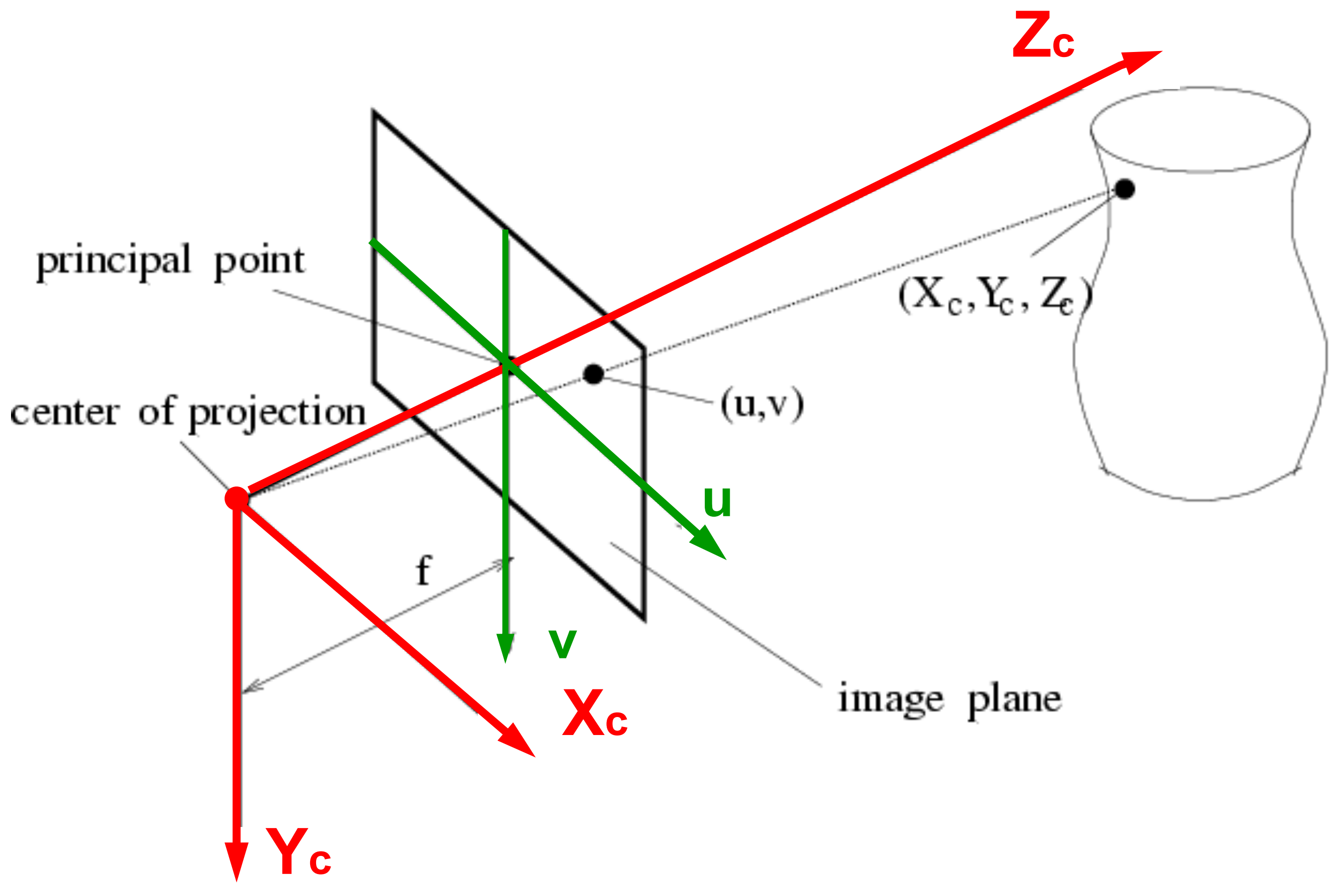
Perspective projection



- origin lies at the center of projection / center of the lens
- the Z_c axis coincides with the optical axis
- X_c-axis || to image rows, Y_c-axis || to columns

