Computer Vision (CS763)

Teaching cameras to "see"

Camera Extrinsics and Intrinsics

Arjun Jain

Camera Calibration Using a 2D Checkerboard (Zhang)

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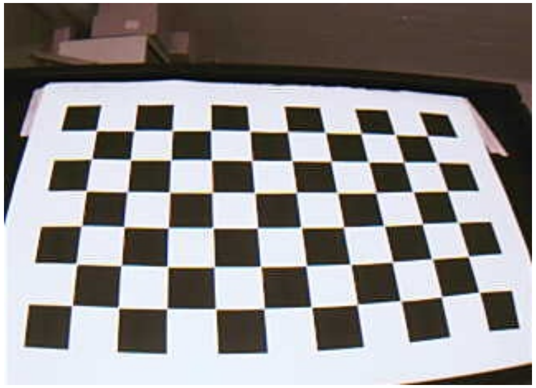
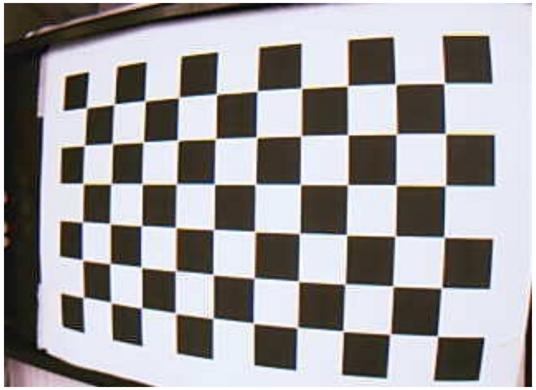
- Observed 2D pattern (checkerboard)
- **Known size and structure**

Trick for Checkerboard Calibration

- **Set the world coordinate system to the corner of the checkerboard**
- All points on the checkerboard lie in the X/Y plane, i.e., Z=0

Simplification

- The Z coordinate of all points on the checkerboard is equal to zero

$$\begin{bmatrix} x \\ y \\ 1 \end{bmatrix} = \begin{bmatrix} c & cs & x_H \\ 0 & c(1+m) & y_H \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} r_{11} & r_{12} & r_{13} & t_1 \\ r_{21} & r_{22} & r_{23} & t_2 \\ r_{31} & r_{32} & r_{33} & t_3 \end{bmatrix} \begin{bmatrix} X \\ Y \\ \boxed{Z} \\ 1 \end{bmatrix}$$

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- We can delete the 3rd column of the extrinsic parameter matrix

Simplification

- The Z coordinate of all points on the checkerboard is equal to zero
- Deleting the 3rd column of the extrinsic parameter matrix leads to

$$\begin{bmatrix} x \\ y \\ 1 \end{bmatrix} = \begin{bmatrix} c & cs & x_H \\ 0 & c(1+m) & y_H \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} r_{11} & r_{12} & t_1 \\ r_{21} & r_{22} & t_2 \\ r_{31} & r_{32} & t_3 \end{bmatrix} \begin{bmatrix} X \\ Y \\ 1 \end{bmatrix}$$

Setting Up the Equations for Determining the Parameter

$$\mathsf{H} = [\boldsymbol{h}_1, \boldsymbol{h}_2, \boldsymbol{h}_3] = \underbrace{\begin{bmatrix} c & cs & x_H \\ 0 & c(1+m) & y_H \\ 0 & 0 & 1 \end{bmatrix}}_{\mathsf{K}} \underbrace{\begin{bmatrix} r_{11} & r_{12} & t_1 \\ r_{21} & r_{22} & t_2 \\ r_{31} & r_{32} & t_3 \end{bmatrix}}_{[\boldsymbol{r}_1, \boldsymbol{r}_2, \boldsymbol{t}]}$$

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One point generates the equation:

$$\begin{bmatrix} x \\ y \\ 1 \end{bmatrix} = \mathsf{H} \begin{bmatrix} X \\ Y \\ 1 \end{bmatrix} = \mathsf{K}[\boldsymbol{r}_1, \boldsymbol{r}_2, \boldsymbol{t}] \begin{bmatrix} X \\ Y \\ 1 \end{bmatrix}$$

Setting Up the Equations for Determining the Parameter

- For multiple points, we obtain

$$\begin{bmatrix} x_i \\ y_i \\ 1 \end{bmatrix} = \underset{3\times 3}{\mathsf{H}} \begin{bmatrix} X_i \\ Y_i \\ 1 \end{bmatrix} \qquad i = 1, \ldots, I$$

How to proceed?

