THE UNIVERSITY OF WESTERN AUSTRALIA

CITS 4402 Computer Vision

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Lecture 08 – Camera Calibration

Summary – Lecture 07

- Feature Detection
- Feature Extraction
- Harris Corner Detector
- Histogram of Oriented Gradients (HOG)
- Local Binary Patterns (LBP)
- Scale Invariant Feature Transform (SIFT)

Overview of this lecture

- What is camera calibration
- Why is it useful
- Pinhole camera model
- Perspective projection
- Camera calibration matrix derivation
- Camera calibration matrix estimation
- Calculating intrinsic and extrinsic camera parameters
- Calibration demo

What is camera calibration?

- The process of estimating camera parameters
- The 3D world coordinates are projected on the 2D image plane (film)
- The relationship between the world coordinates and image coordinates is defined by the camera parameters
- There are 5 intrinsic and 6 extrinsic camera parameters

Why do we need to calibrate cameras?

- To estimate the 3D geometry of the world

- To correct imaging artefacts caused by imperfect lenses

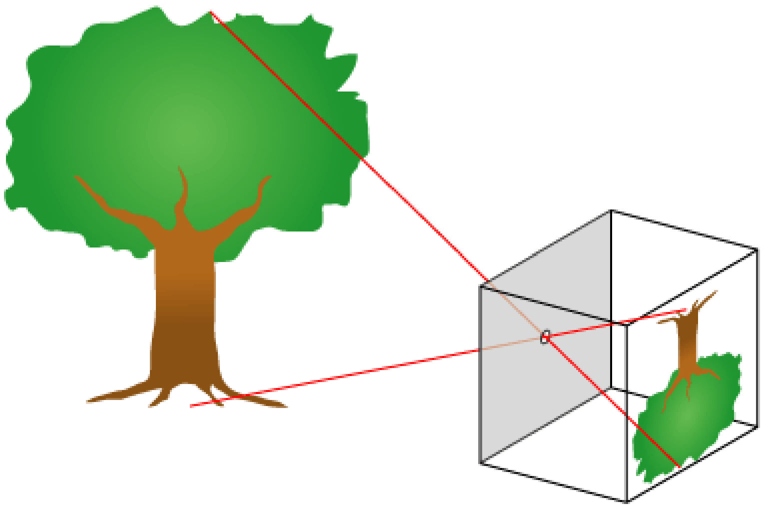
- Examples include
  - Stereo reconstruction
  - Multiview reconstruction
  - Single view measurements such as the height of a person
  - Lens distortion correction

Camera parameters

- Intrinsic parameters (total 5)
  - Focal length in pixel coordinates (2 if the pixels are rectangular)
  - Principle point (2 coordinates)
  - Skew
- Extrinsic parameters (total 6)
  - 3 rotations
  - 3 translations

The pinhole camera model

- A box with a pinhole will make an inverted image of the object on its back plane
- The holes must be a point which is practically impossible
- Used as a simplified model of the real camera
- Why pinhole?
  - If the hole is not small, rays of light will not be focused



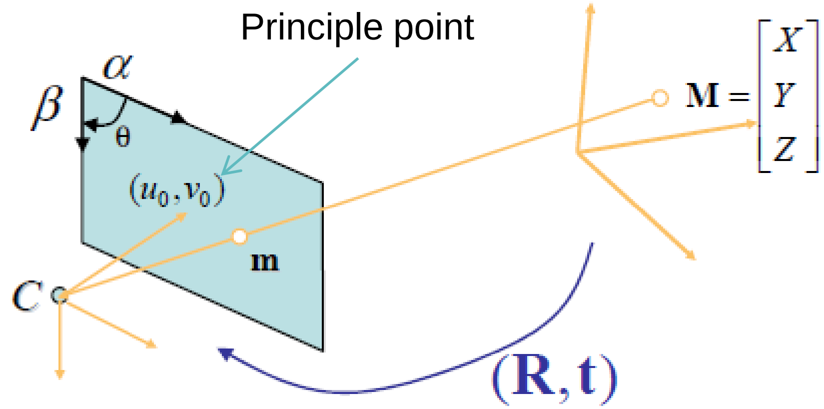
Camera calibration : Quick overview

- Imagine a pinhole camera with the imaging plane in front

- C is the optical center, M is a point in 3D space and m is its projection

$$s\mathrm{m} = \mathrm{K}[\mathrm{R} \;\; \mathrm{t}]\mathrm{M}$$

$$\mathrm{K} = \begin{bmatrix} \alpha & \gamma & u_0 \\ 0 & \beta & v_0 \\ 0 & 0 & 1 \end{bmatrix}$$



'**K**' contains the 5 intrinsic parameters and is called the camera intrinsic matrix

'**R**' is the rotation matrix and '**t**' the translation vector. **R** and **t** are the extrinsic parameters and have 3 degrees of freedom each.

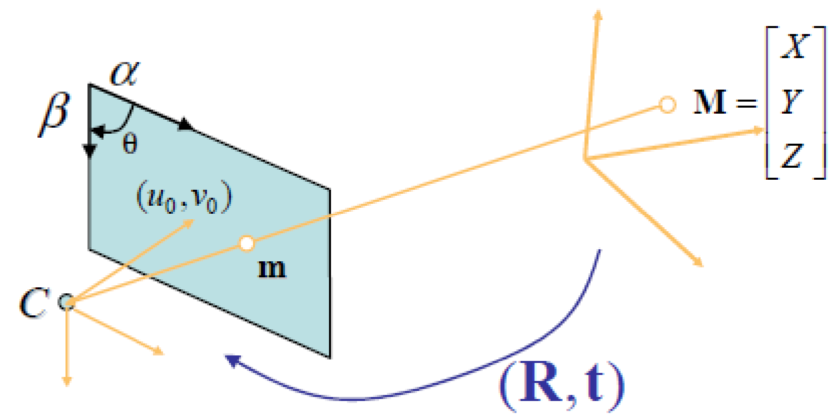
$\gamma = \alpha \cot \theta$ Axis skew causes shear distortion

Camera calibration : Quick overview (cont'd)

- Let us expand this equation

$$s\mathbf{m} = \mathbf{K}[\mathbf{R} \;\; \mathbf{t}]\mathbf{M}$$

- Pixel coordinates (u,v) start from the top left corner of the image



Rotation matrix

Translation vector

$$\begin{bmatrix} su \\ sv \\ s \end{bmatrix} = \begin{bmatrix} \alpha & \gamma & u_0 & 0 \\ 0 & \beta & v_0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} r_{11} & r_{12} & r_{13} & t_x \\ r_{21} & r_{22} & r_{23} & t_y \\ r_{31} & r_{32} & r_{33} & t_z \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} X \\ Y \\ Z \\ 1 \end{bmatrix}$$

Pixel coordinates World coordinates

Camera calibration : Quick overview (cont'd)

$$\begin{bmatrix} su \\ sv \\ s \end{bmatrix} = \begin{bmatrix} \alpha & \gamma & u_0 & 0 \\ 0 & \beta & v_0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} \boxed{\begin{bmatrix} r_{11} & r_{12} & r_{13} & t_x \\ r_{21} & r_{22} & r_{23} & t_y \\ r_{31} & r_{32} & r_{33} & t_z \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} X \\ Y \\ Z \\ 1 \end{bmatrix}}$$

3D location of the point
in Camera coordinates

Camera calibration : Quick overview (cont'd)

$$\begin{bmatrix} su \\ sv \\ s \end{bmatrix} = \underbrace{\begin{bmatrix} \alpha & \gamma & u_0 & 0 \\ 0 & \beta & v_0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} r_{11} & r_{12} & r_{13} & t_x \\ r_{21} & r_{22} & r_{23} & t_y \\ r_{31} & r_{32} & r_{33} & t_z \\ 0 & 0 & 0 & 1 \end{bmatrix}}_{\text{3x4 Camera Calibration Matrix}} \begin{bmatrix} X \\ Y \\ Z \\ 1 \end{bmatrix}$$

