Single-View Geometry

EECS 442 – Prof. David Fouhey Winter 2019, University of Michigan

http://web.eecs.umich.edu/~fouhey/teaching/EECS442_W19/

Application: Single-view modeling







A. Criminisi, I. Reid, and A. Zisserman, Single View Metrology, IJCV 2000

Application: Measuring Height



Application: Measuring Height



- CSI before CSI
- Covered criminal cases talking to random scientists (e.g., footwear experts)
- How do you tell how tall someone is if they're not kind enough to stand next to a ruler?

Application: Camera Calibration

Calibration a HUGE pain











Application: Camera Calibration

- What if 3D coordinates are unknown?
- Use scene features such as vanishing points



Slide from Efros, Photo from Criminisi

Camera calibration revisited

- What if 3D coordinates are unknown?
- Use scene features such as vanishing points



Slide from Efros, Photo from Criminisi

Recall: Vanishing points



 All lines having the same *direction* share the same vanishing point

Consider a scene with 3 orthogonal directions v_1 , v_2 are *finite* vps, v_3 *infinite* vp Want to align world coordinates with directions





• V₂

$P_{3x4} \equiv [p_1 \ p_2 \ p_3 \ p_4]$

It turns out that

 $p_1 \equiv P [1,0,0,0]^T$ VP in X direction

 $p_2 \equiv P [0,1,0,0]^T$ VP in Y direction

 $p_3 \equiv P [0,0,1,0]^T$ VP in Z direction

 $p_4 \equiv P [0,0,0,1]^T$ Projection of origin

Note the usual \equiv (i.e., all of this is up to scale) as well as the 0 for the vps

• Let's align the world coordinate system with the three orthogonal vanishing directions:

$$\boldsymbol{e_1} = \begin{bmatrix} 1\\0\\0 \end{bmatrix} \quad \boldsymbol{e_2} = \begin{bmatrix} 0\\1\\0 \end{bmatrix} \quad \boldsymbol{e_3} = \begin{bmatrix} 0\\0\\1 \end{bmatrix}$$

$$\begin{split} \lambda \boldsymbol{v}_{i} &= \boldsymbol{K}[\boldsymbol{R},\boldsymbol{t}] \begin{bmatrix} \boldsymbol{e}_{i} \\ \boldsymbol{0} \end{bmatrix} \\ \lambda \boldsymbol{v}_{i} &= \boldsymbol{K} \boldsymbol{R} \boldsymbol{e}_{i} & \text{Drop the t} \\ \boldsymbol{R}^{-1} \boldsymbol{K}^{-1} \lambda \boldsymbol{v}_{i} &= \boldsymbol{e}_{i} & \text{Inverses} \end{split}$$

So $e_i = R^{-1}K^{-1}\lambda v_i$, but who cares? What are some properties of axes? Know $e_i^T e_i = 0$ for $i \neq j$, so K, R have to satisfy $\left(\boldsymbol{R}^{-1}\boldsymbol{K}^{-1}\boldsymbol{\lambda}_{i}\boldsymbol{\nu}_{i}\right)^{T}\left(\boldsymbol{R}^{-1}\boldsymbol{K}^{-1}\boldsymbol{\lambda}_{i}\boldsymbol{\nu}_{i}\right)=\boldsymbol{0}$ $(\mathbf{R}^{T}\mathbf{K}^{-1}\lambda_{i}\boldsymbol{\nu}_{i})^{T}(\mathbf{R}^{T}\mathbf{K}^{-1}\lambda_{i}\boldsymbol{\nu}_{i}) = \mathbf{0}$ $R^{-1} = R^T$ $\lambda_i \lambda_i (\mathbf{R}^T \mathbf{K}^{-1} \mathbf{v}_i)^T (\mathbf{R}^T \mathbf{K}^{-1} \mathbf{v}_i) = \mathbf{0}$ Move scalars $v_i K^{-T} R R^T K^{-1} v_i = 0$ Clean up $v_i K^{-T} K^{-1} v_i = 0$ $RR^T = I$

 Intrinsics (focal length f, principal point u₀,v₀) have to ensure that the rays corresponding to supposedly orthogonal vanishing points are orthogonal

$$v_j K^{-T} K^{-1} v_i = 0$$





2 finite vanishing points, 1 infinite vanishing point



3 finite vanishing points









Can solve for focal length, principal point

Directions and vanishing points

Given vanishing point v camera calibration $K: K^{-1}v$ is direction corresponding to that vanishing point.



V₂

V₁

 $\begin{bmatrix} f & 0 & 0 \\ 0 & f & 0 \\ 0 & 0 & 1 \end{bmatrix}^{-1} v_3$ $\mathbf{v_2} \qquad \begin{bmatrix} f & 0 & 0 \\ 0 & f & 0 \\ 0 & 0 & 1 \end{bmatrix}^{-1} \begin{bmatrix} 0 \\ 10^{10} \\ 1 \end{bmatrix}$ $\begin{bmatrix} 1/f & 0 & 0\\ 0 & 1/f & 0\\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} 0\\ 10^{10}\\ 1 \end{bmatrix} = \begin{bmatrix} 0\\ 10^{10}/f\\ 1 \end{bmatrix}$ $\begin{vmatrix} 0\\10^6/f \end{vmatrix} \rightarrow \approx \begin{bmatrix} 0\\1\\0 \end{vmatrix}$

Directions and vanishing points



Directions and vanishing points



Directions and vanishing points If v vanishing point, and K the camera intrinsics, $K^{-1}v$ is the corresponding direction.