Setting Up the Equations for Determining the Parameter

- For multiple points, we obtain

$$\begin{bmatrix} x_i \\ y_i \\ 1 \end{bmatrix} = \underset{3\times 3}{\mathsf{H}} \begin{bmatrix} X_i \\ Y_i \\ 1 \end{bmatrix} \qquad i = 1, \ldots, I$$

- Analogous to **steps 1-3 of the DLT**

DLT-Like Estimation

- We estimate a 3x3 homography instead of a 3x4 projection matrix
- Rest is identical (instead of Z coord.)
- We use $\boldsymbol{a}_{x_i}^{\mathsf{T}} \boldsymbol{h} = 0$

  $\boldsymbol{a}_{y_i}^{\mathsf{T}} \boldsymbol{h} = 0$
- with

$$
\begin{aligned}
\boldsymbol{h} &= (h_k) = \mathrm{vec}(\mathsf{H}^{\mathsf{T}}) \\
\boldsymbol{a}_{x_i}^{\mathsf{T}} &= (-X_i, -Y_i, \cancel{-Z_i}, -1, 0, 0, \cancel{0}, 0, x_i X_i, x_i Y_i, \cancel{x_i Z_i}, x_i) \\
\boldsymbol{a}_{y_i}^{\mathsf{T}} &= (0, 0, \cancel{0}, 0, -X_i, -Y_i, \cancel{-Z_i}, -1, y_i X_i, y_i Y_i, \cancel{y_i Z_i}, y_i)
\end{aligned}
$$

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\end{aligned}
$$

DLT-Like Estimation

- Solving a system of linear equation leads to an estimate of H
- We need to identify at least 4 points as H has 8 DoF and each point consists of two observations

We estimated H **and**
now we need to compute K **from** H

Computing K Given H

$$\mathsf{H} = [\boldsymbol{h}_1, \boldsymbol{h}_2, \boldsymbol{h}_3] = \underbrace{\begin{bmatrix} c & cs & x_H \\ 0 & c(1+m) & y_H \\ 0 & 0 & 1 \end{bmatrix}}_{\mathsf{K}} \underbrace{\begin{bmatrix} r_{11} & r_{12} & t_1 \\ r_{21} & r_{22} & t_2 \\ r_{31} & r_{32} & t_3 \end{bmatrix}}_{[\boldsymbol{r}_1,\, \boldsymbol{r}_2,\, \boldsymbol{t}]}$$

no rotation matrix, thus QR decomposition is not applicable as for DLT

Computing K Given H is Different From the DLT Solution

- Homography H has only 8 DoF
- No direct decomposition as in DLT
- Exploit constraints on the intrinsic parameters

$$\mathsf{H} = [\boldsymbol{h}_1, \boldsymbol{h}_2, \boldsymbol{h}_3] = \underbrace{\begin{bmatrix} c & cs & x_H \\ 0 & c(1+m) & y_H \\ 0 & 0 & 1 \end{bmatrix}}_{\mathsf{K}} \underbrace{\begin{bmatrix} r_{11} & r_{12} & t_1 \\ r_{21} & r_{22} & t_2 \\ r_{31} & r_{32} & t_3 \end{bmatrix}}_{[\boldsymbol{r}_1, \boldsymbol{r}_2, \boldsymbol{t}]}$$

$$[\boldsymbol{h}_1, \boldsymbol{h}_2, \boldsymbol{h}_3] = \mathsf{K}[\boldsymbol{r}_1, \boldsymbol{r}_2, \boldsymbol{t}]$$

Exploiting Constraints for Determining the Parameter

$$\mathsf{H} = [\boldsymbol{h}_1, \boldsymbol{h}_2, \boldsymbol{h}_3] = \underbrace{\begin{bmatrix} c & cs & x_H \\ 0 & c(1+m) & y_H \\ 0 & 0 & 1 \end{bmatrix}}_{\mathsf{K}} \underbrace{\begin{bmatrix} r_{11} & r_{12} & t_1 \\ r_{21} & r_{22} & t_2 \\ r_{31} & r_{32} & t_3 \end{bmatrix}}_{[\boldsymbol{r}_1, \boldsymbol{r}_2, \boldsymbol{t}]}$$

$$[\boldsymbol{h}_1, \boldsymbol{h}_2, \boldsymbol{h}_3] = \mathsf{K}[\boldsymbol{r}_1, \boldsymbol{r}_2, \boldsymbol{t}]$$

$$\Rightarrow \quad \boldsymbol{r}_1 = \mathsf{K}^{-1}\boldsymbol{h}_1 \qquad \boldsymbol{r}_2 = \mathsf{K}^{-1}\boldsymbol{h}_2$$