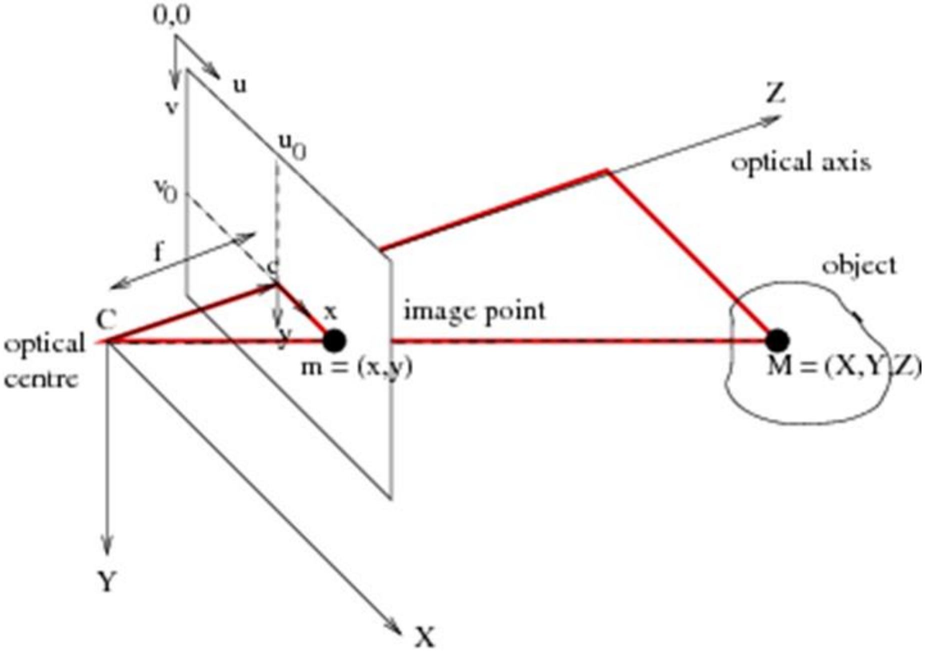
Perspective projection

- The projection of a 3D point relative to the camera coordinate system is

$$x = \frac{Xf}{Z}, \quad y = \frac{Yf}{Z}$$

- We can write this in matrix form using homogeneous coordinates

$$\begin{bmatrix} sx \\ sy \\ s \end{bmatrix} = \begin{bmatrix} f & 0 & 0 & 0 \\ 0 & f & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} X \\ Y \\ Z \\ 1 \end{bmatrix}$$



- Pixel coordinates are define w.r.t. the top left corner of the image

$$u = u_0 + x$$
$$v = v_0 + y$$

Intrinsic camera matrix derivation

- Substituting these values

$$x = u - u_0$$
$$y = v - v_0$$

- in the perspective projection equation

$$\begin{bmatrix} s(u-u_0) \\ s(v-v_0) \\ s \end{bmatrix} = \begin{bmatrix} f & 0 & 0 & 0 \\ 0 & f & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} X \\ Y \\ Z \\ 1 \end{bmatrix}$$

- and rearranging

$$\begin{bmatrix} su \\ sv \\ s \end{bmatrix} = \boxed{\begin{bmatrix} f & 0 & u_0 & 0 \\ 0 & f & v_0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix}} \begin{bmatrix} X \\ Y \\ Z \\ 1 \end{bmatrix}$$

Note that for the simple case, we only have 3 intrinsic parameters but for the general case we have 5.

Looking back at the general case

$$\begin{bmatrix} su \\ sv \\ s \end{bmatrix} = \begin{bmatrix} \alpha & \gamma & u_0 & 0 \\ 0 & \beta & v_0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} r_{11} & r_{12} & r_{13} & t_x \\ r_{21} & r_{22} & r_{23} & t_y \\ r_{31} & r_{32} & r_{33} & t_z \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} X \\ Y \\ Z \\ 1 \end{bmatrix}$$

- The world coordinates are fist rotated and translated to the camera coordinates
- α and β are the focal length expressed in pixels. Due to rectangular pixels, scale factors differ along the x and y dimensions.
- γ is non-zero if there is skew in the image plane.

Camera calibration matrix

$$\begin{bmatrix} su \\ sv \\ s \end{bmatrix} = \underbrace{\begin{bmatrix} \alpha & \gamma & u_0 & 0 \\ 0 & \beta & v_0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} r_{11} & r_{12} & r_{13} & t_x \\ r_{21} & r_{22} & r_{23} & t_y \\ r_{31} & r_{32} & r_{33} & t_z \\ 0 & 0 & 0 & 1 \end{bmatrix}} \begin{bmatrix} X \\ Y \\ Z \\ 1 \end{bmatrix}$$

$$P = \begin{bmatrix} q_{11} & q_{12} & q_{13} & q_{14} \\ q_{21} & q_{22} & q_{23} & q_{24} \\ q_{31} & q_{32} & q_{33} & q_{34} \end{bmatrix}$$

$$\begin{bmatrix} su \\ sv \\ s \end{bmatrix} = \boxed{\begin{bmatrix} q_{11} & q_{12} & q_{13} & q_{14} \\ q_{21} & q_{22} & q_{23} & q_{24} \\ q_{31} & q_{32} & q_{33} & 1 \end{bmatrix}} \begin{bmatrix} X \\ Y \\ Z \\ 1 \end{bmatrix}$$

The aim of camera calibration is to find these unknowns given a set of known XYZ world points and their corresponding uv locations in an image

The camera calibration matrix *P* is defined only up to an unknown scale s. Thus the last term in *P* can be set to 1.

For i = 1 …. N points

$$\begin{bmatrix} su_i \\ sv_i \\ s \end{bmatrix} = \begin{bmatrix} q_{11} & q_{12} & q_{13} & q_{14} \\ q_{21} & q_{22} & q_{23} & q_{24} \\ q_{31} & q_{32} & q_{33} & 1 \end{bmatrix} \begin{bmatrix} X_i \\ Y_i \\ Z_i \\ 1 \end{bmatrix}$$

$$s = X_i q_{31} + Y_i q_{32} + Z_i q_{33} + 1$$

$$u_i = \frac{X_i q_{11} + Y_i q_{12} + Z_i q_{13} + q_{14}}{X_i q_{31} + Y_i q_{32} + Z_i q_{33} + 1}$$

$$v_i = \frac{X_i q_{21} + Y_i q_{22} + Z_i q_{23} + q_{24}}{X_i q_{31} + Y_i q_{32} + Z_i q_{33} + 1}$$

Writing as a system of linear equations (Aq = b)

$$X_i q_{11} + Y_i q_{12} + Z_i q_{13} + q_{14} - u_i X_i q_{31} - u_i Y_i q_{32} - u_i Z_i q_{33} = u_i$$

$$X_i q_{21} + Y_i q_{22} + Z_i q_{23} + q_{24} - v_i X_i q_{31} - v_i Y_i q_{32} - v_i Z_i q_{33} = v_i$$

How many equations do we need to solve this?