Computer Vision

Perspective projection



$$u = f\frac{X}{Z} \qquad v = f\frac{Y}{Z}$$

Computer Vision

Pseudo-orthographic projection

$$u = f\frac{X}{Z} \qquad v = f\frac{Y}{Z}$$

If Z is constant $\Rightarrow x = kX$ and $y = kY$,
where $k = f/Z$

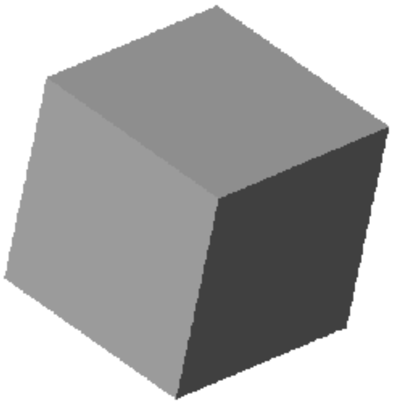
i.e. *orthographic* projection (k=1) + a scaling

Also called a pseudo-perspective projection

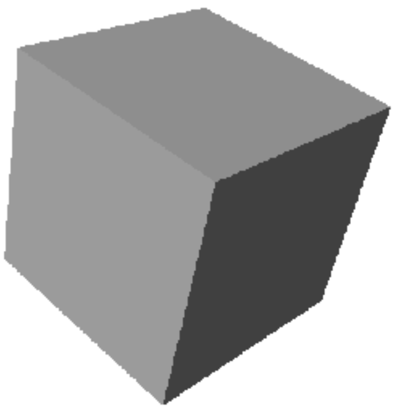
Good approximation if $f/Z \approx$ constant, i.e. if objects are small compared to their distance from the camera

Pictoral comparison

Pseudo - orthographic



Perspective



Projection matrices

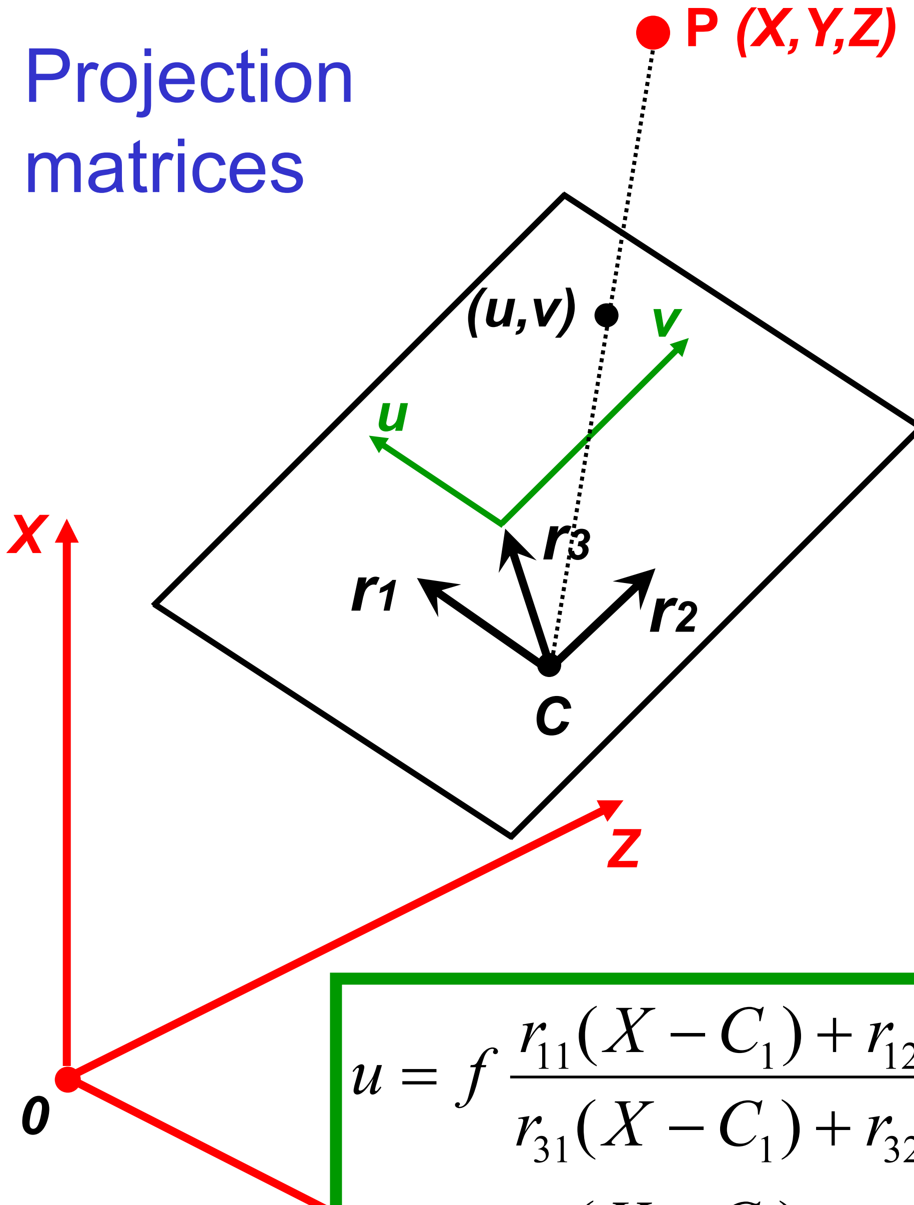
the perspective projection model is incomplete : what if :