Exploiting Constraints for Determining the Parameter

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$$[\boldsymbol{h}_1, \boldsymbol{h}_2, \boldsymbol{h}_3] = \mathsf{K}[\boldsymbol{r}_1, \boldsymbol{r}_2, \boldsymbol{t}]$$

$$\boldsymbol{r}_1 = \mathsf{K}^{-1}\boldsymbol{h}_1 \qquad \boldsymbol{r}_2 = \mathsf{K}^{-1}\boldsymbol{h}_2$$

As $\boldsymbol{r}_1, \boldsymbol{r}_2, \boldsymbol{r}_3$ form an orthonormal basis

$$\boldsymbol{r}_1^T \boldsymbol{r}_2 = 0 \qquad \|\boldsymbol{r}_1\| = \|\boldsymbol{r}_2\| = 1$$

Exploiting Constraints

$$\boldsymbol{r}_1 = \mathsf{K}^{-1}\boldsymbol{h}_1 \qquad \boldsymbol{r}_2 = \mathsf{K}^{-1}\boldsymbol{h}_2$$

$$\xrightarrow{\boldsymbol{r}_1^T\boldsymbol{r}_2 = 0} \qquad \boldsymbol{h}_1^T\mathsf{K}^{-T}\mathsf{K}^{-1}\boldsymbol{h}_2 = 0$$

Exploiting Constraints

$$\boldsymbol{r}_1 = \mathsf{K}^{-1}\boldsymbol{h}_1 \qquad \boldsymbol{r}_2 = \mathsf{K}^{-1}\boldsymbol{h}_2$$

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Exploiting Constraints

$$\boldsymbol{r}_1 = \mathsf{K}^{-1}\boldsymbol{h}_1 \qquad \boldsymbol{r}_2 = \mathsf{K}^{-1}\boldsymbol{h}_2$$

$\boldsymbol{r}_1^T\boldsymbol{r}_2 = 0$

$$\Rightarrow \quad \boldsymbol{h}_1^T\mathsf{K}^{-T}\mathsf{K}^{-1}\boldsymbol{h}_2 = 0$$

$\|\boldsymbol{r}_1\| = \|\boldsymbol{r}_2\| = 1$

$$\Rightarrow \quad \boldsymbol{h}_1^T\mathsf{K}^{-T}\mathsf{K}^{-1}\boldsymbol{h}_1 = \boldsymbol{h}_2^T\mathsf{K}^{-T}\mathsf{K}^{-1}\boldsymbol{h}_2$$

$$\boldsymbol{h}_1^T\mathsf{K}^{-T}\mathsf{K}^{-1}\boldsymbol{h}_1 - \boldsymbol{h}_2^T\mathsf{K}^{-T}\mathsf{K}^{-1}\boldsymbol{h}_2 = 0$$

Exploiting Constraints

$$\boldsymbol{r}_1 = \mathsf{K}^{-1}\boldsymbol{h}_1 \qquad \boldsymbol{r}_2 = \mathsf{K}^{-1}\boldsymbol{h}_2$$

$$\boxed{\boldsymbol{h}_1^T \mathsf{K}^{-T}\mathsf{K}^{-1}\boldsymbol{h}_2 = 0}$$

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Exploiting Constraints

$$\boldsymbol{h}_1^T \underline{\mathsf{K}^{-T}\mathsf{K}^{-1}} \boldsymbol{h}_2 = 0$$

$$\boldsymbol{h}_1^T \underline{\mathsf{K}^{-T}\mathsf{K}^{-1}} \boldsymbol{h}_1 - \boldsymbol{h}_2^T \underline{\mathsf{K}^{-T}\mathsf{K}^{-1}} \boldsymbol{h}_2 = 0$$

- Define symmetric and positive definite matrix $\mathsf{B} := \mathsf{K}^{-T}\mathsf{K}^{-1}$