How many points do we need to solve this?

$$\begin{bmatrix} X_i & Y_i & Z_i & 1 & 0 & 0 & 0 & 0 & -u_i X_i & -u_i Y_i & -u_i Z_i \\ 0 & 0 & 0 & 0 & X_i & Y_i & Z_i & 1 & -v_i X_i & -v_i Y_i & -v_i Z_i \end{bmatrix} \begin{bmatrix} q_{11} \\ q_{12} \\ q_{13} \\ q_{14} \\ q_{21} \\ q_{22} \\ q_{23} \\ q_{24} \\ q_{31} \\ q_{32} \\ q_{33} \end{bmatrix} = \begin{bmatrix} u_i \\ v_i \end{bmatrix}$$

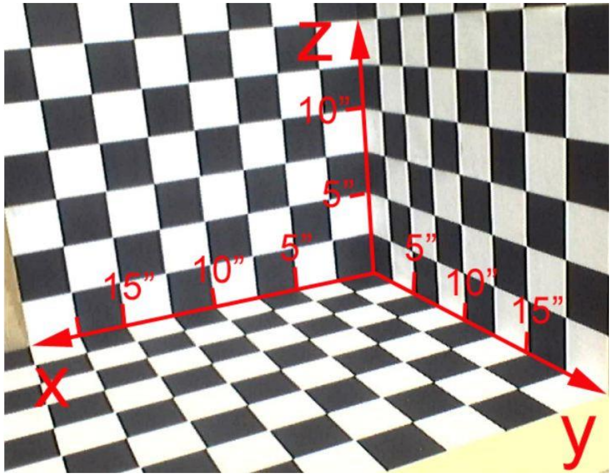
2N x 11 Matrix

11 vector of unknowns

2N vector

Camera calibration targets

- 3D checker board makes a good calibration target
- Any 3D structure where precise XYZ locations of some points (>5) are known can be used
- 3D targets
  - Calibration is easy with single image
  - Most accurate approach
  - Expensive target
  - Visibility of points can be an issue in case of multiple cameras located at different view points
- 2D planar targets
  - Simpler target and better visibility for multiple cameras
  - Needs multiple images after rotating the target
- 1D line targets
  - Simplest target and can be seen from 360 degrees
  - Still very new



Solving for q

- Since every point gives two equations, we need at least 6 non-coplanar points to solve $A\mathbf{q} = \mathbf{b}$

- We can solve this using linear least squares

$$\begin{aligned} A\mathbf{q} &= \mathbf{b} \\ \Rightarrow A^T A\mathbf{q} &= A^T\mathbf{b} \\ \Rightarrow \mathbf{q} &= (A^T A)^{-1} A^T\mathbf{b} \end{aligned}$$

- Can be solved in one line of Matlab $\mathbf{q} = A\backslash\mathbf{b};$

- For a unique solution, $A^T A$ must be non-singular i.e. $\mathrm{rank}(A^T A)$ or $\mathrm{rank}(A)$ must be 11. Need $2N \geq 11,\ N \geq 6$ non-coplanar points.

Calculating the camera calibration matrix (2nd method)

- Removing the condition $q_{34} = 1$

$$\begin{bmatrix} su_i \\ sv_i \\ s \end{bmatrix} = \begin{bmatrix} q_{11} & q_{12} & q_{13} & q_{14} \\ q_{21} & q_{22} & q_{23} & q_{24} \\ q_{31} & q_{32} & q_{33} & q_{34} \end{bmatrix} \begin{bmatrix} X_i \\ Y_i \\ Z_i \\ 1 \end{bmatrix}$$

$$s = X_i q_{31} + Y_i q_{32} + Z_i q_{33} + q_{34}$$

$$u_i = \frac{X_i q_{11} + Y_i q_{12} + Z_i q_{13} + q_{14}}{X_i q_{31} + Y_i q_{32} + Z_i q_{33} + q_{34}}$$

$$v_i = \frac{X_i q_{21} + Y_i q_{22} + Z_i q_{23} + q_{24}}{X_i q_{31} + Y_i q_{32} + Z_i q_{33} + q_{34}}$$

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Calculating the camera calibration matrix (2nd method)

$$X_i q_{11} + Y_i q_{12} + Z_i q_{13} + q_{14} - u_i X_i q_{31} - u_i Y_i q_{32} - u_i Z_i q_{33} - u_i q_{34} = 0$$

$$X_i q_{21} + Y_i q_{22} + Z_i q_{23} + q_{24} - v_i X_i q_{31} - v_i Y_i q_{32} - v_i Z_i q_{33} - v_i q_{34} = 0$$

$$\underbrace{\begin{bmatrix} X_i & Y_i & Z_i & 1 & 0 & 0 & 0 & 0 & -u_i X_i & -u_i Y_i & -u_i Z_i & -u_i \\ 0 & 0 & 0 & 0 & X_i & Y_i & Z_i & 1 & -v_i X_i & -v_i Y_i & -v_i Z_i & -v_i \end{bmatrix}}_{\text{2N x 12 Matrix}} \underbrace{\begin{bmatrix} q_{11} \\ q_{12} \\ q_{13} \\ q_{14} \\ q_{21} \\ q_{22} \\ q_{23} \\ q_{24} \\ q_{31} \\ q_{32} \\ q_{33} \\ q_{34} \end{bmatrix}}_{\text{12 vector of unknowns}} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

$$A\mathbf{q} = 0$$

Solving for q using Eigen decomposition (Direct Linear Transformation or DLT)

- To find the solution of $A\mathbf{q} = 0$
- We need to find the non-trivial **null vector** of A.
- 'A' can have up to 12 eigenvalues.
- Case 1: If rank(A) is 12, its nullity is zero. There is no non-trivial null vector of A.
- Case 2: If rank(A) is 11, it will have exactly one zero eigenvalue and the corresponding eigenvector will be the solution of $A\mathbf{q} = 0$
- Case 3: If rank(A) < 11, there are infinite solutions to $A\mathbf{q} = 0$
  Check if data is degenerate. Recalibrate.

Solving for q

- In practice, the smallest eigenvalue of ‘A’ will not be exactly equal to zero but will have a small value due to noise.
- The smallest eigenvector of ‘A’ is our solution i.e. q.
- Rule of thumb: Always check the smallest eigenvalue and/or the ratio between the largest and smallest values to estimate noise in the data.
- High levels of noise mean error in the construction of the matrix A.

Problem Statement:

Given n correspondences $x_i \leftrightarrow X_i$, where X_i is a scene point and x_i its image:

Compute

$P = K\,[R|\,t]$ such that $x_i = PX_i$.

The algorithm for camera calibration has two parts:

(i) Compute the matrix P from a set of point correspondences.

(ii) Decompose P into K, R and t via the QR decomposition.

Decomposition of the P matrix

$$\begin{bmatrix} su \\ sv \\ s \end{bmatrix} = \begin{bmatrix} \alpha & \gamma & u_0 & 0 \\ 0 & \beta & v_0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} r_{11} & r_{12} & r_{13} & t_x \\ r_{21} & r_{22} & r_{23} & t_y \\ r_{31} & r_{32} & r_{33} & t_z \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} X \\ Y \\ Z \\ 1 \end{bmatrix}$$

$$\begin{bmatrix} su \\ sv \\ s \end{bmatrix} = \begin{bmatrix} \alpha & \gamma & u_0 & 0 \\ 0 & \beta & v_0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} \mathbf{r}_1^T & t_x \\ \mathbf{r}_2^T & t_y \\ \mathbf{r}_3^T & t_z \\ \mathbf{0}^T & 1 \end{bmatrix} \begin{bmatrix} X \\ Y \\ Z \\ 1 \end{bmatrix}$$

$$P = \begin{bmatrix} \alpha\mathbf{r}_1^T + \gamma\mathbf{r}_2^T + u_0\mathbf{r}_3^T & \alpha t_x + \gamma t_y + u_0 t_z \\ \beta\mathbf{r}_2^T + v_0\mathbf{r}_3^T & \beta t_y + v_0 t_z \\ \mathbf{r}_3^T & t_z \end{bmatrix} \approx \begin{bmatrix} \mathbf{q}_1^T & q_{14} \\ \mathbf{q}_2^T & q_{24} \\ \mathbf{q}_3^T & q_{34} \end{bmatrix}$$

- The ‘q’ matrix computed with DLT differs from ‘P’ by an unknown scale ‘s’

Properties of a rotation matrix R

- Can be used to decompose the P matrix into intrinsic and extrinsic parameters

- Sum of squares of the elements in each row or column = 1

$$||\mathbf{r}_1|| = ||\mathbf{r}_2|| = ||\mathbf{r}_3|| = 1$$

$$\mathbf{r}_1^T \cdot \mathbf{r}_1^T = \mathbf{r}_2^T \cdot \mathbf{r}_2^T = \mathbf{r}_3^T \cdot \mathbf{r}_3^T = 1$$

- Dot product of any pair of rows or any pair or columns = 0

$$\mathbf{r}_1^T \cdot \mathbf{r}_2^T = \mathbf{r}_1^T \cdot \mathbf{r}_3^T = \mathbf{r}_2^T \cdot \mathbf{r}_3^T = 0$$

- The rows of R represent the coordinates axes of the rotated space in the original space. (vise versa for columns of R)

- Determinant of R is +1.

