



Perception for Autonomous Systems 31392:

Camera Matrix and Camera Calibration

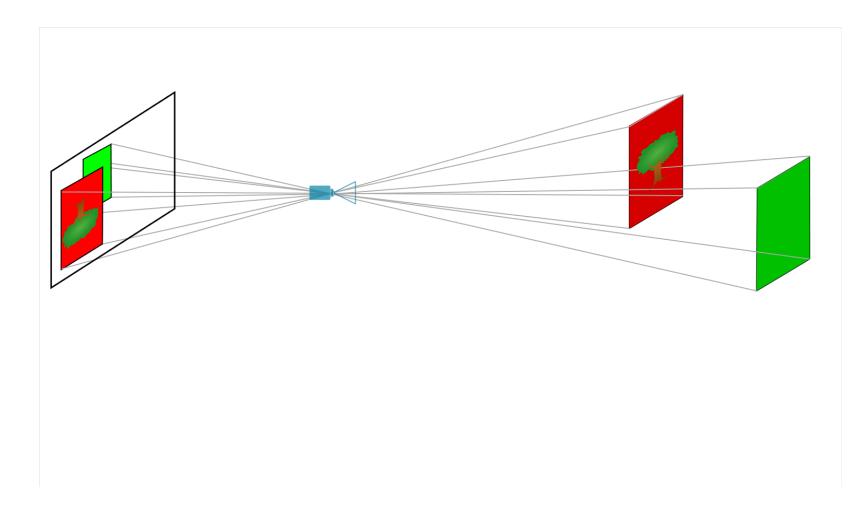
Lecturer: Evangelos Boukas—PhD



- Image formation
- Camera model Project form World to sensor
- Camera calibration The 3D case
- Camera calibration The realistic case
- Camera radial distortion



 Let's look at the most simplistic case.
 What's weird about it?





- Let's look at the most simplistic case.
 What's weird about it?
- Let's Fix that

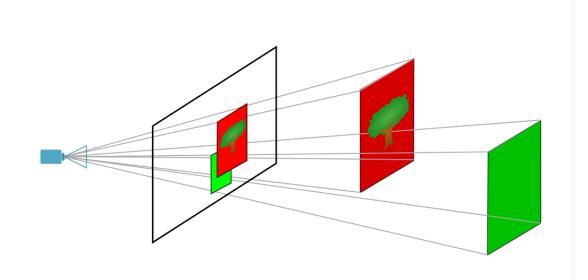
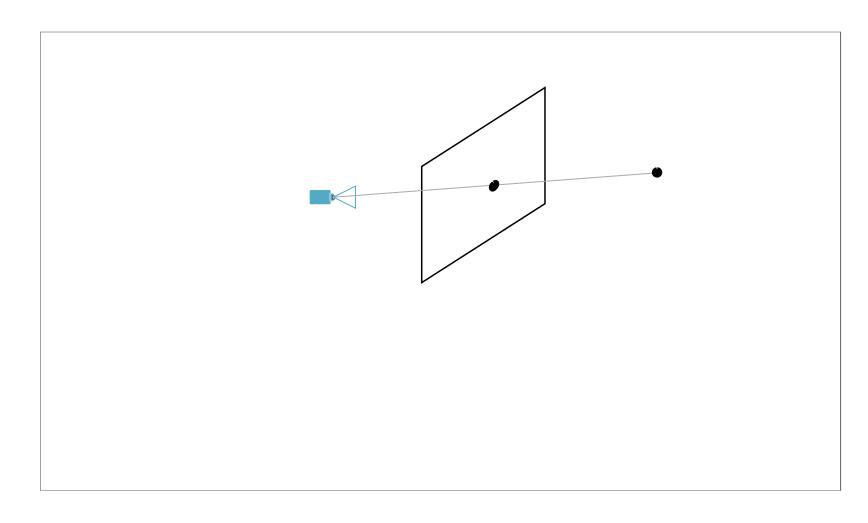




Image Formation

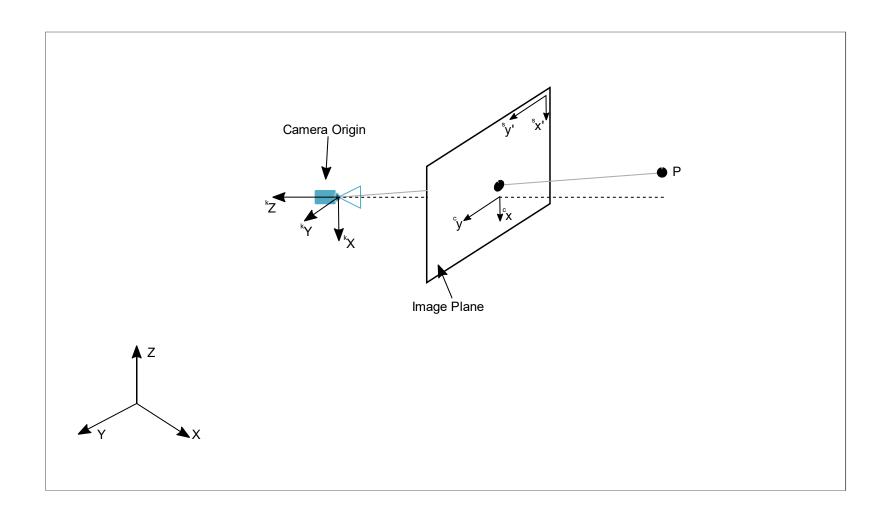
- Let's look at the most simplistic case. What's weird about it?
- Let's Fix that