1. 3D coordinates are specified in a *world coordinate frame*

2. Image coordinates are expressed as *row and column numbers*

We will not consider additional refinements, such as radial distortions,...

Projection matrices



$$u = f\,\frac{\langle r_1, P - C\rangle}{\langle r_3, P - C\rangle}$$

$$v = f\,\frac{\langle r_2, P - C\rangle}{\langle r_3, P - C\rangle}$$

$$u = f\,\frac{r_{11}(X - C_1) + r_{12}(Y - C_2) + r_{13}(Z - C_3)}{r_{31}(X - C_1) + r_{32}(Y - C_2) + r_{33}(Z - C_3)}$$

$$v = f\,\frac{r_{21}(X - C_1) + r_{22}(Y - C_2) + r_{23}(Z - C_3)}{r_{31}(X - C_1) + r_{32}(Y - C_2) + r_{33}(Z - C_3)}$$

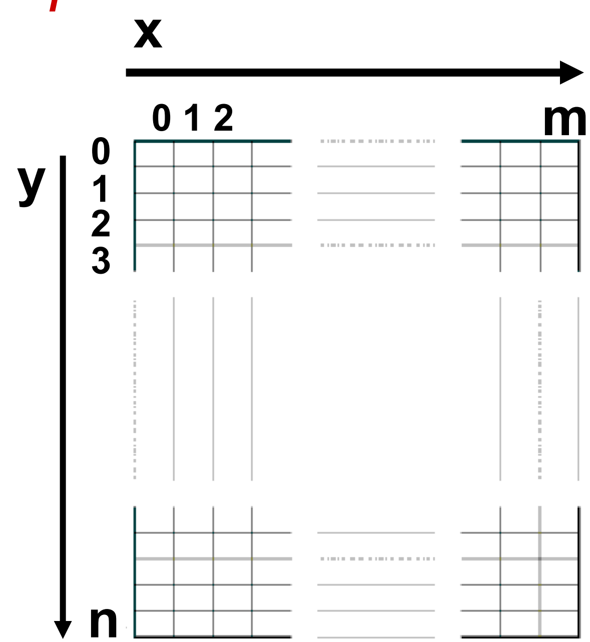
Computer Vision

ACQUIS.

illumination
cameras

Projection matrices

Image coordinates are to be expressed as *pixel coordinates*



$$\begin{cases} x = k_x u + s\,v + x_0 \\ y = k_y v + y_0 \end{cases}$$

with :

→ (x_0, y_0) the pixel coordinates of the principal point

→ k_x the number of pixels per unit length horizontally

→ k_y the number of pixels per unit length vertically

→ s indicates the skew, i.e. how much it deviates from a rectangle, typically $s = 0$