Decomposing the P matrix

We can write the camera matrix P as follows:

$$P = [M| \ -MC] = [M| \ b]$$

M is a 3x3 invertible matrix and C is the camera center position in world coordinates.

- Good to project 3D into 2D
- It does not tell you about the camera pose
- It does not tell you about the camera's internal geometry

We can decompose this into intrinsic and extrinsic matrices as follows:

$$P = K [R| \ -RC] = K [R| \ t]$$

Where K is the camera intrinsic matrix and R is the rotation matrix.
t = –RC is the translation vector or the position of the world origin in camera coordinates

$$\begin{aligned} M &= KR \\ b &= Kt \end{aligned}$$

Recovering the intrinsic parameters

$$
\begin{aligned}
M &= KR \\
B = MM^T = KK^T &= \begin{bmatrix} \alpha^2+\gamma^2+u_0^2 & \gamma\beta+u_0v_0 & u_0 \\ \gamma\beta+u_0v_0 & \beta^2+v_0^2 & v_0 \\ u_0 & v_0 & 1 \end{bmatrix}
\end{aligned}
$$

Since **P** is defined up to a scale factor, the last element is usually not 1. Therefore, we have to normalize **B** so that the last element is 1. Intrinsic parameters are then calculated as follows:

$$
\begin{aligned}
u_0 &= B_{13} \\
v_0 &= B_{23} \\
\beta &= \sqrt{B_{22}-v_0^2} \\
\gamma &= \frac{B_{12}-u_0v_0}{\beta} \\
\alpha &= \sqrt{B_{11}-u_0^2-\gamma^2}
\end{aligned}
$$

Both $\alpha > 0$ and $\beta > 0$, and thus unambiguous.

Recovering the extrinsic parameters

- Once intrinsic parameters are known, K is known.
- Extrinsic parameters can be calculated as

$$\begin{aligned} R &= K^{-1} M \\ t &= K^{-1} b \end{aligned}$$

Decomposing matrix P with RQ-factorization

- Can also recover intrinsic and extrinsic parameters with RQ-factorization
- Recall $$P = [M| \; -MC] = [M| \; b]$$ $$P = K\,[R| \; -RC] = K\,[R| \; t]$$ $$M = KR$$
- Notice that K is an upper triangular matrix and R is an orthonormal matrix.
- We can recover K and R by RQ-factorization of M.
- 't' can be recovered by $t = -RC$ where $C = -M^{-1}b$

```
[K, R, C, pp, pv] = decomposecamera(P); % use Peter Kovesi's Matlab code
```

Remarks

- Since RQ-factorization doesn't have a unique solution, the diagonal entries are forced to be positive. (Negating a col in K and the corresponding row in R will give the same camera matrix P). This is a correct approach if
  - Your image's X/Y axes point in the same direction as your camera's X/Y axes
  - Your camera looks in the positive-z direction

- If the z-coordinates of the camera and world are pointing in the opposite direction, things can go wrong e.g. in OpenGL, the camera points in the negative z direction.

- For the general case some checks must be performed:
  - If camera and world x-axes are opposite, negate the 1st col of K and row of R.
  - If camera and world y-axes are opposite, negate the 2nd col of K and row of R.
  - If camera and world z-axes are opposite, negate the 3rd col of K and row of R.
  - If det(K) = -1, multiply K by -1.

Limitations of the linear approach

- Using least square minimization to get ‘**q**’ has little physical meaning.
- The method ignores constraints on the elements of ‘**P’**. The elements of ‘**P’** are not arbitrary e.g. we may not be able to decompose it into an intrinsic and extrinsic parameter matrix.
- A more accurate approach is to use constrained non-linear optimization to find the calibration matrix.

Constrained non-linear optimization

- Estimate P using one of the linear methods. $P = \begin{bmatrix} p_{11} & p_{12} & p_{13} & p_{14} \\ p_{21} & p_{22} & p_{23} & p_{24} \\ p_{31} & p_{32} & p_{33} & p_{34} \end{bmatrix}$

- Use this P as an initial guess and reproject the points on the image plane.

- Minimize the distance between all measured and reprojected image points.

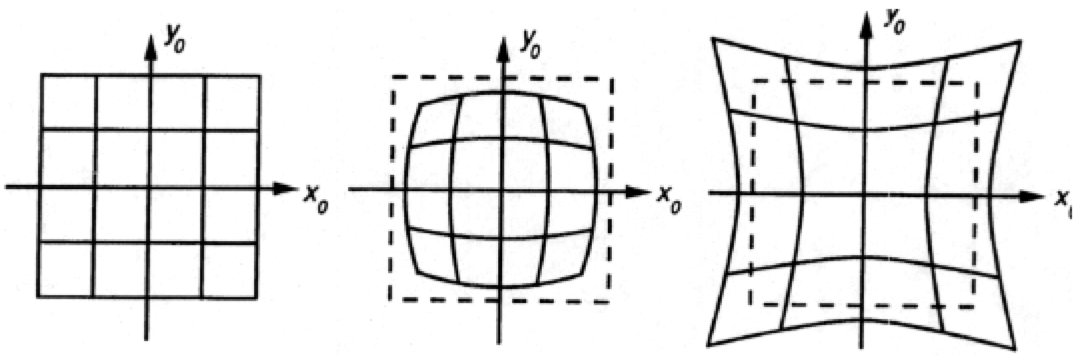
$$\min_{\alpha,\beta,\gamma,u_0,v_0,R,t} \sum_{i=1}^{N} \left\{ \left(\frac{p_{11}X_i + p_{12}Y_i + p_{13}Z_i + p_{14}}{p_{31}X_i + p_{32}Y_i + p_{33}Z_i + p_{34}} - u_i \right)^2 + \left(\frac{p_{21}X_i + p_{22}Y_i + p_{23}Z_i + p_{24}}{p_{31}X_i + p_{32}Y_i + p_{33}Z_i + p_{34}} - v_i \right)^2 \right\}$$

- Ensure that R remains a rotation matrix

- Iterate until convergence

Radial distortion

- Barrel distortion
  - Image magnification decreases with distance from the optical axis
- Pincussion distortion
  - Image magnification increases with distance from the optical axis
- Distortion is higher as we move away from the center of the image
- Thus distortion is a function of the radius ‘r’



No distortion Barrel distortion Pincussion distortion

Radial distortion correction

- We can model radial distortion in the projection by applying a simple polynomial transformation

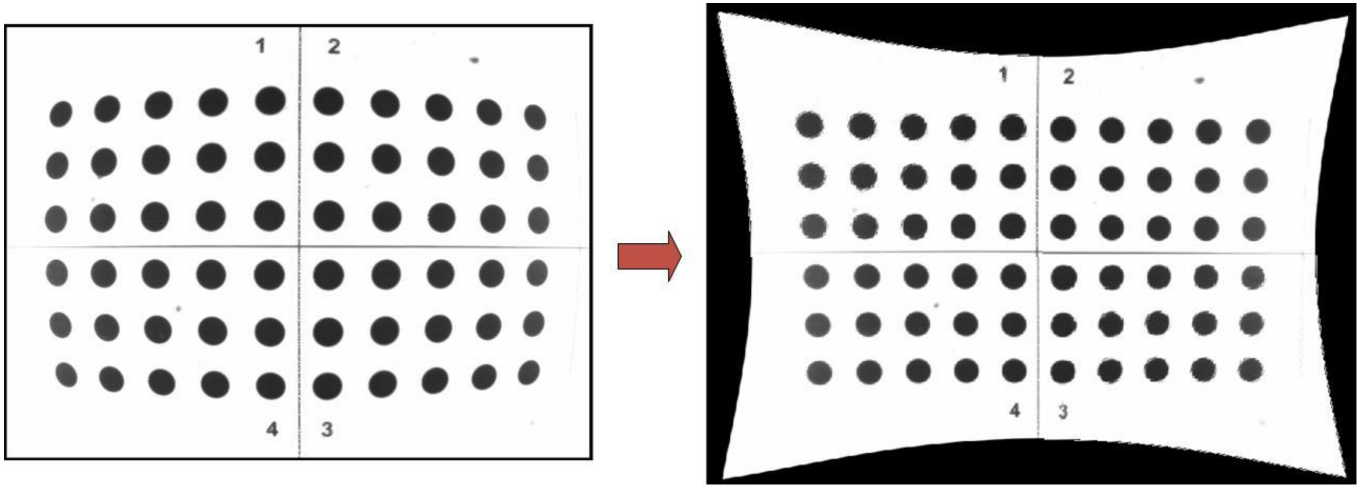
- Apply radial distortion to normalized camera coordinates

