# Lecture 12: Camera Models (cont.) 

COMP 590/776: Computer Vision
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Course Website:
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## Today's Class

- Camera Calibration
- Vanishing Points and Lines


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- Vanishing Points and Lines


## Big picture: 3 key components in 3D



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## Big picture: 3 key components in 3D

## Multiview Stereo

 (more than 2 cameras)

## Big picture: 3 key components in 3D



|  | Structure <br> (scene geometry) | Motion <br> (camera parameters) | Measurements <br> (camera parameters) |
| :---: | :---: | :---: | :---: |
| Camera Calibration <br> (Pose Estimation) | known | estimate | $3 D$ to 2D <br> correspondences |
| Triangulation <br> (Stereo, Multi-view Stereo) | estimate | known | 2D to 2D <br> coorespondences |
| Reconstruction <br> (Structure from Motion, SLAM) | estimate | estimate | 2D to 2D <br> coorespondences |

## Pose Estimation



Given a single image,
estimate the exact position of the photographer

+ the intrinsics of the camera (focal length)


## Geometric camera calibration

Given a set of matched points

$$
\left\{\begin{array}{c}
\{2,20 \\
\text { point in 3D } \\
\text { space } \\
\text { point in the } \\
\text { image }
\end{array}\right.
$$

Same setup as homography estimation
(slightly different derivation here)
and camera model

## $\boldsymbol{x}=\underset{\substack{\text { popectar } \\ \text { moded }}}{\boldsymbol{f}}(\mathbf{X} ; \boldsymbol{p})=\underset{\substack{\text { camanesees } \\ \text { matix }}}{\mathbf{P}}$

Find the (pose) estimate of

Mapping between 3D point and image points

$$
\begin{aligned}
& {\left[\begin{array}{l}
x \\
y \\
z
\end{array}\right]=\left[\begin{array}{cccc}
p_{1} & p_{2} & p_{3} & p_{4} \\
p_{5} & p_{6} & p_{7} & p_{8} \\
p_{9} & p_{10} & p_{11} & p_{12}
\end{array}\right]\left[\begin{array}{c}
X \\
Y \\
Z \\
1
\end{array}\right]} \\
& {\left[\begin{array}{l}
x \\
y \\
z
\end{array}\right]=\left[\begin{array}{ll}
- & \boldsymbol{p}_{1}^{\top}- \\
- & \boldsymbol{p}_{2}^{\top}-
\end{array}\right]\left[\begin{array}{c}
\mid \\
\boldsymbol{X} \\
\mid
\end{array}\right]}
\end{aligned}
$$

$$
x^{\prime}=\frac{\boldsymbol{p}_{1}^{\top} \boldsymbol{X}}{\boldsymbol{p}_{3}^{\top} \boldsymbol{X}} \quad y^{\prime}=\frac{\boldsymbol{p}_{2}^{\top} \boldsymbol{X}}{\boldsymbol{p}_{3}^{\top} \boldsymbol{X}}
$$

(non-linear relation between coordinates)
How can we make these relations linear?

$$
x^{\prime}=\frac{\boldsymbol{p}_{1}^{\top} \boldsymbol{X}}{\boldsymbol{p}_{3}^{\top} \boldsymbol{X}} \quad y^{\prime}=\frac{\boldsymbol{p}_{2}^{\top} \boldsymbol{X}}{\boldsymbol{p}_{3}^{\top} \boldsymbol{X}}
$$

Make them linear with algebraic manipulation...

$$
\begin{aligned}
& \boldsymbol{p}_{2}^{\top} \boldsymbol{X}-\boldsymbol{p}_{3}^{\top} \boldsymbol{X} y^{\prime}=0 \\
& \boldsymbol{p}_{1}^{\top} \boldsymbol{X}-\boldsymbol{p}_{3}^{\top} \boldsymbol{X} x^{\prime}=0
\end{aligned}
$$

Now we can setup a system of linear equations with multiple point correspondences

$$
\begin{aligned}
& \boldsymbol{p}_{2}^{\top} \boldsymbol{X}-\boldsymbol{p}_{3}^{\top} \boldsymbol{X} y^{\prime}=0 \\
& \boldsymbol{p}_{1}^{\top} \boldsymbol{X}-\boldsymbol{p}_{3}^{\top} \boldsymbol{X} x^{\prime}=0
\end{aligned}
$$

In matrix form $\ldots .\left[\begin{array}{ccc}\boldsymbol{X}^{\top} & \mathbf{0} & -x^{\prime} \boldsymbol{X}^{\top} \\ \mathbf{0} & \boldsymbol{X}^{\top} & -y^{\prime} \boldsymbol{X}^{\top}\end{array}\right]\left[\begin{array}{l}\boldsymbol{p}_{1} \\ \boldsymbol{p}_{2} \\ \boldsymbol{p}_{3}\end{array}\right]=\mathbf{0}$