Computer Vision

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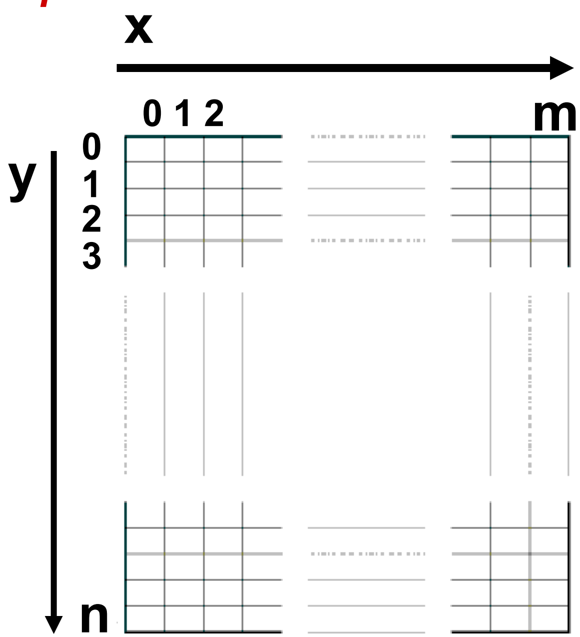
Projection matrices

Image coordinates are to be expressed as *pixel coordinates*



$$\begin{cases} x = k_x u + s\,v + x_0 \\ y = k_y v + y_0 \end{cases}$$

with :

NB1: often only integer pixel coordinates matter

Computer Vision

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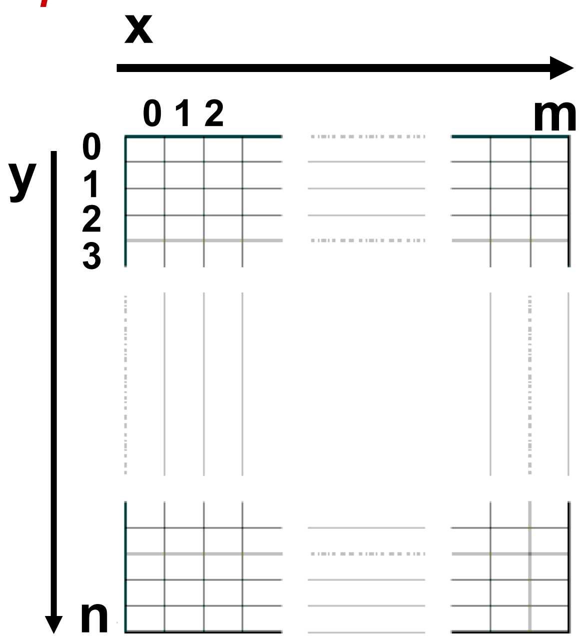
Projection matrices

Image coordinates are to be expressed as *pixel coordinates*



$$\begin{cases} x = k_x u + s\,v + x_0 \\ y = k_y v + y_0 \end{cases}$$

with :

NB2 : k_y/k_x is called the *aspect ratio*
Deviations indicate non-square pixels

Computer Vision

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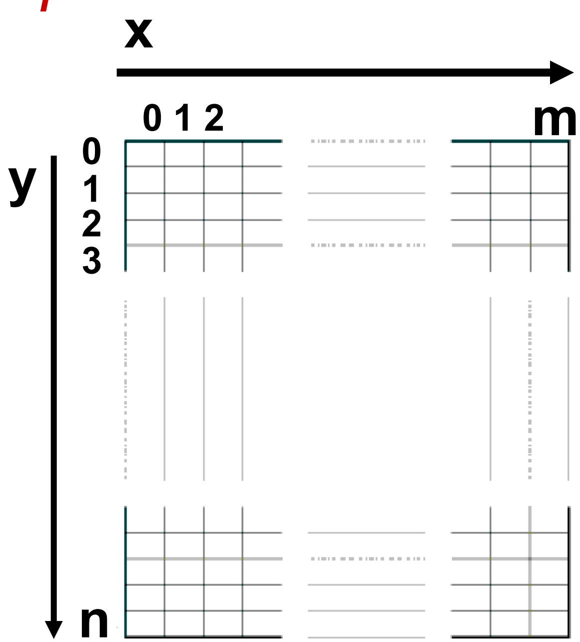
Projection matrices

