## Camera model and calibration

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## Pinhole camera principle



[^0]
## Pinhole camera principle



[^1]
## Pinhole camera principle



[^2]
## Camera Obscura - room-sized



Used by the art department at the UNC at Chapel Hill

[^3]
## 1D Pinhole camera projects 2D to 1D



## Distant objects are smaller



1D Pinhole camera projects 2D to 1D


## 1D Pinhole camera projects 2D to 1D



- We move image plane in front of $C$ to get rid of $(-)$ sign.

$$
x=f \frac{X}{Z}
$$

How does the 3D world project to the 2D image plane?

## A 3D point $X$ in a world coordinate system



## A pinhole camera observes a scene



Point $X$ projects to the image plane, point x


## Scene projection



## Scene projection



## 3D $\rightarrow$ 2D Projection

We remember that:

$$
\begin{aligned}
& {\left[\begin{array}{l}
x \\
y
\end{array}\right]=\left[\begin{array}{c}
f \frac{X}{Z} \\
f \frac{Y}{Z}
\end{array}\right]} \\
& {\left[\begin{array}{c}
Z x \\
Z y
\end{array}\right]=\left[\begin{array}{c}
f X \\
f Y
\end{array}\right]} \\
& {\left[\begin{array}{c}
\lambda x \\
\lambda y \\
\lambda
\end{array}\right]=\left[\begin{array}{c}
f X \\
f Y \\
Z
\end{array}\right]}
\end{aligned}
$$



## 3D $\rightarrow$ 2D Projection

Homogeneous coordinates:
$\mathbf{x}=\left[\begin{array}{lll}x & y & 1\end{array}\right]^{\top}$ and $\mathbf{X}=\left[\begin{array}{lll}X & Y & Z\end{array}\right]^{\top}$ yield

$$
\begin{gathered}
{\left[\begin{array}{c}
\lambda x \\
\lambda y \\
\lambda
\end{array}\right]=\left[\begin{array}{c}
f X \\
f Y \\
Z
\end{array}\right]} \\
\lambda \mathbf{x}=\left[\begin{array}{llll}
f & & & 0 \\
& f & & 0 \\
& & 1 & 0
\end{array}\right] \mathbf{X} \\
\lambda_{[1 \times 1]} \mathbf{x}_{[3 \times 1]}=\mathrm{K}_{[3 \times 3]}[\mathrm{I} \mid \mathbf{0}] \mathbf{X}_{[4 \times 1]}
\end{gathered}
$$

but . . .

${ }^{4}$ for the notation conventions, see the talk notes

## Transform X into the camera coordinate system

Rotate the vector:

$$
\mathbf{X}^{e}=\mathrm{R}_{w}^{\top}\left(\mathbf{X}_{w}^{e}-\mathbf{C}_{w}\right)
$$

Use homogeneous coordinates to get a matrix equation

$$
\mathbf{X}=\left[\begin{array}{cc}
\mathrm{R}_{w}^{\top} & -\mathrm{R}_{w}^{\top} \mathbf{C}_{w} \\
\mathbf{0} & 1
\end{array}\right] \mathbf{X}_{w}
$$

Translation of the world in the camera

$$
\mathbf{t}=-\mathrm{R}_{w}^{\top} \mathbf{C}_{w}
$$

Rotation of the world in the camera


$$
\mathrm{R}=\mathrm{R}_{w}^{\top}
$$

## Camera matrix

- t and R are called External parameters of the camera.
- The matrix K is called Internal parameters of the camera.

$$
\begin{aligned}
\lambda \mathbf{x} & =\mathrm{KX}= \\
& =\mathrm{K}\left[\begin{array}{ll}
\mathrm{R} & \mathbf{t}
\end{array}\right] \mathbf{X}_{w}= \\
& =\mathrm{PX}_{w}
\end{aligned}
$$



We omit the world index and write simply $\lambda \mathrm{x}=\mathrm{PX}$

## Estimation of camera parameters-camera calibration

The goal: estimate the $3 \times 4$ camera projection matrix $P$ from calibration object.

Assume: known correspondence between 2D camera coordinates $[u, v]^{\top}$ and 3D point $\left[\begin{array}{lll}X & Y & Z\end{array}\right]^{\top}$ with known coordinates


$$
\begin{gathered}
{\left[\begin{array}{c}
\lambda u \\
\lambda v \\
\lambda
\end{array}\right]=\left[\begin{array}{c}
\mathbf{p}_{1}^{\top} \\
\mathbf{p}_{2}^{\top} \\
\mathbf{p}_{3}^{\top}
\end{array}\right]\left[\begin{array}{c}
X \\
Y \\
Z \\
1
\end{array}\right]} \\
\frac{\lambda u}{\lambda}=\frac{\mathbf{p}_{1}^{\top} \mathbf{X}}{\mathbf{p}_{3}^{\top} \mathbf{X}} \text { and } \frac{\lambda v}{\lambda}=\frac{\mathbf{p}_{2}^{\top} \mathbf{X}}{\mathbf{p}_{3}^{\top} \mathbf{X}}
\end{gathered}
$$