Exploiting Constraints

$$\boldsymbol{h}_1^T \underline{\mathsf{B}} \boldsymbol{h}_2 = 0$$

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$$\mathbf{h}_1^T \mathsf{B} \mathbf{h}_1 - \mathbf{h}_2^T \mathsf{B} \mathbf{h}_2 = 0$$

- Define symmetric and positive definite matrix $\mathsf{B} := \mathsf{K}^{-T}\mathsf{K}^{-1}$
- If B is known, the calibration matrix can be recovered through Cholesky decomp.

$$\mathsf{B} = \begin{pmatrix} b_{11} & b_{12} & b_{13} \\ b_{12} & b_{22} & b_{23} \\ b_{13} & b_{23} & b_{33} \end{pmatrix}$$

$$\mathrm{chol}(\mathsf{B}) = \mathsf{A}\mathsf{A}^T$$

$$\mathsf{A} = \mathsf{K}^{-T}$$

Recap: Cholesky Decomposition

- Cholesky decomposition or Cholesky factorization is a decomposition of a positive-definite matrix into the product of a lower triangular matrix and its transpose

$$\begin{pmatrix} 4 & 12 & -16 \\ 12 & 37 & -43 \\ -16 & -43 & 98 \end{pmatrix} = \begin{pmatrix} 2 & 0 & 0 \\ 6 & 1 & 0 \\ -8 & 5 & 3 \end{pmatrix} \begin{pmatrix} 2 & 6 & -8 \\ 0 & 1 & 5 \\ 0 & 0 & 3 \end{pmatrix}$$

Exploiting Constraints

- Define a vector $\boldsymbol{b} = (b_{11}, b_{12}, b_{13}, b_{22}, b_{23}, b_{33})$ of unknowns

$$\mathrm{B} = \begin{pmatrix} b_{11} & b_{12} & b_{13} \\ b_{12} & b_{22} & b_{23} \\ b_{13} & b_{23} & b_{33} \end{pmatrix}$$

Exploiting Constraints

- Define a vector $\boldsymbol{b} = (b_{11}, b_{12}, b_{13}, b_{22}, b_{23}, b_{33})$ of unknowns

$$\mathsf{B} = \begin{pmatrix} b_{11} & b_{12} & b_{13} \\ b_{12} & b_{22} & b_{23} \\ b_{13} & b_{23} & b_{33} \end{pmatrix}$$

- Construct a system of linear equations $V\boldsymbol{b} = 0$ using $\boldsymbol{h}_i^T \mathsf{B} \boldsymbol{h}_j = \boldsymbol{v}_{ij}^T \boldsymbol{b}$ ($\boldsymbol{v}_{ij}$ see next slide) exploiting the constraints:

$$\boldsymbol{v}_{12}^T \boldsymbol{b} = 0$$

(first constraint)

$\boldsymbol{r}_1^T \boldsymbol{r}_2 = 0$

$$\boldsymbol{v}_{11}^T \boldsymbol{b} - \boldsymbol{v}_{22}^T \boldsymbol{b} = 0$$

(second constraint)

$\|\boldsymbol{r}_1\| = \|\boldsymbol{r}_2\| = 1$

The Matrix V

- The matrix V is given as

$$V = \begin{pmatrix} \boldsymbol{v}_{12}^T \\ \boldsymbol{v}_{11}^T - \boldsymbol{v}_{22}^T \end{pmatrix} \quad \text{with} \quad \boldsymbol{v}_{ij} = \begin{bmatrix} h_{1i}h_{1j} \\ h_{1i}h_{2j} + h_{2i}h_{1j} \\ h_{3i}h_{1j} + h_{1i}h_{3j} \\ h_{2i}h_{2j} \\ h_{3i}h_{2j} + h_{2i}h_{3j} \\ h_{3i}h_{3j} \end{bmatrix}$$

elements of H

- For one image, we obtain

$$\begin{pmatrix} \boldsymbol{v}_{12}^T \\ \boldsymbol{v}_{11}^T - \boldsymbol{v}_{22}^T \end{pmatrix} \boldsymbol{b} = \boldsymbol{0}$$

The Matrix V

- For multiple images, we stack the matrices to a 2n x 6 matrix

$$
\begin{array}{l}
\text{image } 1 \\
\\
\\
\text{image } n \\
\\
\end{array}
\begin{pmatrix}
\boldsymbol{v}_{12}^{\mathsf{T}} \\
\boldsymbol{v}_{11}^{\mathsf{T}} - \boldsymbol{v}_{22}^{\mathsf{T}} \\
\cdots \\
\boldsymbol{v}_{12}^{\mathsf{T}} \\
\boldsymbol{v}_{11}^{\mathsf{T}} - \boldsymbol{v}_{22}^{\mathsf{T}}
\end{pmatrix} \boldsymbol{b} = \boldsymbol{0}
$$

