

# Vision and Image Processing: Camera Models, Homographies

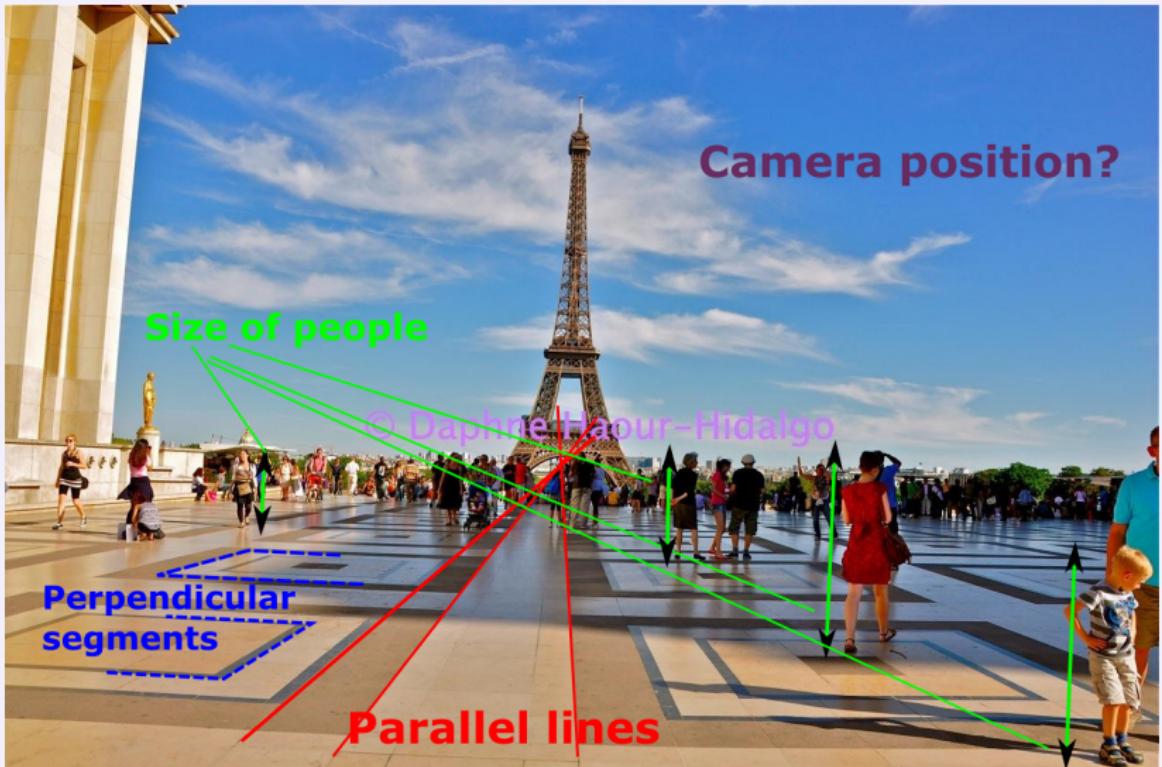
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# Plan for today

- Introduction to Camera Models, specifically the pinhole model and the perspective transformation
- Vanishing points and vanishing lines
- Homogeneous coordinates, Homographies
- Camera matrices and parameters
- Camera calibration
- Triangulation
- Questions for assignment 4

# Cameras and projections

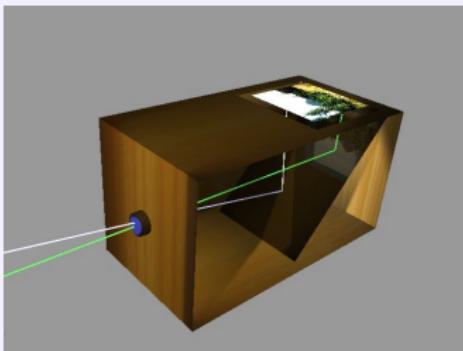


# Questions

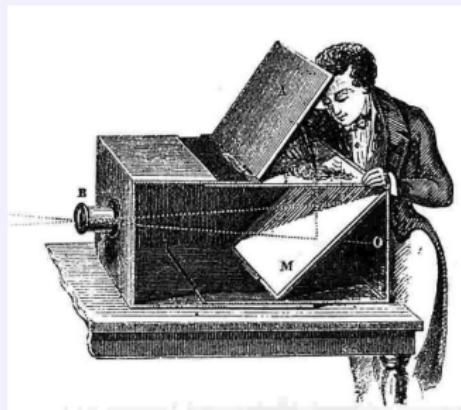
Previous picture raises some questions about:

- Lines?
- Parallelism?
- Angles / orthogonality?
- Sizes?
- Camera position / Horizon?

# Camera Obscura



Principle of Camera Obscura



18th Century Camera Obscura

- Known from old Chinese writings
- Mentioned by Aristotle
- Plaque with photosensitive material: Photographic camera!