Image coordinates are to be expressed as *pixel coordinates*



$$\begin{cases} x = k_x u + s\, v + x_0 \\ y = k_y v + y_0 \end{cases}$$

with :

NB3 : k_x, k_y, s, x_0 and y_0 are called *internal camera parameters*

Computer Vision

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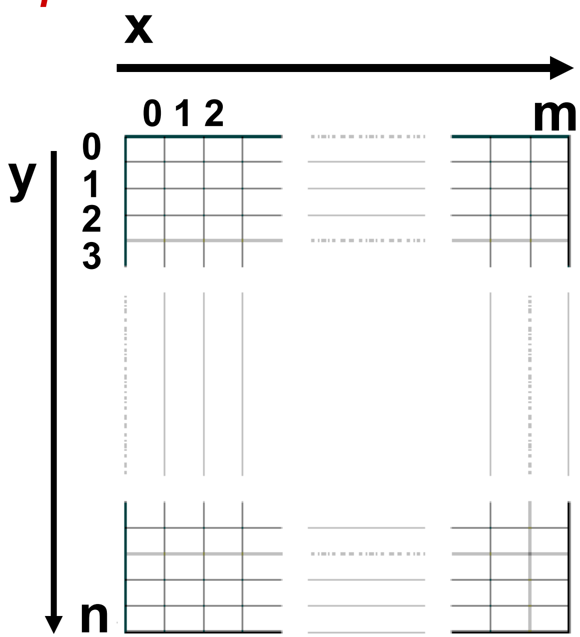
cameras

Projection matrices

Image coordinates are to be expressed as *pixel coordinates*



$$\begin{cases} x = k_x u + s\, v + x_0 \\ y = k_y v + y_0 \end{cases}$$

with :

NB4 : when they are known, the camera is *internally calibrated*

Computer Vision

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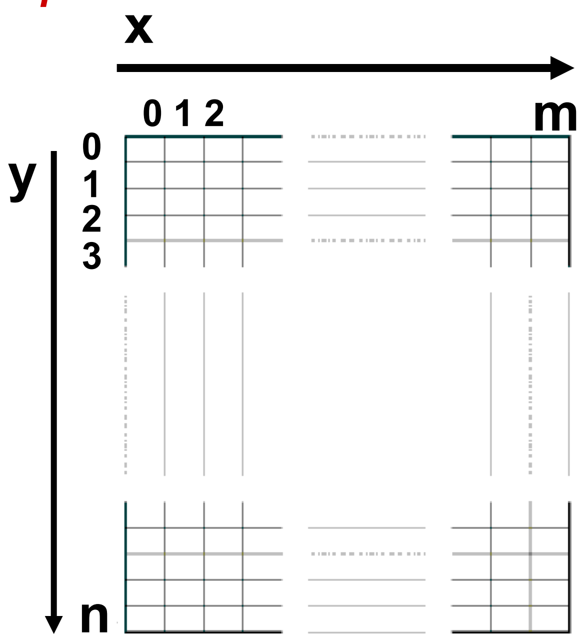
cameras

Projection matrices

Image coordinates are to be expressed as *pixel coordinates*



$$\begin{cases} x = k_x u + s\,v + x_0 \\ y = \qquad\quad k_y v + y_0 \end{cases}$$

with :