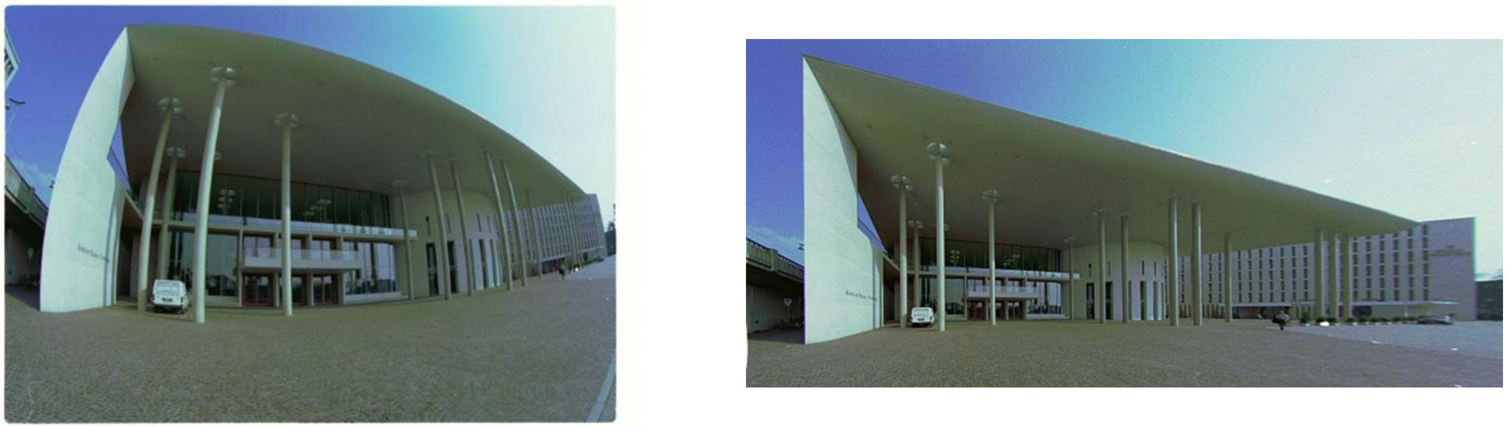
$$
\begin{aligned}
x_n &= X/Z, \quad y_n = Y/Z \quad \text{(normalized image coordinates)} \\
r^2 &= x_n^2 + y_n^2 \\
x_d &= x_n(1 + \kappa_1 r^2 + \kappa_2 r^4 \cdots) \\
y_d &= y_n(1 + \kappa_1 r^2 + \kappa_2 r^4 \cdots)
\end{aligned}
$$