# The Very First Photography, 1826



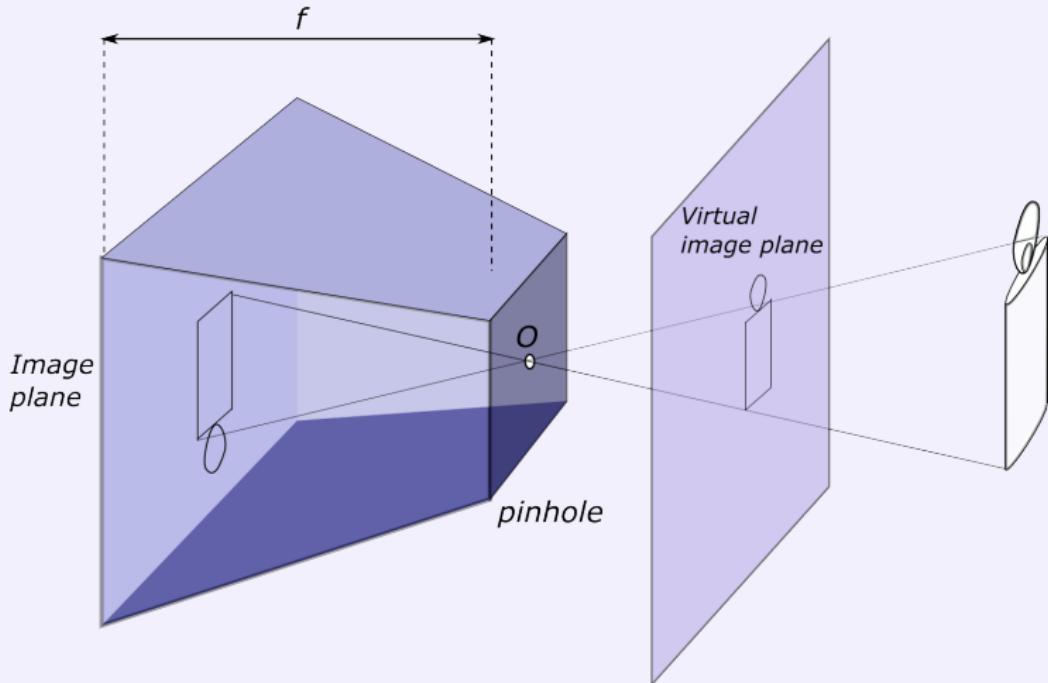
J.N. Niépce, View from the window at Le Gras, Saint Loup de Varennes, France – Now at University of Texas at Austin.

# The pin-hole camera



Magnesium light was used to make light enough enter the pin-hole box.

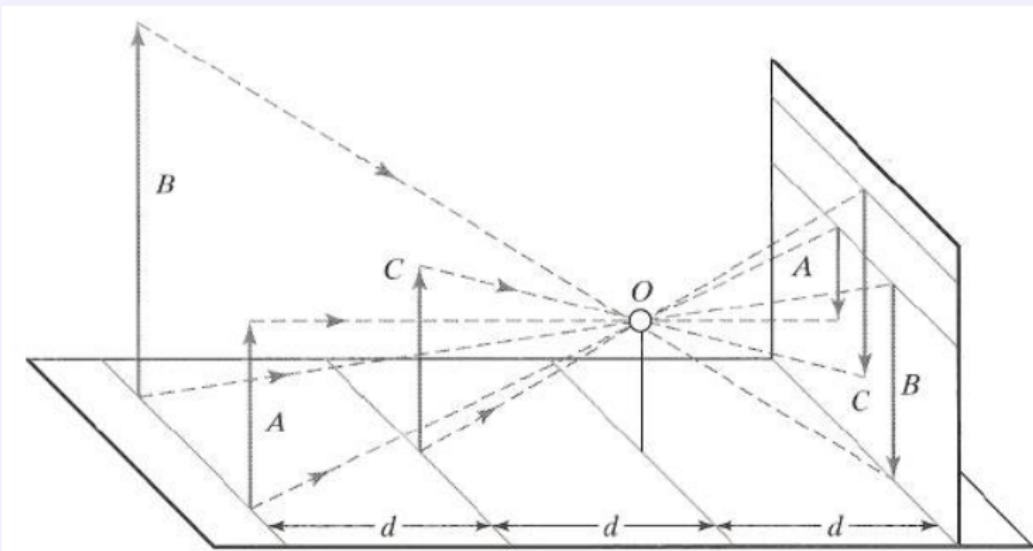
# The Pinhole Camera Model



- $f$  is the focal length,
- $O$  is the camera center.