NB5 : vector C and matrix R∈ SO (3) are the *external camera parameters*

Computer Vision

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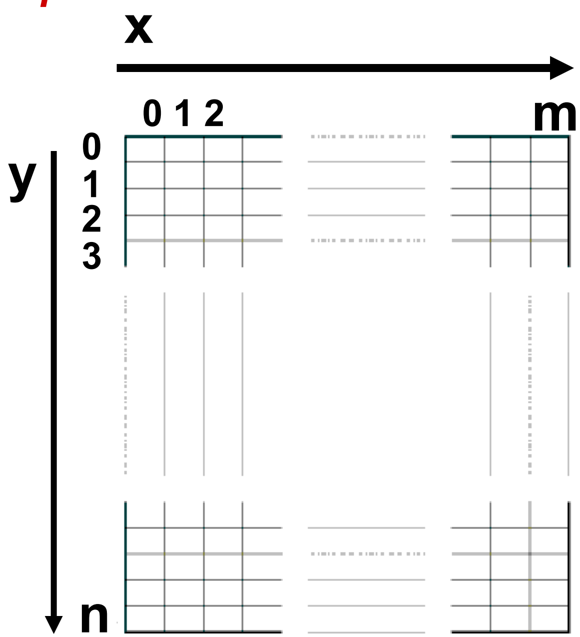
cameras

Projection matrices

Image coordinates are to be expressed as *pixel coordinates*



$$\begin{cases} x = k_x u + s\, v + x_0 \\ y = \qquad k_y v + y_0 \end{cases}$$

with :

NB6 : when these are known, the camera is *externally calibrated*

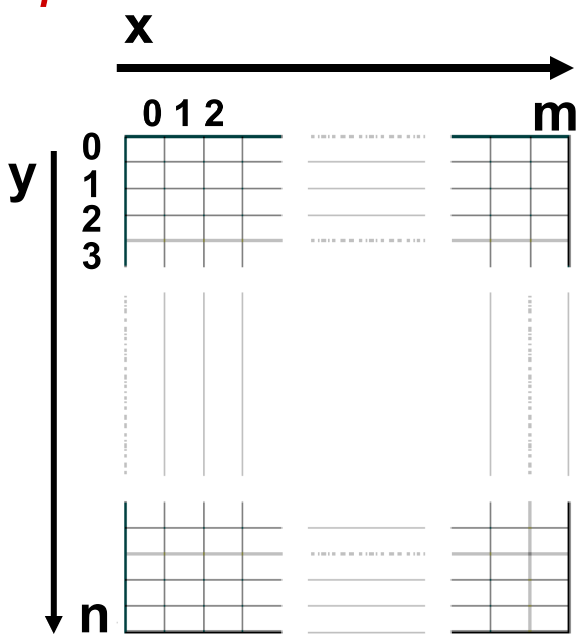
Computer Vision

ACQUIS.

illumination
cameras

Projection matrices

Image coordinates are to be expressed as *pixel coordinates*



$$\begin{cases} x = k_x u + s\,v + x_0 \\ y = k_y v + y_0 \end{cases}$$

with :

NB7 : *fully calibrated* means internally and externally calibrated

Homogeneous coordinates

Often used to linearize non-linear relations

2D
$$\begin{pmatrix} x \\ y \\ z \end{pmatrix} \to \begin{pmatrix} x/z \\ y/z \end{pmatrix}$$

3D
$$\begin{pmatrix} X \\ Y \\ Z \\ W \end{pmatrix} \to \begin{pmatrix} X/W \\ Y/W \\ Z/W \end{pmatrix}$$

Homogeneous coordinates are only defined up to a factor

Projection matrices

$$u = f\,\frac{r_{11}(X-C_1)+r_{12}(Y-C_2)+r_{13}(Z-C_3)}{r_{31}(X-C_1)+r_{32}(Y-C_2)+r_{33}(Z-C_3)}$$

$$v = f\,\frac{r_{21}(X-C_1)+r_{22}(Y-C_2)+r_{23}(Z-C_3)}{r_{31}(X-C_1)+r_{32}(Y-C_2)+r_{33}(Z-C_3)}$$

Exploiting homogeneous coordinates :

$$\tau\begin{pmatrix}u\\ v\\ 1\end{pmatrix} = \begin{pmatrix} f\,r_{11} & f\,r_{12} & f\,r_{13}\\ f\,r_{21} & f\,r_{22} & f\,r_{23}\\ r_{31} & r_{32} & r_{33}\end{pmatrix}\begin{pmatrix}X-C_1\\ Y-C_2\\ Z-C_3\end{pmatrix}$$

Projection matrices

$$\begin{cases} x = k_x u + s\,v + x_0 \\ y = \qquad\quad k_y v + y_0 \end{cases}$$