- Use distorted camera coordinates to calculate image coordinates

$$
\begin{aligned}
u &= f x_d + u_0 \\
v &= f y_d + v_0
\end{aligned}
$$

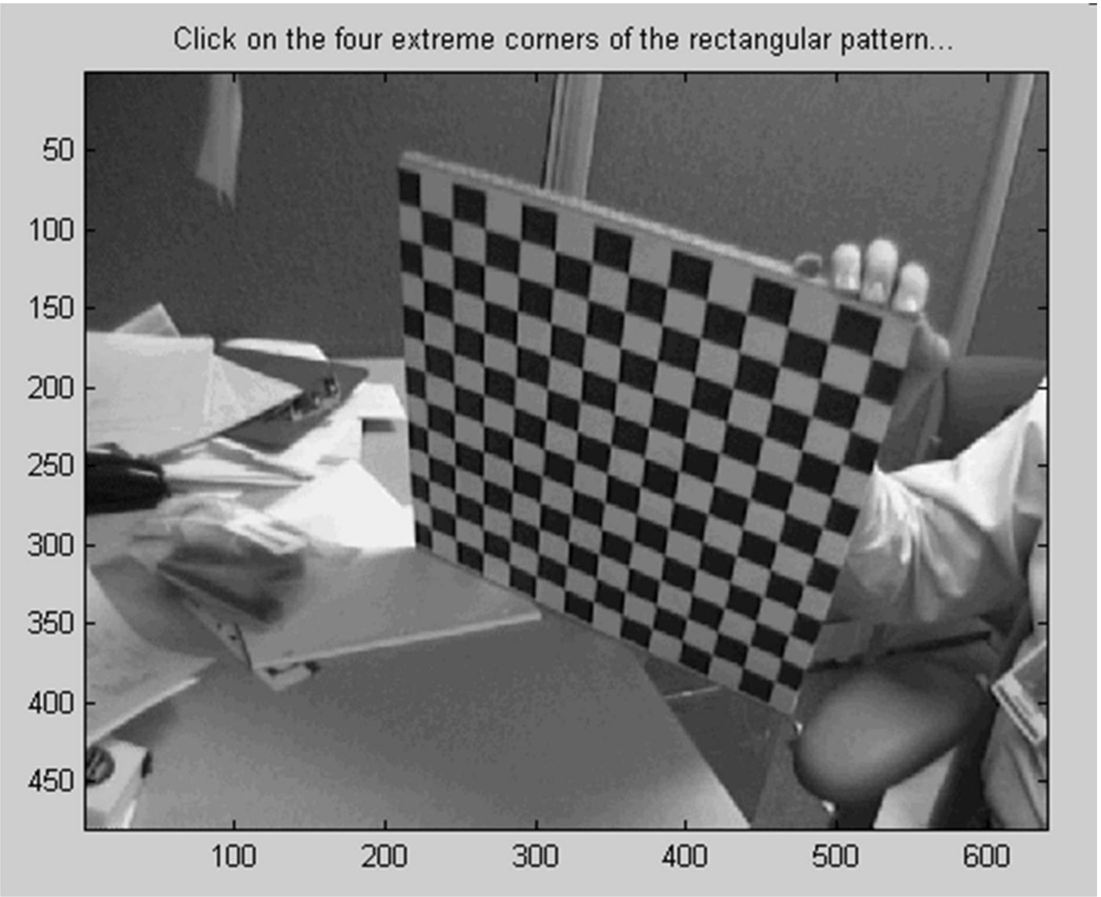
Barrel distortion correction example



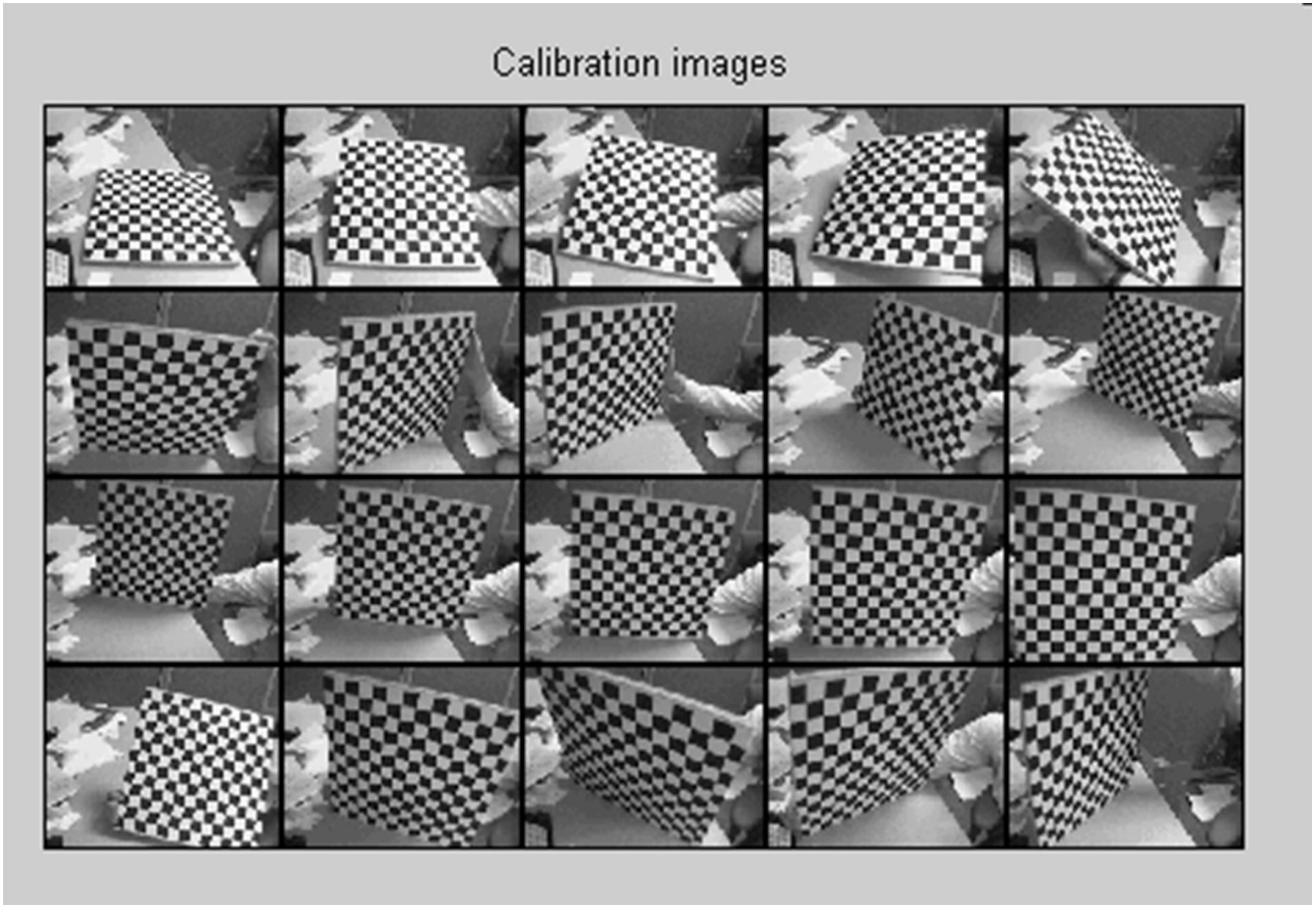


Calibration Demo

Camera Calibration Toolbox for Matlab J. Bouguet – [1998-2000]