For N points ...

$$
\left[\begin{array}{ccc}
\boldsymbol{X}_{1}^{\top} & \mathbf{0} & -x^{\prime} \boldsymbol{X}_{1}^{\top} \\
\mathbf{0} & \boldsymbol{X}_{1}^{\top} & -y^{\prime} \boldsymbol{X}_{1}^{\top} \\
\vdots & \vdots & \vdots \\
\boldsymbol{X}_{N}^{\top} & \mathbf{0} & -x^{\prime} \boldsymbol{X}_{N}^{\top} \\
\mathbf{0} & \boldsymbol{X}_{N}^{\top} & -y^{\prime} \boldsymbol{X}_{N}^{\top}
\end{array}\right]\left[\begin{array}{c}
\boldsymbol{p}_{1} \\
\boldsymbol{p}_{2} \\
\boldsymbol{p}_{3}
\end{array}\right]=\mathbf{0} \quad \begin{aligned}
& \text { How do we solve } \\
& \text { this system? }
\end{aligned}
$$

$\hat{\boldsymbol{x}}=\underset{\boldsymbol{x}}{\arg \min }\|\mathbf{A} \boldsymbol{x}\|^{2}$ subject to $\|\boldsymbol{x}\|^{2}=1$ $\boldsymbol{x}$
$\mathbf{A}=\left[\begin{array}{ccc}\boldsymbol{X}_{1}^{\top} & \mathbf{0} & -x^{\prime} \boldsymbol{X}_{1}^{\top} \\ \mathbf{0} & \boldsymbol{X}_{1}^{\top} & -y^{\prime} \boldsymbol{X}_{1}^{\top} \\ \vdots & \vdots & \vdots \\ \boldsymbol{X}_{N}^{\top} & \mathbf{0} & -x^{\prime} \boldsymbol{X}_{N}^{\top} \\ \mathbf{0} & \boldsymbol{X}_{N}^{\top} & -y^{\prime} \boldsymbol{X}_{N}^{\top}\end{array}\right]$

$$
\boldsymbol{x}=\left[\begin{array}{l}
\boldsymbol{p}_{1} \\
\boldsymbol{p}_{2} \\
\boldsymbol{p}_{3}
\end{array}\right]
$$

Solution $\mathbf{x}$ is the column of $\mathbf{V}$ corresponding to smallest singular value of

$$
\mathbf{A}=\mathbf{U} \boldsymbol{\Sigma} \mathbf{V}^{\top}
$$

Equivalently, solution $\boldsymbol{x}$ is the Eigenvector corresponding to smallest Eigenvalue of
$\mathbf{A}^{\top} \mathbf{A}$

Now we have: $\quad \mathbf{P}=\left[\begin{array}{cccc}p_{1} & p_{2} & p_{3} & p_{4} \\ p_{5} & p_{6} & p_{7} & p_{8} \\ p_{9} & p_{10} & p_{11} & p_{12}\end{array}\right]$
How do you get the intrinsic and extrinsic parameters from the projection matrix?

Decomposition of the Camera Matrix

$$
\begin{aligned}
& \mathbf{P}=\left[\begin{array}{ccc|c}
p_{1} & p_{2} & p_{3} & p_{4} \\
p_{5} & p_{6} & p_{7} & p_{8} \\
p_{9} & p_{10} & p_{11} & p_{12}
\end{array}\right] \\
& \begin{aligned}
\mathbf{P} & =\mathbf{K}[\mathbf{R} \mid \mathbf{t}] \\
& =\mathbf{K}[\mathbf{R} \mid-\mathbf{R c}] \\
& =[\mathbf{M} \mid-\mathbf{M c}]
\end{aligned}
\end{aligned}
$$

## Decomposition of the Camera Matrix

$$
\begin{array}{rlr}
\mathbf{P}=\left[\begin{array}{ccc|c}
p_{1} & p_{2} & p_{3} & p_{4} \\
p_{5} & p_{6} & p_{7} & p_{8} \\
p_{9} & p_{10} & p_{11} & p_{12}
\end{array}\right] & & \text { Let } \mathrm{v}=[\mathrm{c} \\
\mathbf{P} & =\mathbf{K}[\mathbf{R} \mid \mathbf{t}] & \\
& =\mathbf{K}[\mathbf{R} \mid-\mathbf{R c}] & \\
& =[\mathbf{M} \mid-\mathbf{M c}] & \text { Then } \mathrm{Pv}=\mathrm{Mc}-\mathrm{Mc}=0
\end{array}
$$



Find intrinsic $\mathbf{K}$ and rotation $\mathbf{R}$

## Decomposition of the Camera Matrix

$$
\begin{aligned}
& \mathbf{P}=\left[\begin{array}{ccc|c}
p_{1} & p_{2} & p_{3} & p_{4} \\
p_{5} & p_{6} & p_{7} & p_{8} \\
p_{9} & p_{10} & p_{11} & p_{12}
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& \begin{aligned}
\mathbf{P} & =\mathbf{K}[\mathbf{R} \mid \mathbf{t}] \\
& =\mathbf{K}[\mathbf{R} \mid-\mathbf{R c}] \\
& =[\mathbf{M} \mid-\mathbf{M c}]
\end{aligned}
\end{aligned}
$$

Find the camera center $\mathbf{C}$ $\mathbf{P c}=\mathbf{0}$

How do we compute the camera center from this?