Re-arrange and assume $\lambda \neq 0$ to get set of homegeneous equations

$$
\begin{aligned}
u \mathbf{X}^{\top} \mathbf{p}_{3}-\mathbf{X}^{\top} \mathbf{p}_{1} & =0 \\
v \mathbf{X}^{\top} \mathbf{p}_{3}-\mathbf{X}^{\top} \mathbf{p}_{2} & =0
\end{aligned}
$$

## Estimation of camera parameters-camera calibration

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\end{aligned}
$$

Re-shuffle into a matrix form:

$$
\underbrace{\left[\begin{array}{ccc}
-\mathbf{X}^{\top} & \mathbf{0}^{\top} & u \mathbf{X}^{\top} \\
\mathbf{0}^{\top} & -\mathbf{X}^{\top} & v \mathbf{X}^{\top}
\end{array}\right]}_{\mathrm{A}_{[2 \times 12]}} \underbrace{\left[\begin{array}{c}
\mathbf{p}_{1} \\
\mathbf{p}_{2} \\
\mathbf{p}_{3}
\end{array}\right]}_{\mathbf{p}_{[12 \times 1]}}=\mathbf{0}_{[2 \times 1]}
$$

A correspondece $\mathbf{u}_{i} \leftrightarrow \mathbf{X}_{i}$ forms two homogeneous equations. P has 12 parameters but scale does not matter. We need at least 6 2D $\leftrightarrow 3 \mathrm{D}$ pairs to get a solution. We constitute $A_{[\geq 12 \times 12]}$ data matrix and solve

$$
\mathbf{p}^{*}=\operatorname{argmin}\|\mathbf{A} \mathbf{p}\| \text { subject to }\|\mathbf{p}\|=1
$$

which is a constrained LSQ problem. p* minimizes algebraic error

## Solution of constrained LSQ problem

We solve $\mathbf{p}^{*}=\operatorname{argmin}\|\mathbf{A p}\|$ subject to $\|\mathbf{p}\|=1$ by Lagrange function

$$
\begin{aligned}
L(\mathbf{p}, \lambda) & =\|\mathbf{A} \mathbf{p}\|+\lambda(1-\|\mathbf{p}\|)= \\
& =\mathbf{p}^{\top} \mathbf{A}^{\top} \mathbf{A} \mathbf{p}+\lambda\left(1-\mathbf{p}^{\top} \mathbf{p}\right)
\end{aligned}
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\end{aligned}
$$

Critical points:

$$
\begin{aligned}
& \frac{\partial L(\mathbf{p}, \lambda)}{\partial \mathbf{p}}=2 \mathrm{~A}^{\top} \mathbf{A p}-2 \lambda \mathbf{p}=\mathbf{0} \\
& \frac{\partial L(\mathbf{p}, \lambda)}{\partial \lambda}=1-\mathbf{p}^{\top} \mathbf{p}=\mathbf{0}
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First equation is characteristic equation $\left(A^{\top} A-\lambda I\right) \mathbf{p}=0$, every eigen-vector $p$ of $A^{\top} A$ with unit length is critical point.

Since cost function $\|A p\|$ in these eigen-vectors is equal to their eigen-values $\|\mathbf{A} \mathbf{p}\|=\mathbf{p}^{\top} \mathrm{A}^{\top} \mathbf{A} \mathbf{p}=\mathbf{p}^{\top} \lambda \mathbf{p}=\lambda \mathbf{p}^{\top} \mathbf{p}=\lambda\|\mathbf{p}\|=\lambda$. the solution is the eigen-vector of $A^{\top} A$ with the smallest eigen-value.

# Decomposition of $P$ into the calibration parameters 

$$
\mathrm{P}=\left[\begin{array}{ll}
\mathrm{KR} & \mathrm{~K} \mathbf{t}
\end{array}\right] \text { and } \mathbf{C}=-\mathrm{R}^{-1} \mathbf{t}
$$

We know that R should be $3 \times 3$ orthonormal, and K upper triangular.

$$
\begin{aligned}
& P=P . / \operatorname{norm}(P(3,1: 3)) ; \\
& {[K, R]=\operatorname{rq}(P(:, 1: 3)) ;} \\
& t=\operatorname{inv}(K) * P(:, 4) ; \\
& C=-R \prime * t ;
\end{aligned}
$$

## References

The book [2] is the ultimate reference. It is a must read for anyone wanting use cameras for 3D computing.

Details about matrix decompositions used throughout the lecture can be found at [1]
[1] Gene H. Golub and Charles F. Van Loan. Matrix Computation. Johns Hopkins Studies in the Mathematical Sciences. Johns Hopkins University Press, Baltimore, USA, 3rd edition, 1996.
[2] Richard Hartley and Andrew Zisserman. Multiple view geometry in computer vision. Cambridge University, Cambridge, 2nd edition, 2003.

End
film/sensor
(image plane)

film/sensor
(image plane)

film/sensor
(image plane)







## X 。













[^0]:    ${ }^{1}$ http://en.wikipedia.org/wiki/Pinhole_camera

[^1]:    ${ }^{2}$ http://en.wikipedia.org/wiki/Pinhole_camera

[^2]:    ${ }^{3}$ http://en.wikipedia.org/wiki/Pinhole_camera

[^3]:    ${ }^{4}$ http://en.wikipedia.org/wiki/Camera_obscura