Calibration Demo



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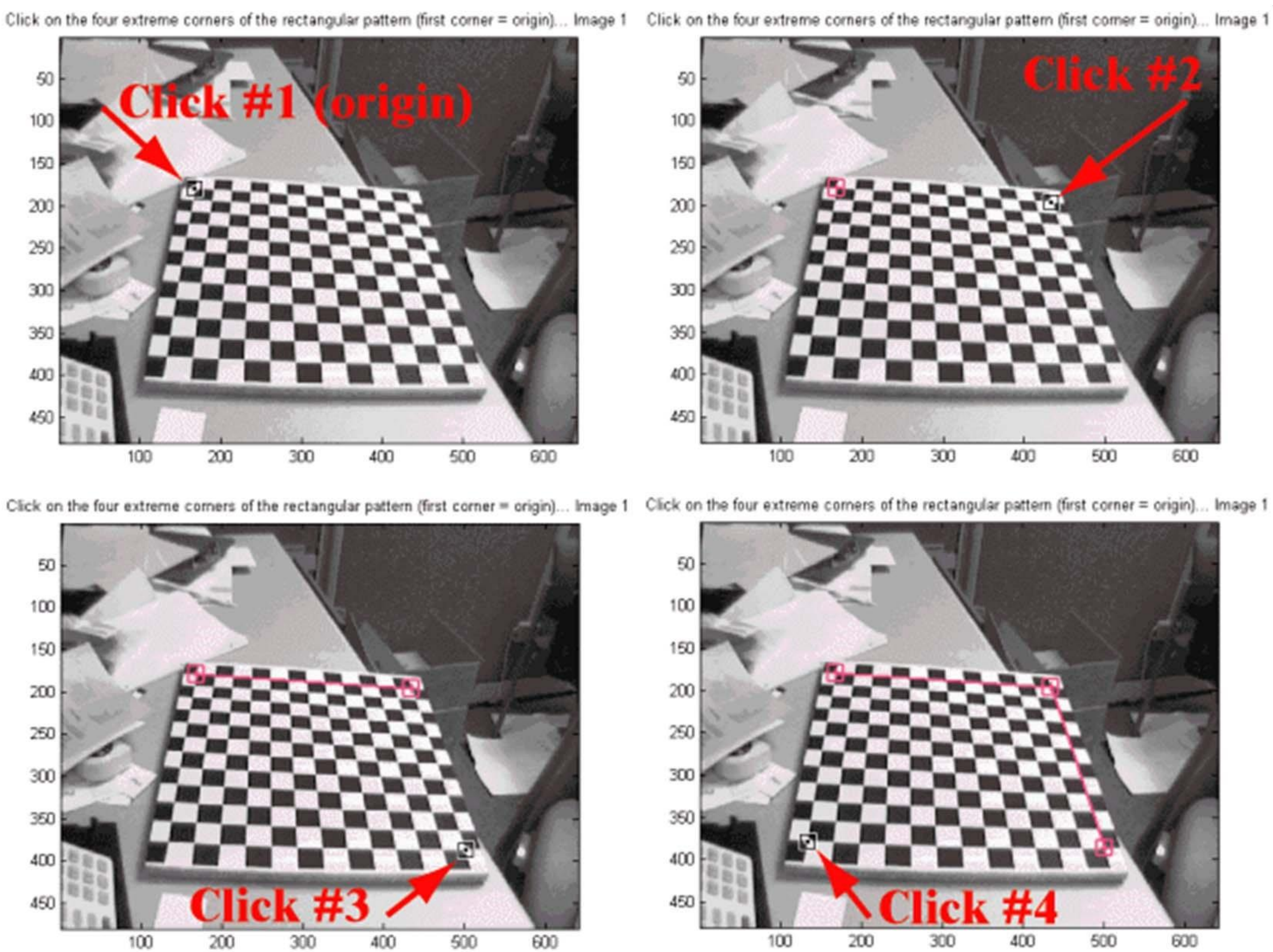
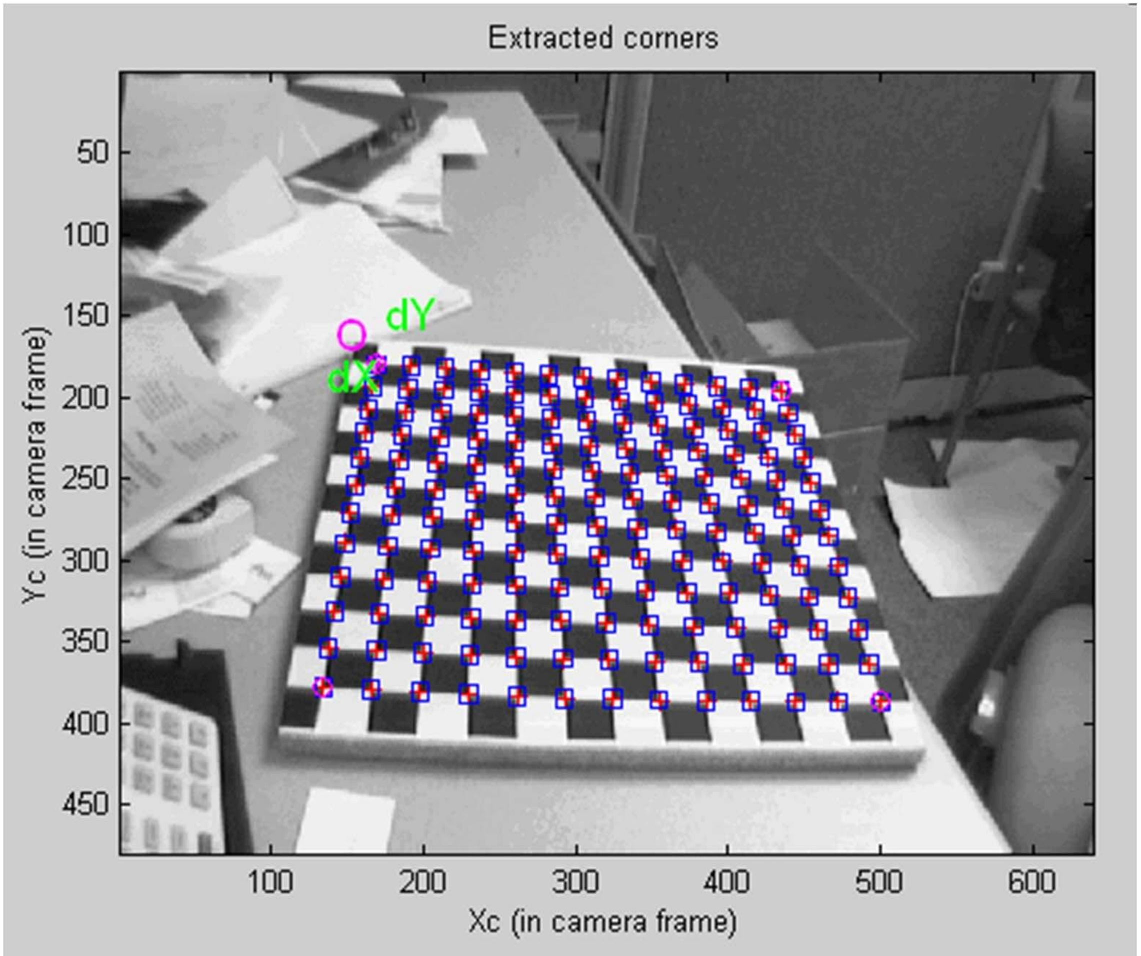
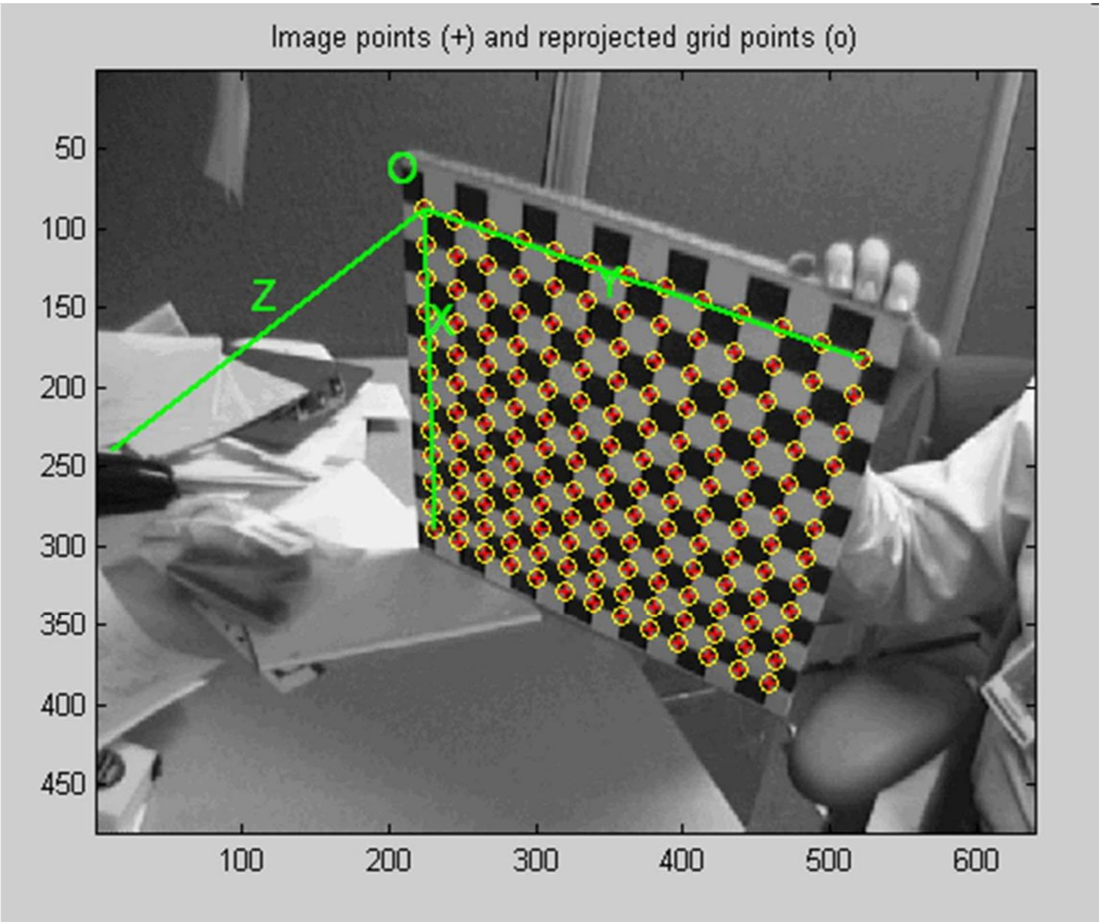