Find intrinsic $\mathbf{K}$ and rotation $\mathbf{R}$

## Decomposition of the Camera Matrix

$$
\begin{aligned}
& \mathbf{P}=\left[\begin{array}{ccc|c}
p_{1} & p_{2} & p_{3} & p_{4} \\
p_{5} & p_{6} & p_{7} & p_{8} \\
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\mathbf{P} & =\mathbf{K}[\mathbf{R} \mid \mathbf{t}] \\
& =\mathbf{K}[\mathbf{R} \mid-\mathbf{R c}] \\
& =[\mathbf{M} \mid-\mathbf{M c}]
\end{aligned}
\end{aligned}
$$

Find the camera center $\mathbf{C}$
Find intrinsic $\mathbf{K}$ and rotation $\mathbf{R}$
$\mathbf{P c}=\mathbf{0}$
SVD of P!
c is the singular vector corresponding to the smallest singular value


Note that we will have c as 4D homogenous coordinate. You will need to convert this to 3D heterogenous coordinate.

## Decomposition of the Camera Matrix

$$
\begin{aligned}
& \mathbf{P}=\left[\begin{array}{ccc|c}
p_{1} & p_{2} & p_{3} & p_{4} \\
p_{5} & p_{6} & p_{7} & p_{8} \\
p_{9} & p_{10} & p_{11} & p_{12}
\end{array}\right] \\
& \begin{aligned}
\mathbf{P} & =\mathbf{K}[\mathbf{R} \mid \mathbf{t}] \\
& =\mathbf{K}[\mathbf{R} \mid-\mathbf{R c}] \\
& =[\mathbf{M} \mid-\mathbf{M c}]
\end{aligned}
\end{aligned}
$$

Find the camera center $\mathbf{C}$

$$
\mathrm{Pc}=\mathbf{0}
$$

SVD of P!
c is the singular vector corresponding to the smallest singular value

Find intrinsic $\mathbf{K}$ and rotation $\mathbf{R}$

$$
\mathbf{M}=\mathbf{K R}
$$

Any useful properties of K and $R$ we can use?

## Decomposition of the Camera Matrix

$$
\begin{aligned}
& \mathbf{P}=\left[\begin{array}{ccc|c}
p_{1} & p_{2} & p_{3} & p_{4} \\
p_{5} & p_{6} & p_{7} & p_{8} \\
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\mathbf{P} & =\mathbf{K}[\mathbf{R} \mid \mathbf{t}] \\
& =\mathbf{K}[\mathbf{R} \mid-\mathbf{R c}] \\
& =[\mathbf{M} \mid-\mathbf{M c}]
\end{aligned}
\end{aligned}
$$

Find the camera center $\mathbf{C}$

$$
\mathrm{Pc}=\mathbf{0}
$$

SVD of P!
c is the singular vector corresponding to the smallest singular value

Find intrinsic $\mathbf{K}$ and rotation $\mathbf{R}$


How do we find $K$ and $R$ ?

## Decomposition of the Camera Matrix

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\begin{aligned}
& \mathbf{P}=\left[\begin{array}{ccc|c}
p_{1} & p_{2} & p_{3} & p_{4} \\
p_{5} & p_{6} & p_{7} & p_{8} \\
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& =[\mathbf{M} \mid-\mathbf{M c}]
\end{aligned}
\end{aligned}
$$

Find the camera center $\mathbf{C}$

$$
\mathrm{Pc}=\mathbf{0}
$$

SVD of P!
c is the singular vector corresponding to the smallest singular value

Find intrinsic $\mathbf{K}$ and rotation $\mathbf{R}$

$$
\mathbf{M}=\mathbf{K R}
$$

QR decomposition

## Geometric camera calibration

Given a set of matched points

$$
\left\{\boldsymbol{X}_{i}, \boldsymbol{\mathscr { X }}_{\boldsymbol{i}}\right\} \quad \begin{gathered}
\text { Where do we get these } \\
\text { matched points from? }
\end{gathered}
$$

point in 3D point in the space
image
and camera model


Find the (pose) estimate of


We'll use a perspective camera model for pose estimation

## Calibration using a reference object

Place a known object in the scene:

- identify correspondences between image and scene
- compute mapping from scene to image


## Issues:

- must know geometry very accurately
- must know 3D->2D correspondence



## Geometric camera calibration

## Advantages:

- Very simple to formulate.
- Analytical solution.