Exploiting homogeneous coordinates :

$$\tau \begin{pmatrix} x \\ y \\ 1 \end{pmatrix} = \begin{pmatrix} k_x & s & x_0 \\ 0 & k_y & y_0 \\ 0 & 0 & 1 \end{pmatrix} \tau \begin{pmatrix} u \\ v \\ 1 \end{pmatrix}$$

Projection matrices

Thus far, we have :

$$\tau \begin{pmatrix} u \\ v \\ 1 \end{pmatrix} = \begin{pmatrix} f\,r_{11} & f\,r_{12} & f\,r_{13} \\ f\,r_{21} & f\,r_{22} & f\,r_{23} \\ r_{31} & r_{32} & r_{33} \end{pmatrix} \begin{pmatrix} X - C_1 \\ Y - C_2 \\ Z - C_3 \end{pmatrix}$$

$$\tau \begin{pmatrix} x \\ y \\ 1 \end{pmatrix} = \begin{pmatrix} k_x & s & x_0 \\ 0 & k_y & y_0 \\ 0 & 0 & 1 \end{pmatrix} \tau \begin{pmatrix} u \\ v \\ 1 \end{pmatrix}$$

Projection matrices

Concatenating the results :

$$\tau\begin{pmatrix} x \\ y \\ 1 \end{pmatrix} = \begin{pmatrix} k_x & s & x_0 \\ 0 & k_y & y_0 \\ 0 & 0 & 1 \end{pmatrix}\begin{pmatrix} f\,r_{11} & f\,r_{12} & f\,r_{13} \\ f\,r_{21} & f\,r_{22} & f\,r_{23} \\ r_{31} & r_{32} & r_{33} \end{pmatrix}\begin{pmatrix} X - C_1 \\ Y - C_2 \\ Z - C_3 \end{pmatrix}$$

Or, equivalently :

$$\tau\begin{pmatrix} x \\ y \\ 1 \end{pmatrix} = \begin{pmatrix} k_x & s & x_0 \\ 0 & k_y & y_0 \\ 0 & 0 & 1 \end{pmatrix}\begin{pmatrix} f & 0 & 0 \\ 0 & f & 0 \\ 0 & 0 & 1 \end{pmatrix}\begin{pmatrix} r_{11} & r_{12} & r_{13} \\ r_{21} & r_{22} & r_{23} \\ r_{31} & r_{32} & r_{33} \end{pmatrix}\begin{pmatrix} X - C_1 \\ Y - C_2 \\ Z - C_3 \end{pmatrix}$$

Projection matrices

Re-combining matrices in the concatenation :

$$\tau \begin{pmatrix} x \\ y \\ 1 \end{pmatrix} = \begin{pmatrix} k_x & s & x_0 \\ 0 & k_y & y_0 \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} f & 0 & 0 \\ 0 & f & 0 \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} r_{11} & r_{12} & r_{13} \\ r_{21} & r_{22} & r_{23} \\ r_{31} & r_{32} & r_{33} \end{pmatrix} \begin{pmatrix} X - C_1 \\ Y - C_2 \\ Z - C_3 \end{pmatrix}$$

yields the calibration matrix *K*:

$$K = \begin{pmatrix} k_x & s & x_0 \\ 0 & k_y & y_0 \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} f & 0 & 0 \\ 0 & f & 0 \\ 0 & 0 & 1 \end{pmatrix} = \begin{pmatrix} f\,k_x & f\,s & x_0 \\ 0 & f\,k_y & y_0 \\ 0 & 0 & 1 \end{pmatrix}$$

Projection matrices

We define

$$p = \begin{pmatrix} x \\ y \\ 1 \end{pmatrix}; \quad P = \begin{pmatrix} X \\ Y \\ Z \end{pmatrix}, \quad \widetilde{P} = \begin{pmatrix} X \\ Y \\ Z \\ 1 \end{pmatrix}$$

yielding

$$\rho p = KR^t(P - C)$$ for some non-zero $\rho \in \mathbb{R}$

or, $$\rho p = K\left(R^t \mid -R^t C\right)\widetilde{P}$$

or, $$\rho p = (M \mid t)\widetilde{P}$$ with rank $M = 3$

From object radiance to pixel grey levels

After the geometric camera model...