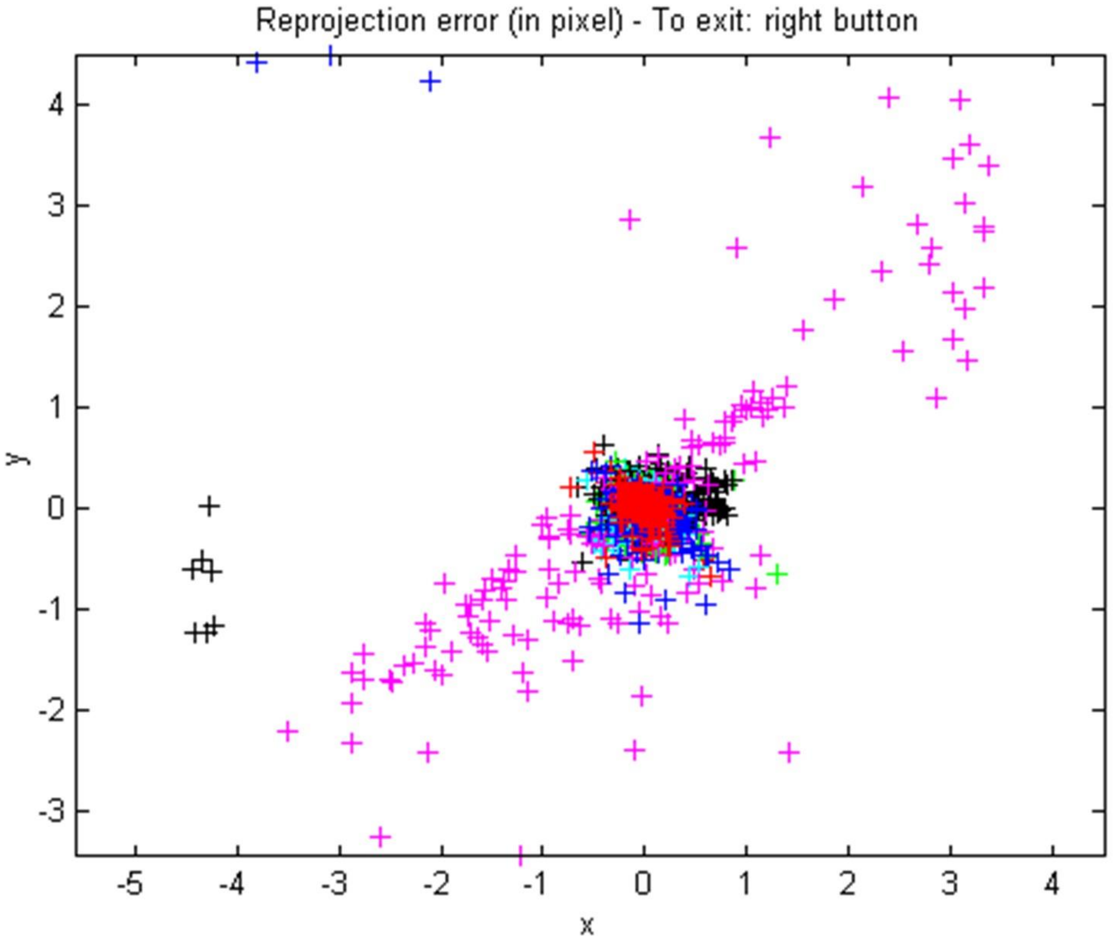
Calibration Demo



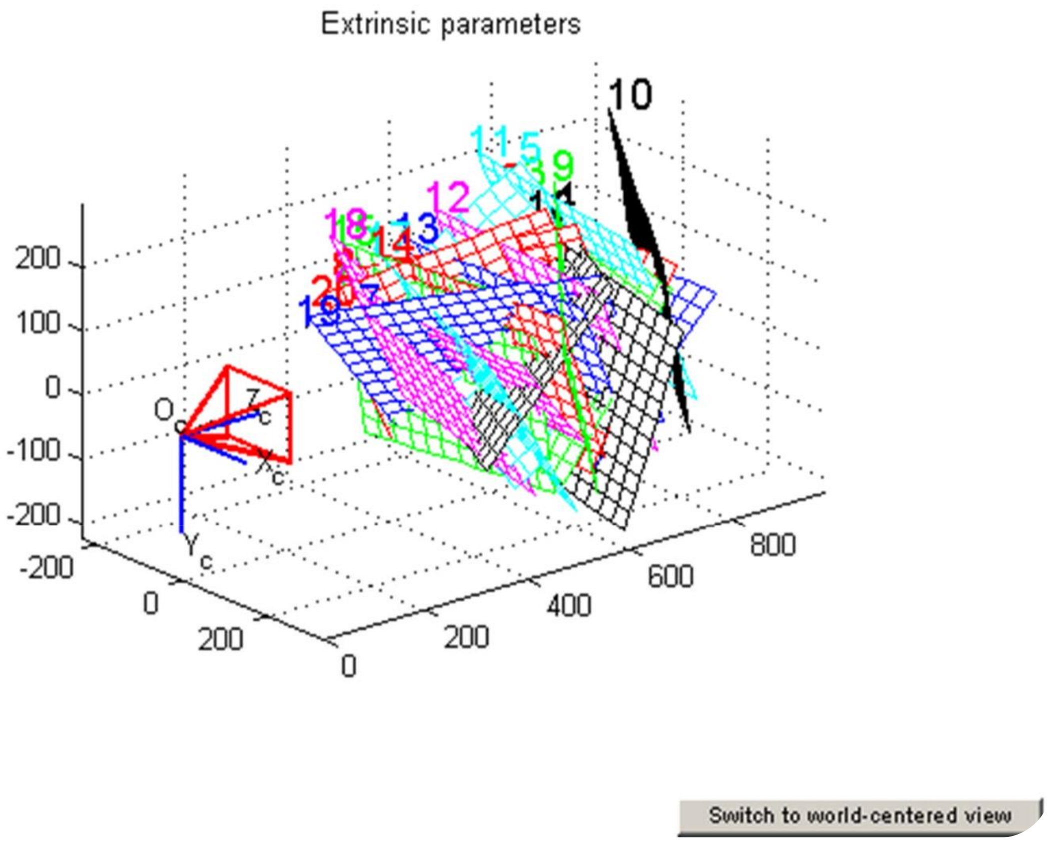
Calibration Demo



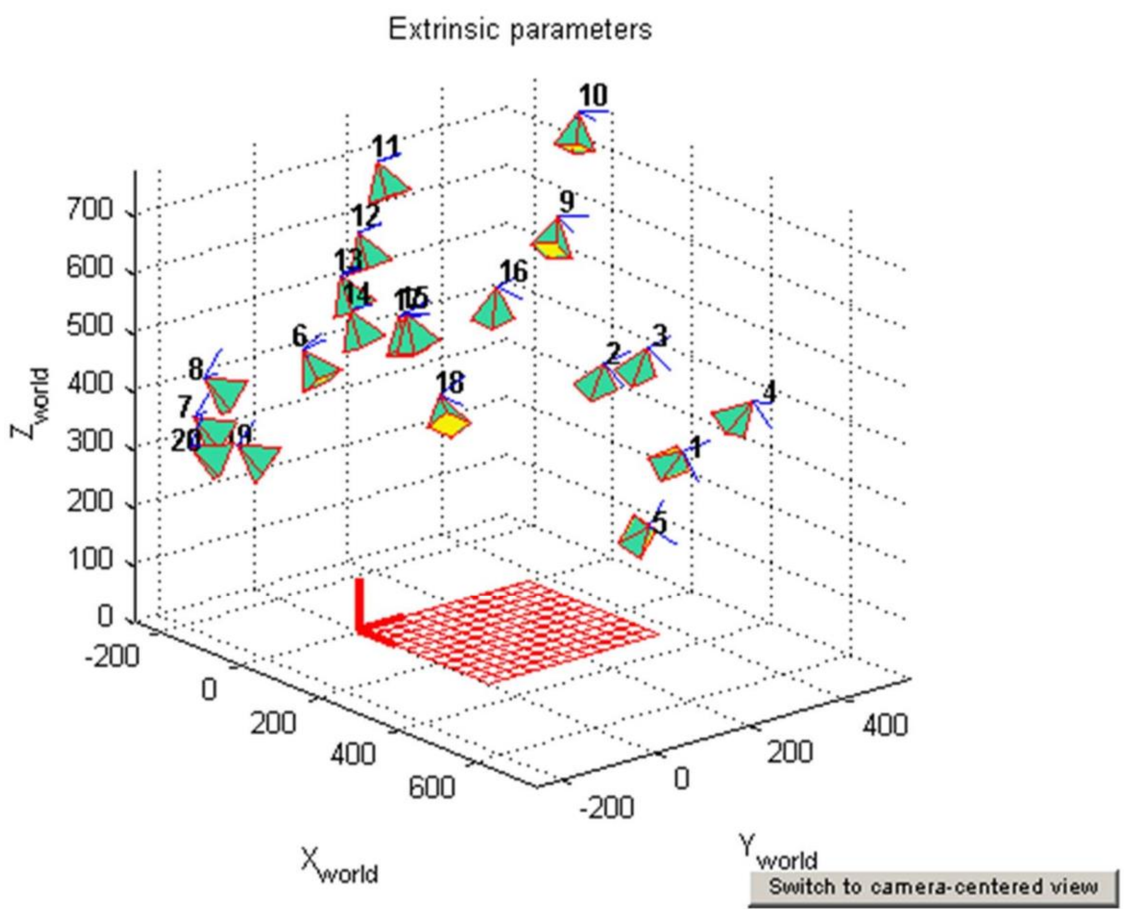
Calibration Demo



Calibration Demo



Calibration Demo



Summary

- What is camera calibration
- Why is it useful
- Perspective projection
- Estimating the camera projection matrix
- Recovering the intrinsic and extrinsic parameters
- Radial distortion
- Calibration demo

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