- We need to solve the linear system $V\boldsymbol{b} = 0$ to obtain $\boldsymbol{b}$ and thus K

Solving the Linear System

- The system $V\boldsymbol{b} = 0$ has a trivial solution which (invalid matrix B)
- Impose additional constraint $\|\boldsymbol{b}\| = 1$

Solving the Linear System

- The system $Vb = 0$ has a trivial solution which (invalid matrix B)
- Impose additional constraint $\|b\| = 1$
- Real measurements are noisy
- Find the solution that minimizes the squares error

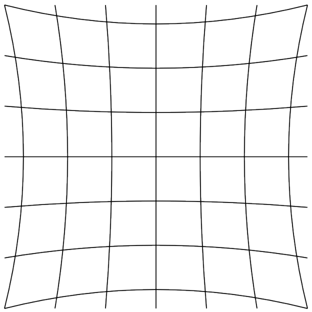
$$b^* = \arg\min_{b} \|Vb\| \text{ with } \|b\| = 1$$

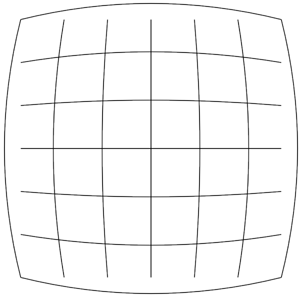
- Eigenvector/Eigenvalue problem similar to the DLT computation

What is Needed?

- We need at least **4 points per plane** to compute the matrix H
- Each **plane** gives us **two equations**
- Since B has 6 DoF, we need at least **3 different views of a plane**
- Solve $Vb = 0$ to compute K

Example Lens Distortion Model





Non-linear effects:

- Radial distortion
- Tangential distortion

- Compute the corrected image point:

(1)
$$x' = x/z$$
$$y' = y/z$$

(2)
$$x'' = x'(1 + k_1 r^2 + k_2 r^4) + 2p_1 x' y' + p_2(r^2 + 2x'^2)$$
$$y'' = y'(1 + k_1 r^2 + k_2 r^4) + p_1(r^2 + 2y'^2) + 2p_2 x' y'$$

where $r^2 = x'^2 + y'^2$ k_1, k_2 : radial distortion coefficients

p_1, p_2 : tangential distortion coefficients

(3)
$$u = f_x \cdot x'' + c_x$$
$$v = f_y \cdot y'' + c_y$$

Error Minimization

Lens distortion can be calculated by minimizing a non-linear error function

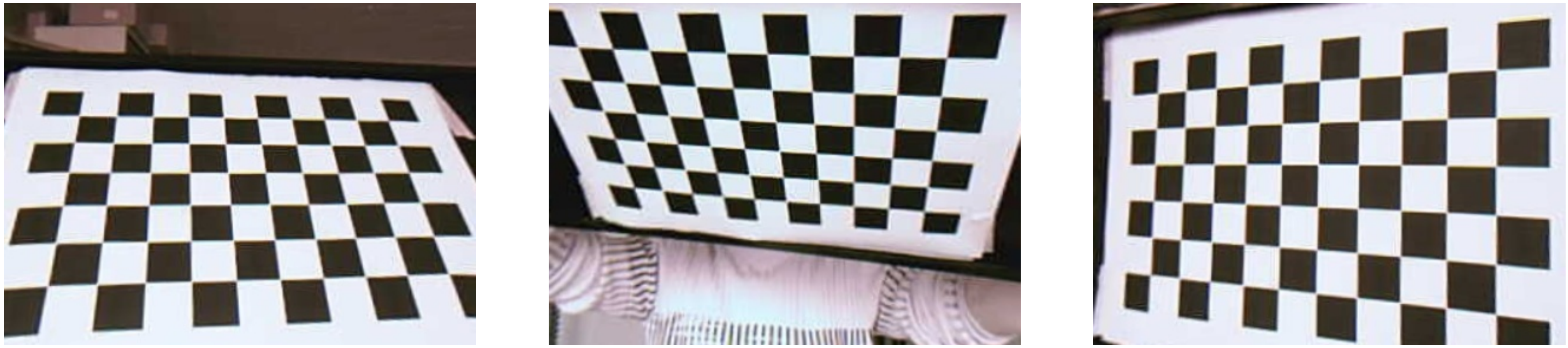
$$\min_{(\mathsf{K},\boldsymbol{q},R_n,\mathrm{t}_n)} \sum_n \sum_i \|\mathbf{x}_{ni} - \hat{\mathbf{x}}(\mathsf{K}, \mathbf{q}, R_n, \mathbf{t}_n, \mathbf{X}_{ni})\|^2$$