# Perspective Effects

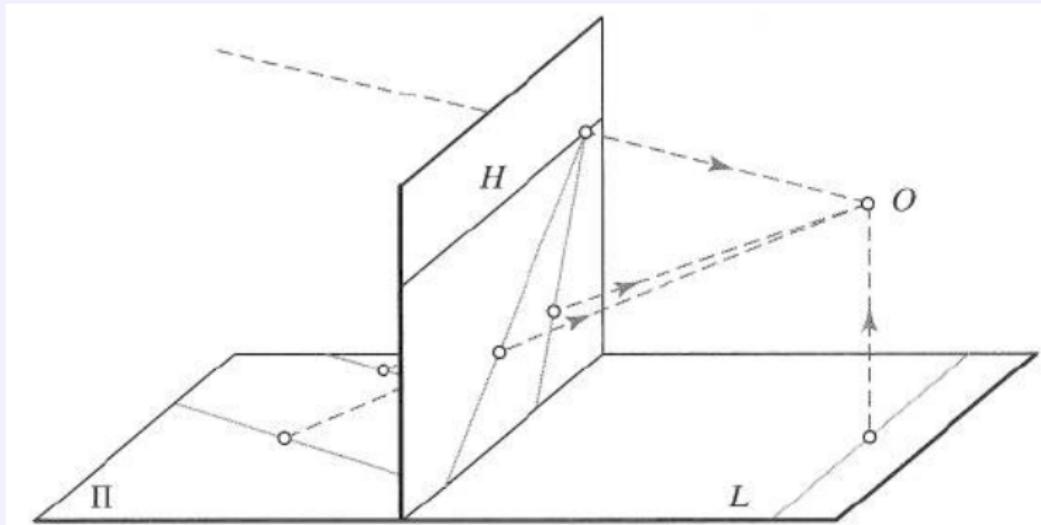
Remember from first lecture



Far objects appear smaller than close ones.

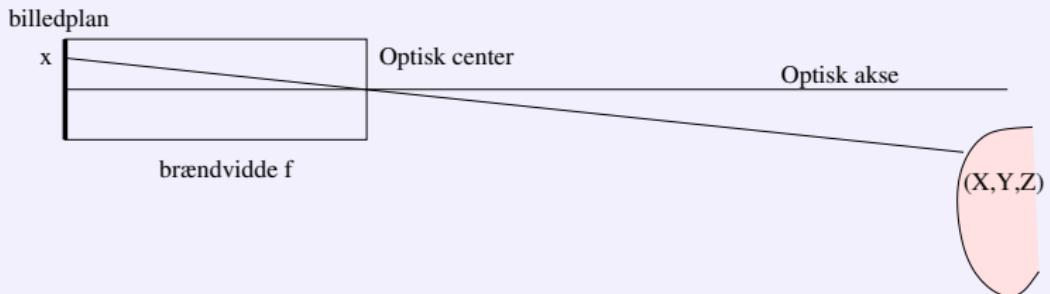
# Perspective Effects

Remember from first lecture again



Images of parallel lines intersect at the horizon (virtual image plane).

# Projection Equations



- Project  $P(X, Y, Z)$  onto  $(x, y, -f)$ . Remember: similar triangles:

$$x = f \frac{X}{Z}, \quad y = f \frac{Y}{Z}$$

- To get non-negative pixel indexes:

$$x = f \frac{X}{Z} + c_x, \quad y = f \frac{Y}{Z} + c_y$$

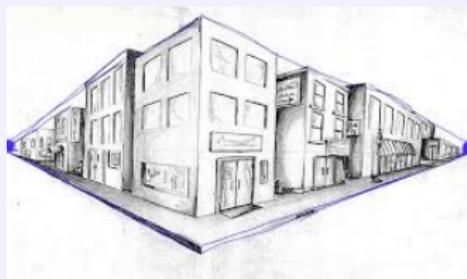
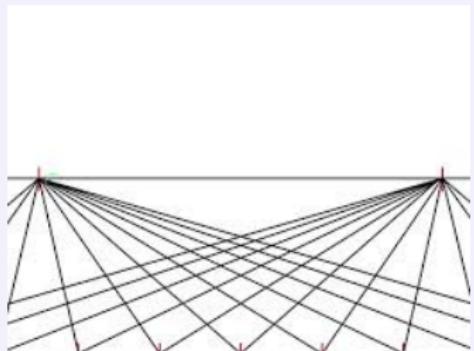
where  $(c_x, c_y)$  is called **the principal point**.

