# Acquisition of Images 

Computer Vision

## Acquisition of images

## We focus on :

## 1. cameras

2. illumination

Image Plane

Sensor Array

Lens System

Light Source

Surface Reflection

Computer Vision

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Computer
Vision
cameras

Computer
Vision

## Optics for image formation

the pinhole model :


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## 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)

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## Camera obscura + lens



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## The thin-lens equation

lens to capture enough light :

assuming
$\square$ spherical lens surfaces
$\square$ incoming light $\pm$ parallel to axis
$\square$ thickness << radii
$\square$ same refractive index on both sides

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## The depth-of-field

Only reasonable sharpness in Z-interval


$$
\Delta Z_{0}^{-}=Z_{0}-Z_{0}^{-}=\frac{Z_{0}\left(Z_{0}-f\right)}{Z_{0}+f d / b-f}
$$

decreases with $d$, increases with $Z_{0}$
strike a balance between incoming light ( $d$ ) and large depth-of-field (usable depth range)

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## The depth-of-field



$$
\Delta Z_{0}^{-}=Z_{0}-Z_{0}^{-}=\frac{Z_{0}\left(Z_{0}-f\right)}{Z_{0}+f d / b-f}
$$

Similar expression for $Z_{O}^{+}-Z_{O}$

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## The depth-of-field



$$
\Delta Z_{0}^{-}=Z_{0}-Z_{0}^{-}=\frac{Z_{0}\left(Z_{0}-f\right)}{Z_{0}+f d / b-f}
$$

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
2. chromatic
geometrical : small for paraxial rays
chromatic : refractive index function of wavelength (Snell's law !!)

## Geometrical aberrations

$\square$ spherical aberration
$\square$ astigmatism

## the most important type

$\square$ radial distortion
$\square$ coma

## Spherical aberration

rays parallel to the axis do not converge
outer portions of the lens yield smaller focal lenghts


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## Radial Distortion

magnification different
for different angles of inclination

barrel

none

pincushion

## Radial Distortion

magnification different
for different angles of inclination

barrel

none

pincushion

The result is pixels moving along lines through the center of the distortion

- typically close to the image center - over a distance $d$, depending on the pixels' distance $r$ to the center

$$
d=\left(1+\kappa_{1} r^{2}+\kappa_{2} r^{4}+\ldots\right)
$$

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## Radial Distortion

## magnification different

for different angles of inclination


This aberration type can be corrected by software if the parameters $\left(\kappa_{1}, \kappa_{2}, \ldots\right)$ are known

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## Radial Distortion

## magnification different

for different angles of inclination


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

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## Chromatic aberration

rays of different wavelengths focused in different planes

cannot be removed completely
but achromatization can be achieved at some well chosen wavelength pair, by combining lenses made of different glasses
sometimes achromatization
 is achieved for more than 2 wavelengths

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## Lens materials


additional considerations :
humidity and temperature resistance, weight, price,...

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Cameras
we consider 2 types:

## 1. $C C D$

## 2. CMOS

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## Cameras

CCD photon to electron CMOS


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

## CCD

separate photo sensor at regular positions no scanning
charge-coupled devices (CCDs) area CCDs and linear CCDs
2 area architectures :
interline transfer and frame transfer
$\square$ photosensitive
$\square$ storage


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## The CCD inter-line camera



## CMOS

## Same sensor elements as CCD

Each photo sensor has its own amplifier
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


## 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

## CCD vs. CMOS

- Niche applications
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- Consumer cameras
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- Random pixel access
- Smart pixels
- On chip integration with other components


In 2015 Sony said to stop CCD chip production

## Colour cameras

- We consider 3 concepts:

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

## Prism colour camera

Separate light in 3 beams using dichroic prism Requires 3 sensors \& precise alignment Good color separation


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## Prism colour camera



## Filter mosaic

## Coat filter directly on sensor



Bayer filter
Demosaicing (obtain full colour \& full resolution image)


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## Filter mosaic

## Sensor Architecture



Color filters lower the effective resolution,
Fuji Corporation 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 |
| :--- | :--- |
| \# sensors | 3 |
| Resolution | High |
| Cost | High |
| Framerate | High |
| Artefacts | Low |
| Bands | 3 |

## High-end <br> cameras

| Mosaic |
| :--- |
| 1 |
| Average |
| Low |
| High |
| Aliasing |
| 3 |

Low-end
cameras

Wheel 1

Good
Average
Low
Motion
3 or more

Scientific applications

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## Odd-man-out X3 technology of Foveon