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$$K^{-1} = \begin{bmatrix} 1/f & 0 & 0 \\ 0 & 1/f & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

Rotation from vanishing points

Know that $\lambda_i v_i = KRe_i$ and have **K**, but want **R**

So: $\lambda K^{-1} v_i = Re_i$

What does Re_i look like?

$$Re_1 = \begin{bmatrix} r_1 & r_2 & r_3 \end{bmatrix} \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix} = r_1$$

The ith column of R is a scaled version of

$$r_i = \lambda K^{-1} v_i$$

- Solve for K (focal length, principal point) using 3 orthogonal vanishing points
- Get rotation directly from vanishing points once calibration matrix known
- Pros:
 - Could be totally automatic!
- Cons:
 - Need 3 vanishing points, estimated accurately, but with at least two finite!

Finding Vanishing Points



What might go wrong with the circled points?

Finding Vanishing Points

- Find edges $E = \{e_1, \dots, e_n\}$
- All $\binom{n}{2}$ intersections of edges $v_{ij} = e_i \times e_j$ are potential vanishing points
- Try all triplets of popular vanishing points, check if the camera's focal length, principal point "make sense"
- What are some options for this?

Finding Vanishing Points





Measuring height



Measuring height





Measuring height without a ruler



Compute Z from image measurements

• Need more than vanishing points to do this

Projective invariant

• We need to use a *projective invariant*. a quantity that does not change under projective transformations (including perspective projection)

Projective invariant

- We need to use a *projective invariant*: a quantity that does not change under projective transformations (including perspective projection)
- The cross-ratio of four points:



$$\frac{\left\|\mathbf{P}_{3}-\mathbf{P}_{1}\right\|\left\|\mathbf{P}_{4}-\mathbf{P}_{2}\right\|}{\left\|\mathbf{P}_{3}-\mathbf{P}_{2}\right\|\left\|\mathbf{P}_{4}-\mathbf{P}_{1}\right\|}$$

This is one of the cross-ratios (can reorder arbitrarily)

Measuring height







Remember This?

- Line equation: ax + by + c = 0
- Vector form: $l^T p = 0, l = [a, b, c], p = [x, y, 1]$
- Line through two points?
 - $l = p_1 \times p_2$
- Intersection of two lines?
 - $p = l_1 \times l_2$
- Intersection of two parallel lines is at infinity





A. Criminisi, I. Reid, and A. Zisserman, <u>Single View Metrology</u>, IJCV 2000 Figure from <u>UPenn CIS580 slides</u>
Another example

• Are the heights of the two groups of people consistent with one another?



Piero della Francesca, Flagellation, ca. 1455

A. Criminisi, M. Kemp, and A. Zisserman, <u>Bringing Pictorial Space to Life: computer techniques for the</u> <u>analysis of paintings</u>, *Proc. Computers and the History of Art*, 2002

Measurements on planes



Measurements on planes



Image rectification: example





Piero della Francesca, Flagellation, ca. 1455

Application: 3D modeling from a single image



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Application: 3D modeling from a single image



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Application: Object Detection



"Reasonable" approximation:

$$y_{object} \approx \frac{hy_{camera}}{v_0 - v}$$

Application: Object detection



(a) input image

Application: Object detection





(b) P(person) = uniform



(c) surface orientation estimate



(d) P(person | geometry)



(e) P(viewpoint | objects)



(f) P(person | viewpoint)



(g) P(person|viewpoint,geometry)

Application: Image Editing



K. Karsch and V. Hedau and D. Forsyth and D. Hoiem, <u>Rendering Synthetic Objects into</u> <u>Legacy Photographs</u>, *SIGGRAPH Asia* 2011

Application: Estimating Layout



V. Hedau, D. Hoiem, D. Forsyth Recovering the spatial layout of cluttered rooms ICCV 2009

Unsupervised Learning Can we learn 3D simply from regularities? Image Collection



D.F. Fouhey, W. Hussain, A. Gupta, M. Hebert. Single Image 3D without a Single 3D Image. ICCV 2015.

Unsupervised Learning Can we learn 3D simply from regularities? Image Tools From Collection Geometry





Vanishing Points

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Fronto-Parallel Image

D.F. Fouhey, W. Hussain, A. Gupta, M. Hebert. Single Image 3D without a Single 3D Image. ICCV 2015.

Factorization



Factorization 3D Structure



Factorization

3D Structure





Factorization

Image

Style



Style Elements













Factorization

Image

3D Structure

Style









Solving for Style

Image



Style



Vanishing Points

Fronto-Parallel Image





Style Element

Input Image

HOG, Dalal and Triggs '05; ELDA from Hariharan et al. '12



Style Element





Style Element







Style Element







Style Element







Style Element







Solving for 3D over a Dataset



Style Element



Set of Images









Factorization

Image

3D Structure

Style









Prior



On average: 3D structure is a camera inside a box, rotated uniformly

Discovered Style Elements

Detections



Element



Detections



Horizontal

Vertical



Element







Input

GT

Output



















Results



Scaling Up To The World

RGBD Datasets

What about?





Places-205, Zhou et al. NIPS 2014

Style Learned from Internet

Automatically Discovered Style Elements

Supermarket



Museum



Laundromat



Locker Room



Places-205, Zhou et al. NIPS 2014
Learning from the Internet