# Vanishing Points

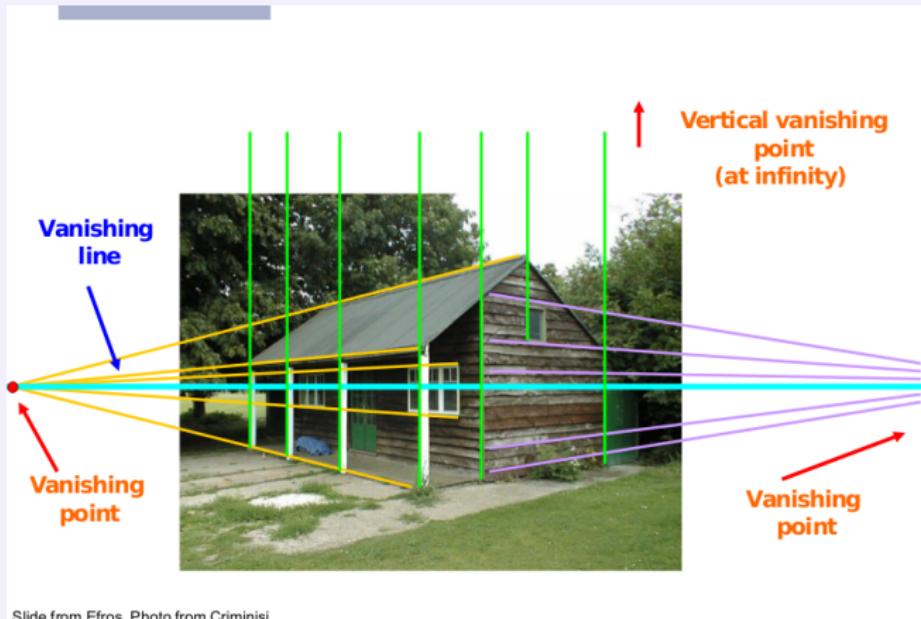


Projections of parallel lines intersect at common points.

# Vanishing line



# Vanishing line



Slide from Efros, Photo from Criminisi

## Shape (VP's) from texture



If we can measure a texture density, then we may estimate the directions of minimal and maximal density change. These points at the VPs. thus giving the VL and the 3D surface normal.

# Homogeneous coordinates 1D

- In 1D coordinate is just 1 number.



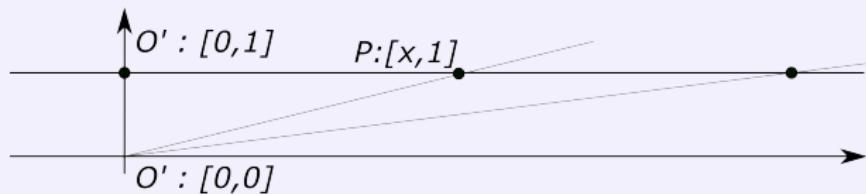
- 1D coordinate to 1D Homogeneous coordinates:

$$x \sim \begin{bmatrix} x \\ 1 \end{bmatrix}$$

- 1D homogeneous coordinate to 1 D coordinate

$$\begin{bmatrix} x \\ w \end{bmatrix} \sim x/w$$

- What can we do with that? we can “tame” infinity!
- A point with homogeneous coordinate  $[x, 0]^T$  has “normal” coordinate  $x/0 = \infty$  as if we took homogeneous coordinate  $[\infty, 1]^T$



# Homogeneous coordinates, 2D

“Natural Coordinates” for projective geometry

- From 2D point coordinate to 2D Homogeneous coordinate

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

- From 2D homogeneous coordinates to 2D coordinates

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

# Homogeneous coordinates, 3D

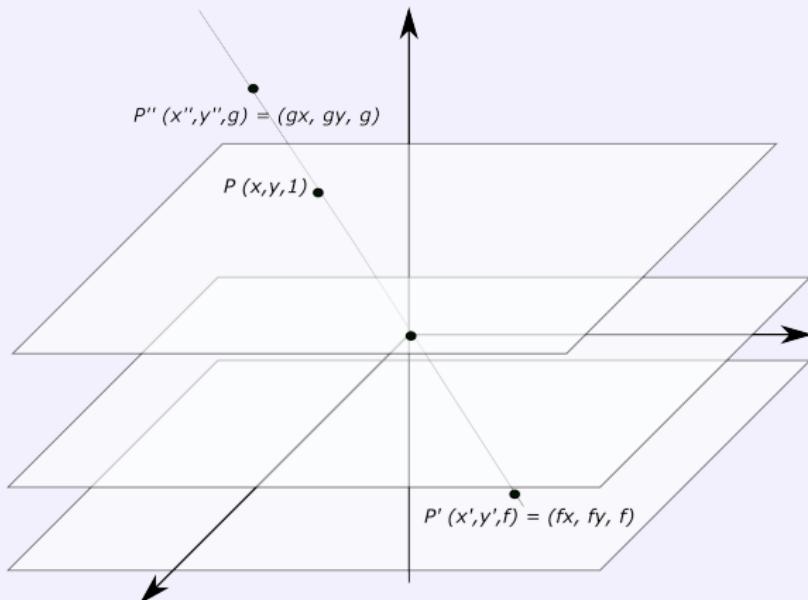
- From 3D point coordinate to 3D Homogeneous coordinate

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

- From 3D homogeneous coordinates to 3D coordinates

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

# Homogeneous coordinates



Homogeneous coordinates in 2D correspond to points in plane  $z = 1$  but also to lines through the origin and this point.