Exploits the wavelength dependent depth to which a photon penetrates silicon
And splits colors without the use of any filters

creates a stack of pixels at one place new CMOS technology

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## Geometric camera model perspective projection


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

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## 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

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## Models for camera projection

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


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## Perspective projection


$\square$ origin lies at the center of projection $Y$
$\square$ the $\mathscr{P}^{2}$ axisfoincides with theoptfalaxis
$\square X_{c}$-axis || to irgage rows, $Y_{c}$-axis || toZolumns

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## Pseudo-orthographic projection

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

If $Z$ is constant $\Rightarrow x=k X$ and $y=k Y$, where $k=f / Z$
i.e. orthographic projection + a scaling

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

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## Pictoral comparison

## Pseudo orthographic

Perspective


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## Pictoral comparison

## Pseudo orthographic

Perspective

## Projection matrices

the perspective projection model is incomplete : what if :

1. 3 D 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,...

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$$
\begin{aligned}
& \text { Projection } \\
& \text { matrices }
\end{aligned}
$$

## Projection matrices

Image coordinates are to be expressed as pixel coordinates

$\rightarrow(x 0, y 0)$ the pixel coordinates of the principal point
NB7 : fully calibrated means internally and externally calibrated


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## Homogeneous coordinates

Often used to linearize non-linear relations

$$
\begin{array}{ll}
\text { 2D } \quad\left(\begin{array}{l}
x \\
y \\
z
\end{array}\right) & \rightarrow\binom{x / z}{y / z} \\
3 \mathrm{D} \quad\left(\begin{array}{l}
X \\
Y \\
Z \\
W
\end{array}\right) & \rightarrow\left(\begin{array}{l}
X / W \\
Y / W \\
Z / W
\end{array}\right)
\end{array}
$$

Homogeneous coordinates are only defined up to a factor

## Projection matrices

$$
\begin{aligned}
& u=f \frac{r_{11}\left(X-C_{1}\right)+r_{12}\left(Y-C_{2}\right)+r_{13}\left(Z-C_{3}\right)}{r_{31}\left(X-C_{1}\right)+r_{32}\left(Y-C_{2}\right)+r_{33}\left(Z-C_{3}\right)} \\
& v=f \frac{r_{21}\left(X-C_{1}\right)+r_{22}\left(Y-C_{2}\right)+r_{23}\left(Z-C_{3}\right)}{r_{31}\left(X-C_{1}\right)+r_{32}\left(Y-C_{2}\right)+r_{33}\left(Z-C_{3}\right)}
\end{aligned}
$$

Exploiting homogeneous coordinates:
$\tau\left(\begin{array}{l}u \\ v \\ 1\end{array}\right)=\left(\begin{array}{ccc}f r_{11} & f r_{12} & f r_{13} \\ f r_{21} & f r_{22} & f r_{23} \\ r_{31} & r_{32} & r_{33}\end{array}\right)\left(\begin{array}{c}X-C_{1} \\ Y-C_{2} \\ Z-C_{3}\end{array}\right)$

## Projection matrices

$$
\left\{\begin{array}{l}
x=k_{x} u+s v+x_{0} \\
y=k_{y} v+y_{0}
\end{array}\right.
$$

Exploiting homogeneous coordinates:

$$
\tau\left(\begin{array}{l}
x \\
y \\
1
\end{array}\right)=\left(\begin{array}{ccc}
k_{x} & s & x_{0} \\
0 & k_{y} & y_{0} \\
0 & 0 & 1
\end{array}\right) \tau\left(\begin{array}{l}
u \\
v \\
1
\end{array}\right)
$$

## Projection matrices

Thus, we have :

$$
\begin{gathered}
\tau\left(\begin{array}{l}
u \\
v \\
1
\end{array}\right)=\left(\begin{array}{cccc}
f r_{11} & f r_{12} & f r_{13} \\
f r_{21} & f r_{22} & f & r_{23} \\
r_{31} & r_{32} & r_{33}
\end{array}\right)\left(\begin{array}{c}
X-C_{1} \\
Y-C_{2} \\
Z-C_{3}
\end{array}\right) \\
\tau\left(\begin{array}{l}
x \\
y \\
1
\end{array}\right)=\left(\begin{array}{ccc}
k_{x} & s & x_{0} \\
0 & k_{y} & y_{0} \\
0 & 0 & 1
\end{array}\right) \tau\left(\begin{array}{l}
u \\
v \\
1
\end{array}\right)
\end{gathered}
$$