...linearize to obtain a quadratic function, compute derivative, set it to 0, solve linear system, iterate...
(solved using Levenberg-Marquardt)

Example Results

- Before calibration:

- After calibration:



Summary on Camera Calibration Using a Checkerboard

- Pinhole camera model (first step)
- Non-linear model for lens distortion (second step)
- Approach to 2D camera calibration that
  - accurately determines the model parameters
  - is easy to realize

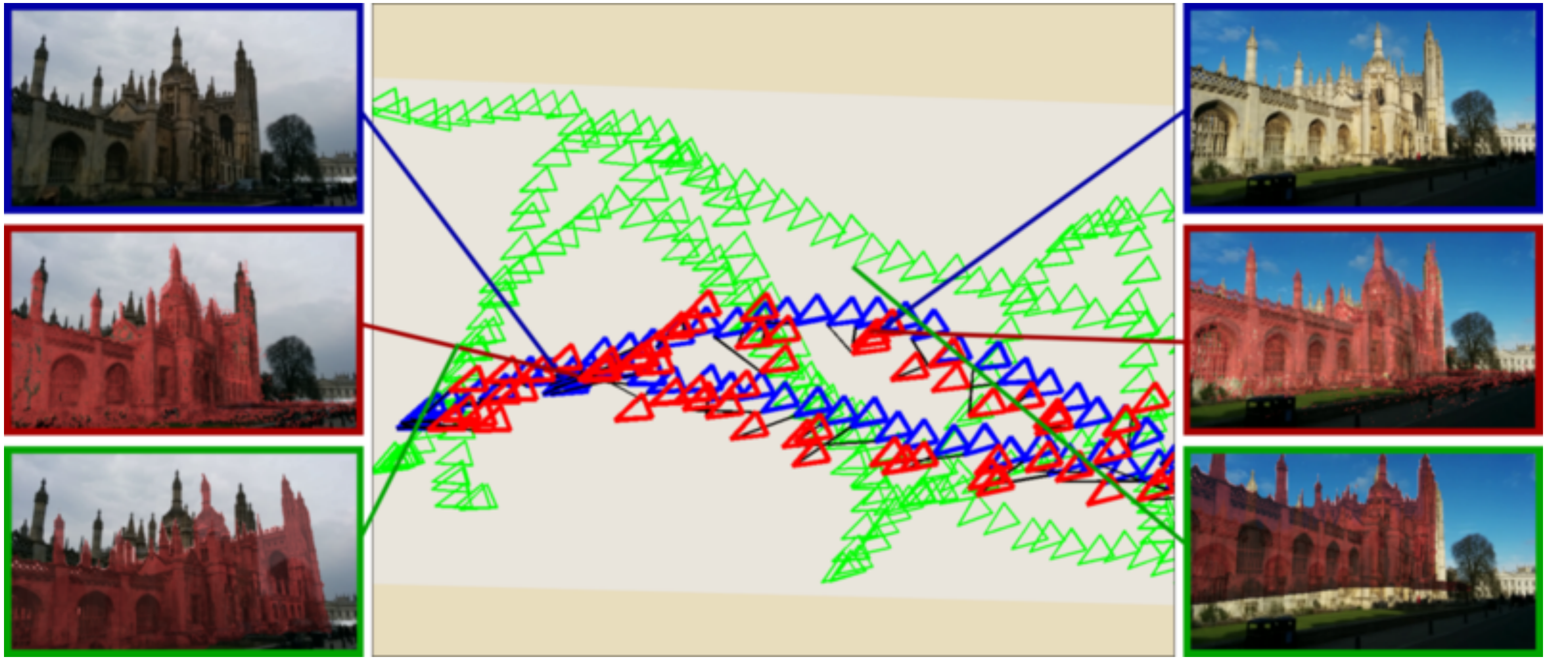
Depth from Single Image

- Using CNN to learn unary and pairwise potential of continuous CRF. Does not require geometric priors.