# Cameras and homogeneous coordinates

- Projection to image plane in standard coordinates:

$$P : (x, y, z) \mapsto P' : (f \frac{x}{z}, f \frac{y}{z})$$

- How does the mapping look like in homogeneous coordinates:

$$P : \begin{bmatrix} x \\ y \\ z \\ 1 \end{bmatrix} \mapsto P' : \begin{bmatrix} fx \\ fy \\ z \end{bmatrix}$$

- Matrix notation

$$\begin{bmatrix} fx \\ fy \\ z \end{bmatrix} = \underbrace{\begin{pmatrix} f & 0 & 0 & 0 \\ 0 & f & 0 & 0 \\ 0 & 0 & 1 & 0 \end{pmatrix}}_K \begin{bmatrix} x \\ y \\ z \\ 1 \end{bmatrix}$$

- $K$  is (a simple version of) the **Camera Calibration Matrix** and contains the intrinsic calibration parameters (here  $f$ ).

# World, Camera and Image Coordinates

In the previous slides we were not precise on the many coordinate systems are implicitly used:

- 3D World Coordinates: Coordinate system of the 3D world.
- Camera Coordinates: 3D coordinate system attached to the camera.
- Image Coordinates: 2D Coordinate system attached to the image plane.
- The coordinate system for the sampled and digitised image

# Intrinsic vs Extrinsic Camera Parameters

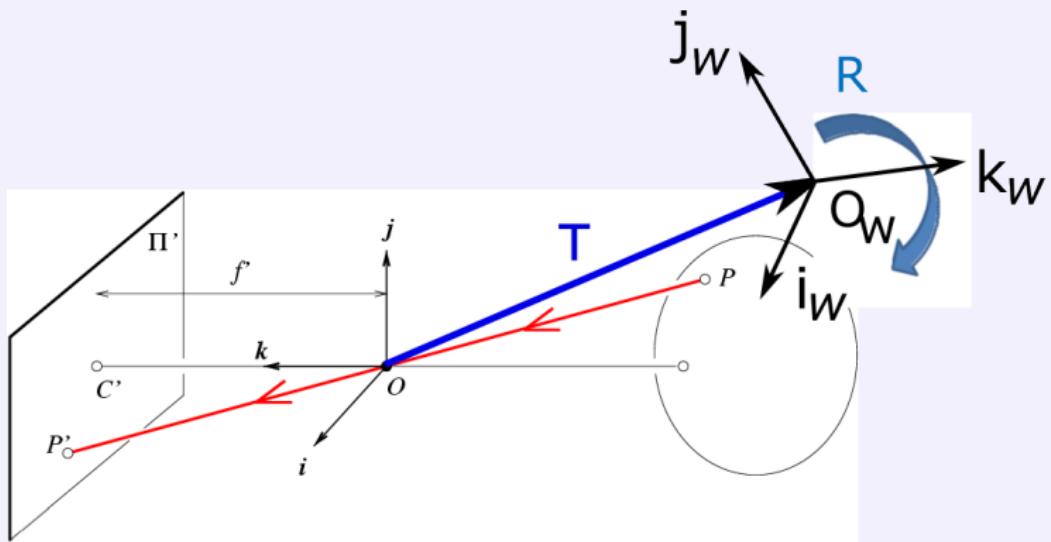
Intrinsic parameters refer to **internal parameters**:

- The principal point: 2 parameters
- Scale factors (or sampling frequencies) for the pixels sizes in both x and y directions: 2 parameters, multiplied by the focal length, resulting in **the effective focal length** ( $f_x, f_y = f \cdot (s_x, s_y)$ ).
- Skewness of pixels: 1 parameter. (Often assumed zero)

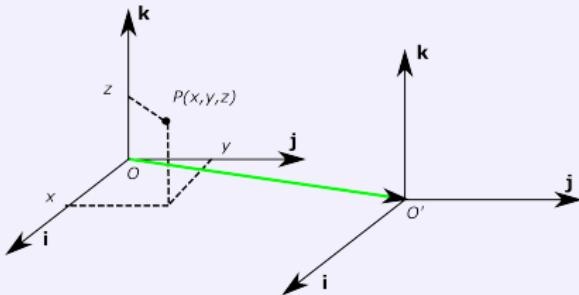
**Extrinsic Camera parameters:**

- Position of the camera coordinate system in the world coordinates system: translation: 3 parameters,
- Orientation of the camera coordinate system in the world coordinates system: rotation: 3 parameters.

# Oriented and Translated Camera



# Translating Coordinate System



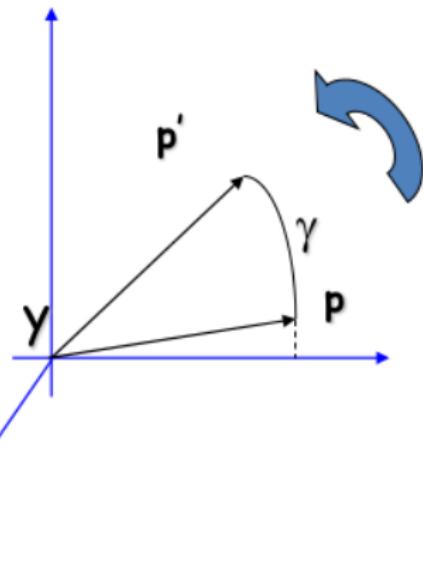
- Subtract the translation vector:

$$\begin{pmatrix} x' \\ y' \\ z' \end{pmatrix} = \begin{pmatrix} x \\ y \\ z \end{pmatrix} - \begin{pmatrix} x_{O'} \\ y_{O'} \\ z_{O'} \end{pmatrix} = \begin{pmatrix} x - x_{O'} \\ y - y_{O'} \\ z - z_{O'} \end{pmatrix}$$