## Projection matrices

Concatenating the results :
$\tau\left(\begin{array}{l}x \\ y \\ 1\end{array}\right)=\left(\begin{array}{ccc}k_{x} & s & x_{0} \\ 0 & k_{y} & y_{0} \\ 0 & 0 & 1\end{array}\right)\left(\begin{array}{cccc}f r_{11} & f & r_{12} & f r_{13} \\ f r_{21} & f & r_{22} & f \\ r_{23} \\ r_{31} & & r_{32} & \\ r_{33}\end{array}\right)\left(\begin{array}{l}X-C_{1} \\ Y-C_{2} \\ Z-C_{3}\end{array}\right)$
Or, equivalently :

$$
\tau\left(\begin{array}{l}
x \\
y \\
1
\end{array}\right)=\left(\begin{array}{ccc}
k_{x} & s & x_{0} \\
0 & k_{y} & y_{0} \\
0 & 0 & 1
\end{array}\right)\left(\begin{array}{ccc}
f & 0 & 0 \\
0 & f & 0 \\
0 & 0 & 1
\end{array}\right)\left(\begin{array}{lll}
r_{11} & r_{12} & r_{13} \\
r_{21} & r_{22} & r_{23} \\
r_{31} & r_{32} & r_{33}
\end{array}\right)\left(\begin{array}{l}
X-C_{1} \\
Y-C_{2} \\
Z-C_{3}
\end{array}\right)
$$

## Projection matrices

Re-combining matrices in the concatenation :

$$
\tau\left(\begin{array}{l}
x \\
y \\
1
\end{array}\right)=\left(\begin{array}{ccc}
k_{x} & s & x_{0} \\
0 & k_{y} & y_{0} \\
0 & 0 & 1
\end{array}\right)\left(\begin{array}{ccc}
f & 0 & 0 \\
0 & f & 0 \\
0 & 0 & 1
\end{array}\right)\left(\begin{array}{lll}
r_{11} & r_{12} & r_{13} \\
r_{21} & r_{22} & r_{23} \\
r_{31} & r_{32} & r_{33}
\end{array}\right)\left(\begin{array}{c}
X-C_{1} \\
Y-C_{2} \\
Z-C_{3}
\end{array}\right)
$$

yields the calibration matrix $K$ :

$$
K=\left(\begin{array}{lll}
k_{x} & s & x_{0} \\
0 & k_{y} & y_{0} \\
0 & 0 & 1
\end{array}\right)\left(\begin{array}{ccc}
f & 0 & 0 \\
0 & f & 0 \\
0 & 0 & 1
\end{array}\right)=\left(\begin{array}{ccc}
f k_{x} f s & x_{0} \\
0 & f k_{y} & y_{0} \\
0 & 0 & 1
\end{array}\right)
$$

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## Projection matrices

We define

$$
p=\left(\begin{array}{l}
x \\
y \\
1
\end{array}\right) ; \quad P=\left(\begin{array}{l}
X \\
Y \\
Z
\end{array}\right), \quad \widetilde{P}=\left(\begin{array}{l}
X \\
Y \\
Z \\
1
\end{array}\right)
$$

yielding
$\rho p=K R^{t}(P-C)$ for some non-zero $\rho \in \mathbb{R}$
or, $\quad \rho p=K\left(R^{t} \mid-R^{t} C\right) \widetilde{P}$
or, $\quad \rho p=(M \mid t) \widetilde{P}$ with rank $M=3$

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## From object radiance to pixel grey levels

After the geometric camera model...
... a p1010m91fle 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?

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## The viewing conditions



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

the $\cos ^{4}$ law

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The $\cos ^{4}$ law cont' d

## Especially strong effects for wide-angle and fisheye lenses



## From irradiance to gray levels

$$
f=\mathcal{E}^{\gamma}=1
$$

## Computer Vision <br> From irradiance to gray levels

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

signal w. cam cap on

Computer
Vision
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...

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## 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

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## Crack detection



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Example directional lighting Vision


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## Example diffuse lighting



## 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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## 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

## 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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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 $\Rightarrow$ same spectral composition of sources!
spectral sensitivity function of the sensors!

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## Example coloured lighting



## Coloured lighting

Example videos: weed-selective herbicide spraying

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## Coloured lighting

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## 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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Stroboscopic lighting


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## Application

Example videos: vegetable inspection

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Application

## MAT 2000