Disadvantages:

- Doesn't model radial distortion.
- Hard to impose constraints (e.g., known f).
- Doesn't minimize the correct error function.

For these reasons, nonlinear methods are preferred

- Define error function E between projected 3D points and image positions
$-E$ is nonlinear function of intrinsics, extrinsics, radial distortion
- Minimize E using nonlinear optimization techniques


## Geometric camera calibration (how to solve in practice)

- Step 1: Use SVD to find $P$ from $N$ pairs of $x_{i}$ and $X_{i}$.
- Step 2: Decompose $P$ to obtain individual elements: $K$ (intrinsics), $R$ (rotation), t (translation).
- Step 3: Formulate a non-linear optimization to obtain optimal set of ( $K, R, \mathrm{t}$ ) that minimizes the re-projection error:

$$
\left\|x_{i}-K^{*} R^{*}\left(X_{i}-t\right)\right\|
$$

Initialize the optimization with ( $\mathrm{K}, \mathrm{R}, \mathrm{t}$ ) obtained from Step 2.

## Alternative: Multi-plane calibration



Advantages:

- Only requires a plane
- Don't have to know positions/orientations
- Great code available online!
- Matlab version: http://www.vision.caltech.edu/bouguetj/calib doc/index.html
- Also available on OpenCV.

Disadvantage: Need to solve non-linear optimization problem.
Used in Practice for many AR applications

## Today's Class

- Camera Calibration
- Vanishing Points and Lines


## Points at infinity





## Vanishing points (1D)



- Vanishing point
- projection of a point at infinity
- can often (but not always) project to a finite point in the image


## Vanishing points (2D)



## Vanishing points



## - Properties

- Any two parallel lines (in 3D) have the same vanishing point v
- The ray from $\mathbf{C}$ through $\mathbf{v}$ is parallel to the lines
- An image may have more than one vanishing point
- in fact, every image point is a potential vanishing point


## Computing vanishing points



## Computing vanishing points



$$
\mathbf{P}_{t}=\left[\begin{array}{c}
P_{X}+t D_{X} \\
P_{Y}+t D_{Y} \\
P_{Z}+t D_{Z} \\
1
\end{array}\right] \cong\left[\begin{array}{c}
P_{X} / t+D_{X} \\
P_{Y} / t+D_{Y} \\
P_{Z} / t+D_{Z} \\
1 / t
\end{array}\right]
$$

- Properties $\quad \mathbf{v}=\boldsymbol{\Pi} \mathbf{P}_{\infty}$
- $\mathbf{P}_{\infty}$ is a point at infinity, $\mathbf{v}$ is its projection
- Depends only on line direction
- Parallel lines $\mathbf{P}_{0}+\mathrm{tD}, \mathbf{P}_{1}+\mathrm{tD}$ intersect at $\mathbf{P}_{\infty}$


## One-point perspective



## Two-point perspective



## Three-point perspective

3 VANISHING POINTS -


## Vanishing lines



- Multiple Vanishing Points
- Any set of parallel lines on the plane define a vanishing point
- The union of all of these vanishing points is the horizon line
- also called vanishing line
- Note that different planes (can) define different vanishing lines


## Vanishing lines



- Multiple Vanishing Points
- Any set of parallel lines on the plane define a vanishing point
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- also called vanishing line
- Note that different planes (can) define different vanishing lines


## Vanishing Lines

.


## Computing vanishing lines




- Properties
- I is intersection of horizontal plane through $\mathbf{C}$ with image plane
- Compute I from two sets of parallel lines on ground plane
- All points at same height as $\mathbf{C}$ project to $\mathbf{I}$
- points higher than C project above I
- Provides way of comparing height of objects in the scene


## Vanishing Lines



Is this parachuter higher or lower than the person taking this picture?

## Perspective cues



## Perspective cues



## Perspective cues



## Comparing heights



## Measuring height



## Slide Credits

- CS5670, Introduction to Computer Vision, Cornell Tech, by Noah Snavely.
- CS 194-26/294-26: Intro to Computer Vision and Computational Photography, UC Berkeley, by Angjoo Kanazawa.
- CS 16-385: Computer Vision, CMU, by Matthew O’Toole


## Additional Reading

- Multiview Geometry, Hartley \& Zisserman, Chapter 6.1, 6.2.

Related Readings from the past

- Multiview Geometry, Hartley \& Zisserman, Chapter 2.1, 2.2, 2.3, 2.4, 2.5, 2.6, 2.7, 3.1, 3.2, 4.1, 4.2