- Transformation in homogeneous coordinates:

$$\begin{bmatrix} x' \\ y' \\ z' \\ 1 \end{bmatrix} = \begin{pmatrix} 1 & 0 & 0 & -x_{O'} \\ 0 & 1 & 0 & -y_{O'} \\ 0 & 0 & 1 & -z_{O'} \\ 0 & 0 & 0 & 1 \end{pmatrix} \begin{bmatrix} x \\ y \\ z \\ 1 \end{bmatrix}$$

# Rotating Coordinate System



Rotations along coordinate axes

$$R_{x\alpha} = \begin{pmatrix} 1 & 0 & 0 \\ 0 & \cos \alpha & -\sin \alpha \\ 0 & \sin \alpha & \cos \alpha \end{pmatrix}$$

$$R_{y\beta} = \begin{pmatrix} \cos \beta & 0 & -\sin \beta \\ 0 & 1 & 0 \\ \sin \beta & 0 & \cos \beta \end{pmatrix}$$

$$R_{z\gamma} = \begin{pmatrix} \cos \gamma & -\sin \gamma & 0 \\ \sin \gamma & \cos \gamma & 0 \\ 0 & 0 & 1 \end{pmatrix}$$

Can also be written in homogeneous coordinates

## 3D rotations

To obtain a 3D rotation apply all 3 single-axis rotations:

$$\begin{aligned} R &= R_{x\alpha} R_{y\beta} R_{z\gamma} \\ &= \begin{pmatrix} 1 & 0 & 0 \\ 0 & \cos \alpha & -\sin \alpha \\ 0 & \sin \alpha & \cos \alpha \end{pmatrix} \begin{pmatrix} \cos \beta & 0 & -\sin \beta \\ 0 & 1 & 0 \\ \sin \beta & 0 & \cos \beta \end{pmatrix} \begin{pmatrix} \cos \gamma & -\sin \gamma & 0 \\ \sin \gamma & \cos \gamma & 0 \\ 0 & 0 & 1 \end{pmatrix} \end{aligned}$$

Please notice that the order of the 3 rotation matrices do matter.  
However, no matter which order  $(\alpha, \beta, \gamma)$  may be found such that the resulting 3D rotation is correct.

# Camera Matrix

- Camera calibration matrix, now extended with Image plane transformation (axis scalings, shear, translation)

$$\mathbf{C} = \mathbf{K} [\mathbf{R} \; \mathbf{t}]$$

- $\mathbf{K}$   $3 \times 3$  matrix encoding the homogeneous transformations inside the camera.  $\mathbf{K}$  specifies the [Intrinsic parameters](#).
- $[\mathbf{R} \; \mathbf{t}]$  Concatenation of world coordinates rotation and origin translation to align camera and world coordinates.

$$\begin{bmatrix} x \\ y \\ 1 \end{bmatrix} = \begin{bmatrix} wx \\ wy \\ w \end{bmatrix} = \underbrace{\begin{pmatrix} f_x & s & u_0 \\ 0 & f_y & v_0 \\ 0 & 0 & 1 \end{pmatrix}}_{\mathbf{K}} \underbrace{\begin{pmatrix} r_{11} & r_{12} & r_{13} & t_x \\ r_{21} & r_{22} & r_{23} & t_y \\ r_{31} & r_{32} & r_{33} & t_z \end{pmatrix}}_{[\mathbf{R} \; \mathbf{t}]} \begin{pmatrix} X \\ Y \\ Z \\ 1 \end{pmatrix}$$

# Exercise

- How many independent parameters are there to estimate in a camera calibration ?

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11: 5 intrinsic and 6 extrinsic (sometimes simplified to 3+6)
- May all calibration parameters be found using Linear algebra ?

## Exercise

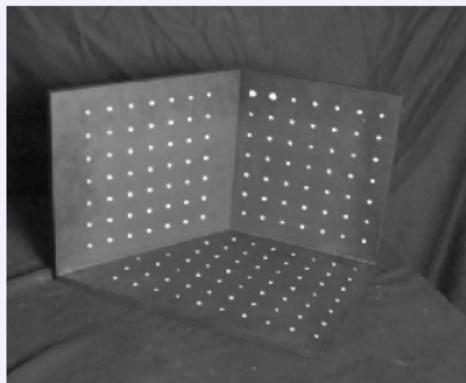
- How many independent parameters are there to estimate in a camera calibration ?  
11: 5 intrinsic and 6 extrinsic (sometimes simplified to 3+6)
- May all calibration parameters be found using Linear algebra ?

No, they don't appear in a linear combinations. Some are multiplied together.