… a **photometric** camera model

2 steps:

1. from object radiance to image irradiance
2. from image irradiance to pixel grey level

Image irradiance and object radiance

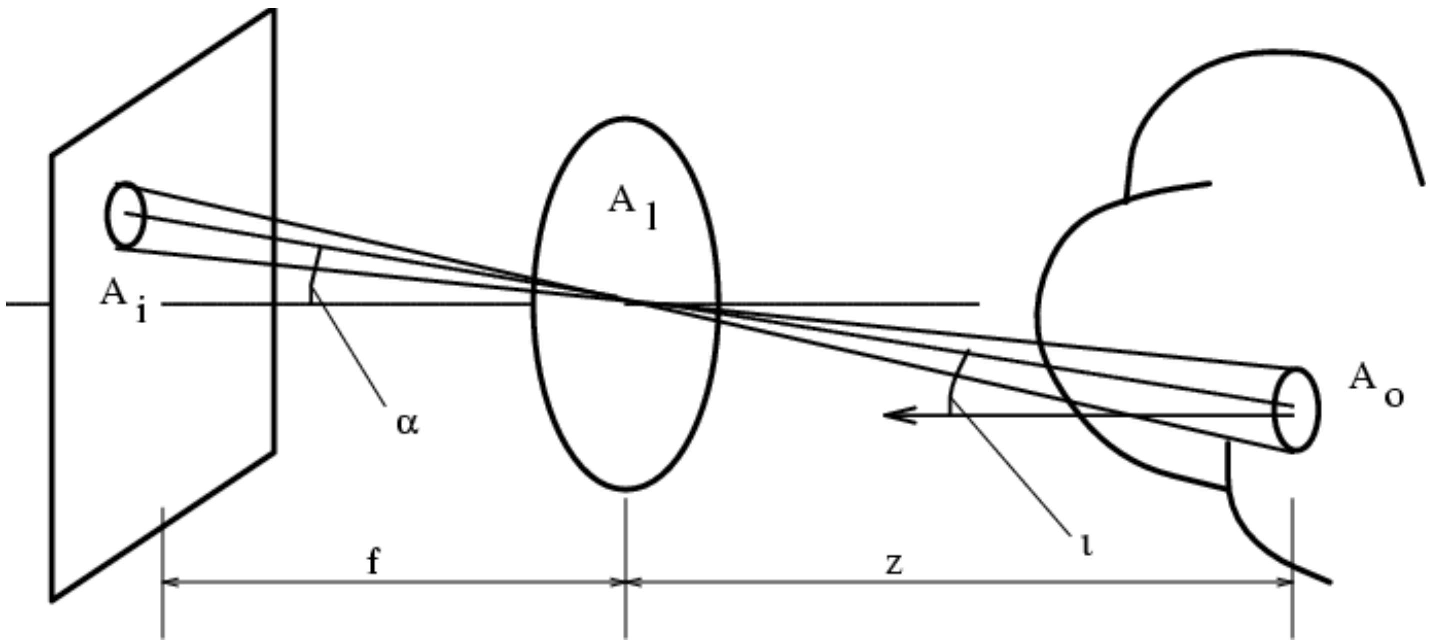
we look at the irradiance that an object patch will cause in the image

assumptions :
radiance *R* assumed known and
object at large distance compared to the focal length

Is image irradiance directly related to the radiance of the image patch?

Computer Vision

The viewing conditions



$$I = R \frac{A_l}{f^2} \cos^4 \alpha$$

the cos^4 law

Computer Vision

The $\cos^4$ law cont’d

Especially strong effects for wide-angle and fisheye lenses

From irradiance to gray levels

$$f = g I^{\gamma} + d$$

Gain

"gamma"

Dark reference

From irradiance to gray levels

$$f = g\, I^{\gamma} + d$$

set w. size diaphragm — Gain

close to 1 nowadays — "gamma"

signal w. cam cap on — Dark reference