Liu et al. CVPR 2015

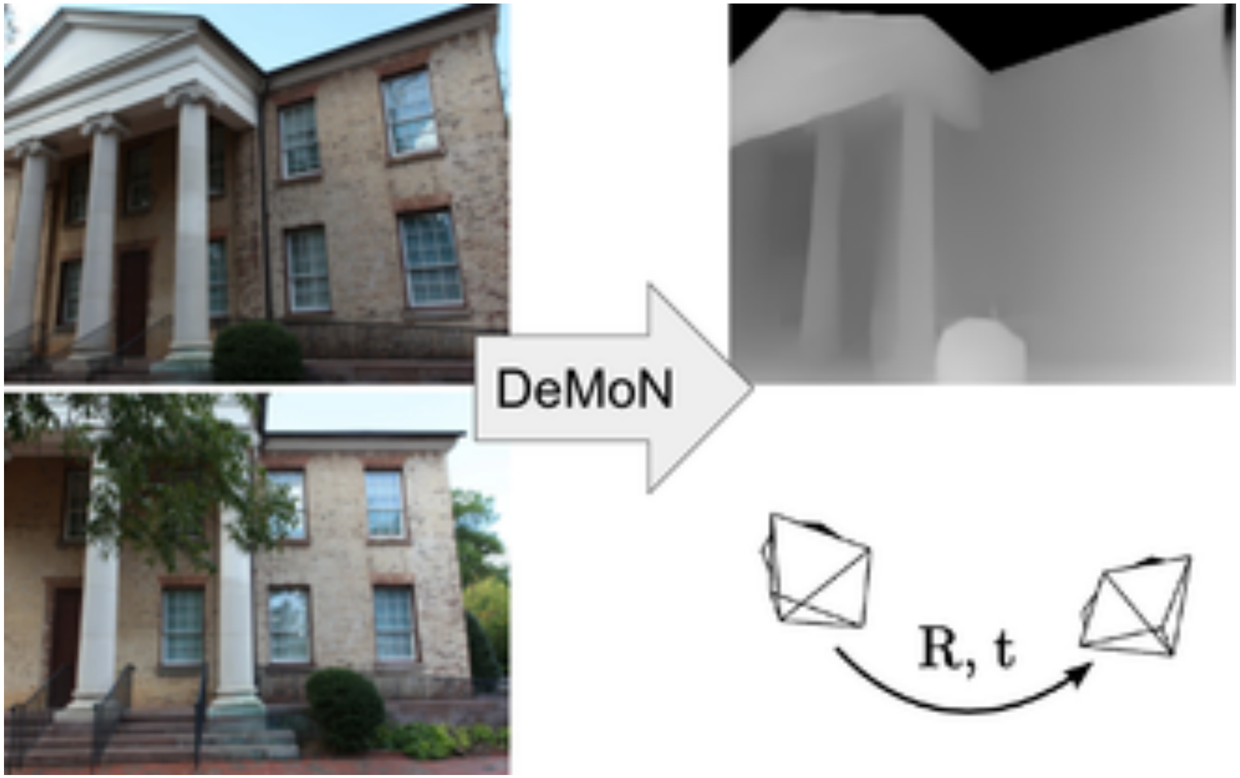
6-DOF Camera Relocalization

- Using CNN to regress a camera's 6-DOF relative to a scene using a RGB image.



Kendall et al. ICCV 2015

Relative Motion Between Two Cameras



Ummenhofer et al. ICCV 2015

Slide Information

- The slides have been created by Cyrill Stachniss (cyrill.stachniss@igg.uni-bonn.de) as part of the photogrammetry and robotics courses.
- A lot of material from Ajit Rajwade's CS763 course
- Thanks to Parag for some slides
- Thanks to Rahul Mitra for DL slides
- **I tried to acknowledge all people from whom I used images or videos. In case I made a mistake or missed someone, please let me know.**
- The photogrammetry material heavily relies on the very well written lecture notes by Wolfgang Förstner and the Photogrammetric Computer Vision book by Förstner & Wrobel.
- Parts of the robotics material stems from the great Probabilistic Robotics book by Thrun, Burgard and Fox.
- If you are a university lecturer, feel free to use the course material. If you adapt the course material, please make sure that you keep the acknowledgements to others and please acknowledge me as well. To satisfy my own curiosity, please send me email notice if you use my slides.

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