# QUESTIONS ?

# Geometric Calibration

- Computing the camera matrix is called geometric calibration.
- Extrinsic parameters:  $(R, t)$ : Usually easy, but requires metric knowledge on scene features.
- Intrinsic parameters:  $(K)$ : Some parameters ( $f$ ) are easy and some  $((u_0, v_0))$  are difficult to estimate correctly.



- Use an object with known geometry
- Use vanishing points / lines
- Use other cues...

## Repetition: The camera matrix

Please recall the definition of the camera matrix:

$$M = K [R \ t]$$

and the projection written out:

$$w \begin{bmatrix} x \\ y \\ 1 \end{bmatrix} = \underbrace{\begin{pmatrix} f_x & 0 & u_0 \\ 0 & f_y & v_0 \\ 0 & 0 & 1 \end{pmatrix}}_{K} \underbrace{\begin{pmatrix} r_{11} & r_{12} & r_{13} & t_x \\ r_{21} & r_{22} & r_{23} & t_y \\ r_{31} & r_{32} & r_{33} & t_z \end{pmatrix}}_{[R \ t]} \underbrace{\begin{pmatrix} X \\ Y \\ Z \\ 1 \end{pmatrix}}_M$$

or

$$w \begin{bmatrix} x \\ y \\ 1 \end{bmatrix} = \begin{pmatrix} \mathbf{m}^1 \\ \mathbf{m}^2 \\ \mathbf{m}^3 \end{pmatrix} \begin{pmatrix} X \\ Y \\ Z \\ 1 \end{pmatrix} = \begin{pmatrix} \mathbf{m}^1 U \\ \mathbf{m}^2 U \\ \mathbf{m}^3 U \end{pmatrix}$$

where  $\mathbf{m}^i$  is the  $i$ 'th row of the camera matrix.

# Camera calibration

In Camera calibration the task is to recover the 12 unknowns  $\mathbf{m}_{ij}$  in the camera calibration matrix. Converting the result before to image coordinates we have:

$$\begin{aligned} x\mathbf{m}_3 U &= \mathbf{m}_1 U \\ y\mathbf{m}_3 U &= \mathbf{m}_2 U \end{aligned}$$

Let  $\mathbf{m} = (m_{11}, \dots, m_{14}, \dots, m_{34})^\top$  be the vector of the 12 unknowns. Isolating these in the equations above lead to:  $A\mathbf{m} = 0$ , where:

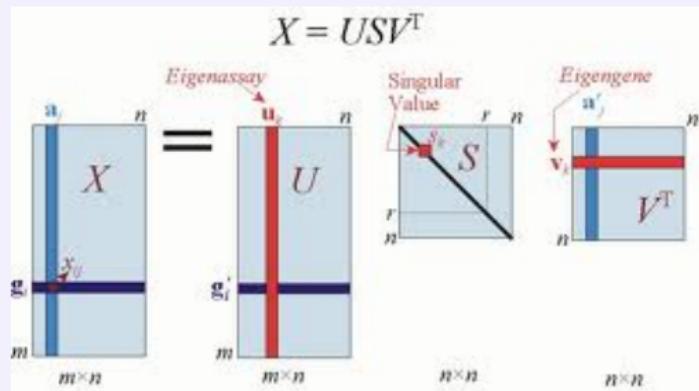
$$A = \left[ \begin{array}{ccccccccccccc} X_1 & Y_1 & Z_1 & 1 & 0 & 0 & 0 & -x_1 X_1 & -x_1 Y_1 & -x_1 Z_1 & -x_1 \\ 0 & 0 & 0 & 0 & X_1 & Y_1 & Z_1 & 1 & -y_1 X_1 & -y_1 Y_1 & -y_1 Z_1 & -y_1 \\ X_2 & Y_2 & Z_2 & 1 & 0 & 0 & 0 & -x_2 X_2 & -x_2 Y_2 & -x_2 Z_2 & -x_2 \\ 0 & 0 & 0 & 0 & X_2 & Y_2 & Z_2 & 1 & -y_2 X_2 & -y_2 Y_2 & -y_2 Z_2 & -y_2 \\ \vdots & \vdots \\ X_N & Y_N & Z_N & 1 & 0 & 0 & 0 & -x_N X_N & -x_N Y_N & -x_N Z_N & -x_N \\ 0 & 0 & 0 & 0 & X_N & Y_N & Z_N & 1 & -y_N X_N & -y_N Y_N & -y_N Z_N & -y_N \end{array} \right]$$

# Solving $Ax = 0$

Many different numerical approaches. **Singular Value Decomposition** (SVD) is based on decomposition of the matrix  $A$  into a product of 3 matrices:

$$A = UDV^T$$

where  $A$  and  $U$  is  $m \times n$  and  $U^T U = I$ ,  
 $D$  is a diagonal  $n \times n$  matrix with non-negative singular values,  
and  $V$  is a  $n \times n$  unitary matrix  $V V^T = V^T V = I$ .



## Singular value decomposition (svd)

$$A \mathbf{x} = UDV^\top \mathbf{x} = 0$$

We are not interested in the trivial solution  $\mathbf{x} = \mathbf{0}$  but rather all solution lying in the **Null-space** of the matrix  $A$ .

The singular values in the diagonal matrix  $D$  specifies the **energy** contained in each of the dimensions. Usually, these are sorted in decreasing order.

Often, due to noise all singular values  $\sigma_i > 0$ . If we know that  $A$  should be singular may find the closest such matrix by zeroing out the smallest singular value.

We get the solution to  $A\mathbf{x} = \mathbf{0}$  as the last column of  $V$ . In MATLAB:

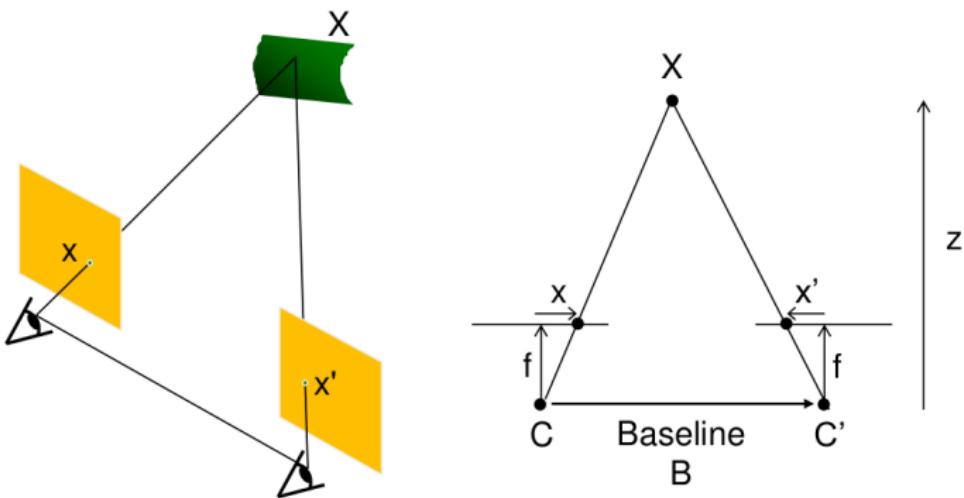
```
[U,D,V] = svd(A); x = V(:,end);
```

Notice that  $\|\mathbf{x}\| = 1$

## Camera calibration continued

- Given 6 points  $(x, y)$  projected from 6 known 3D points  $(X, Y, Z)$  we can solve for the camera matrix elements  $m_{ij}$ .
- In practise many more than 6 points are preferred to cancel noise.
- From the 12 elements  $m_{ij}$  it is possible to recover all 11 parameters  $f_x, f_y, \alpha, \beta, \gamma$ , etc.
- There exist more advanced calibration methods than the shown linear calibration.

# Simple depth recovery



If we can recover  $x'$  from  $x$  we can recover depth:  $z = -\frac{fB}{x' - x}$ .

## Linear triangulation for 2 calibrated cameras

Let  $U = (X, Y, Z, 1)^\top$ . For the first coordinate in the left camera we have:

$$x^L = \frac{\mathbf{m}_L^1 U}{\mathbf{m}_L^3 U}$$

and similar for the  $y$ -coordinate and the right camera. Multiplying by the denominator we get:

$$\mathbf{m}_L^3 x_L U = \mathbf{m}_L^1 U$$

$$\mathbf{m}_L^3 y_L U = \mathbf{m}_L^2 U$$

$$\mathbf{m}_R^3 x_R U = \mathbf{m}_R^1 U$$

$$\mathbf{m}_R^3 y_R U = \mathbf{m}_R^2 U$$

Subtracting the right side and putting  $U$  outside a parenthesis we get the homogeneous equation  $AU = 0$ , where:

$$A = \begin{pmatrix} \mathbf{m}_L^3 x_L - \mathbf{m}_L^1 \\ \mathbf{m}_L^3 y_L - \mathbf{m}_L^2 \\ \mathbf{m}_R^3 x_R - \mathbf{m}_R^1 \\ \mathbf{m}_R^3 y_R - \mathbf{m}_R^2 \end{pmatrix}$$

# More triangulation

- If the calibration matrices  $\mathbf{M}_{L/R}$  is not available, a projective reconstruction still is possible. This will be relative to say the left camera and valid up to a projective transformation only.
- Notice that the derived triangulation is for points. No concepts of surfaces etc. is imposed. Analysis of the derived point cloud data is a topic in itself.
- Remember that no (true) reconstructions are possible for partially occluded areas (often related to surface discontinuities).
- There is no evidence that humans do triangulations. Stereo analysis is a significant 3D information source, but seem to be based on disparity information alone.

# QUESTIONS ?

QUESTIONS ?

QUESTIONS to assignment 4 ?

## Next time

Next time, our first meeting in 2022, we will continue with stereo analysis, multi view geometry and may be a bit about image stitching.