≅Image Formation

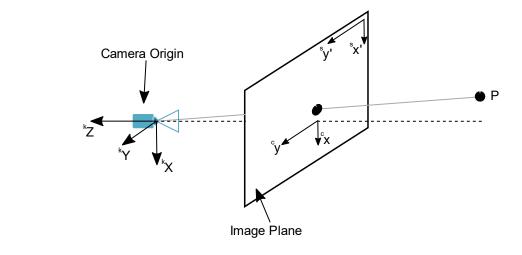
- Let's look at the most simplistic case. What's weird about it?
- Let's Fix that
- Let's get some notation

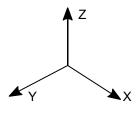




Camera Extrinsics and Instrisics

- The orientation of the camera wrt Word coordinates is called extrinsics
- The rest of Parameters are called intrinsics
- We will see how points in 3D are projected on the sensor







Camera Extrinsics

 We need to express a 3D point P $\boldsymbol{x}_p = [\boldsymbol{x}_p \quad \boldsymbol{y}_p \quad \boldsymbol{z}_p]^T$ in the camera coordinates

$${}^{k}\boldsymbol{x}_{p} = \left[{}^{k}\boldsymbol{x}_{p} \quad {}^{k}\boldsymbol{y}_{p} \quad {}^{k}\boldsymbol{z}_{p} \right]^{T}$$

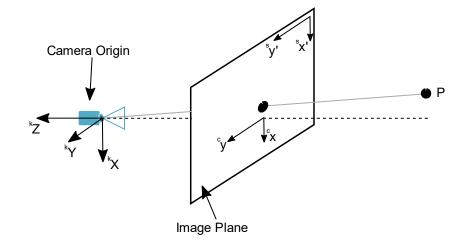
 To do so we need to use the camera Origin

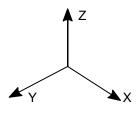
$${}^{k}x = \left[{}^{k}x \quad {}^{k}y \quad {}^{k}z \right]^{T}$$

• Then:

$$\begin{bmatrix} \mathbf{x}_{p} \\ 1 \end{bmatrix} = \begin{bmatrix} {}^{w}\mathbf{R}_{c} & {}^{w}\mathbf{t}_{c} \\ \mathbf{0}_{1x3} & 1 \end{bmatrix} \begin{bmatrix} {}^{k}\mathbf{x}_{p} \\ 1 \end{bmatrix}$$

$$\Rightarrow \begin{bmatrix} {}^{k}\boldsymbol{x}_{\boldsymbol{p}} \\ 1 \end{bmatrix} = \begin{bmatrix} {}^{w}\boldsymbol{R}_{c}^{T} & -{}^{w}\boldsymbol{R}_{c}^{T} {}^{w}\boldsymbol{t}_{c} \\ \boldsymbol{0}_{1x3} & 1 \end{bmatrix}$$





$$\Rightarrow \begin{bmatrix} {}^{k}\boldsymbol{x}_{\boldsymbol{p}} \\ 1 \end{bmatrix} = \begin{bmatrix} {}^{w}\boldsymbol{R}_{c}^{T} & -{}^{w}\boldsymbol{R}_{c}^{Tw}\boldsymbol{t}_{c} \\ \boldsymbol{0}_{1x3} & 1 \end{bmatrix} \begin{bmatrix} \boldsymbol{x}_{\boldsymbol{p}} \\ 1 \end{bmatrix} \Rightarrow \begin{bmatrix} {}^{k}\boldsymbol{x}_{\boldsymbol{p}} \\ 1 \end{bmatrix} = \begin{bmatrix} \boldsymbol{R} & \boldsymbol{0}_{3x1} \\ \boldsymbol{0}_{1x3} & 1 \end{bmatrix} \begin{bmatrix} \boldsymbol{I}_{3x3} & \boldsymbol{t} \\ \boldsymbol{0}_{1x3} & 1 \end{bmatrix} \begin{bmatrix} \boldsymbol{x}_{\boldsymbol{p}} \\ 1 \end{bmatrix}$$



Camera Extrinsics

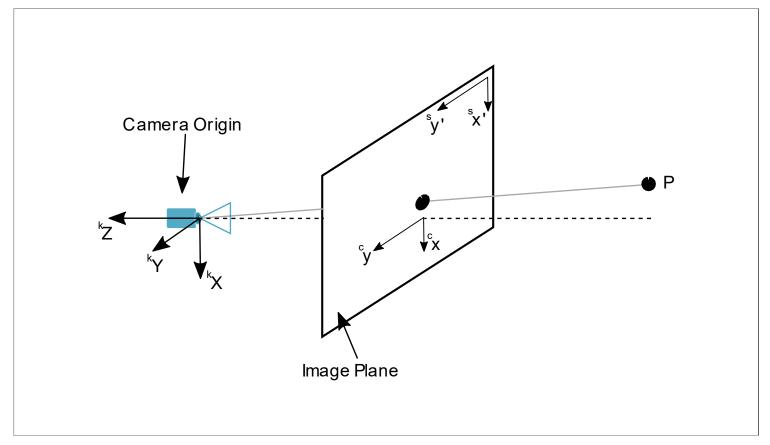
So now we have a description for the 3D point in camera frame

$$\begin{bmatrix} {}^k x_p & {}^k y_p & {}^k z_p & 1 \end{bmatrix}^T = \begin{bmatrix} \mathbf{R}_{3x3} & \mathbf{0}_{3x1} \\ \mathbf{0}_{1x3} & 1 \end{bmatrix} \begin{bmatrix} \mathbf{I}_{3x3} & \mathbf{t}_{3x1} \\ \mathbf{0}_{1x3} & 1 \end{bmatrix} \begin{bmatrix} x_p & y_p & z_p & 1 \end{bmatrix}^T$$
rotation translation Homogeneous Point In World Coordinates

• To get to the image frame we will have to drop a dimension

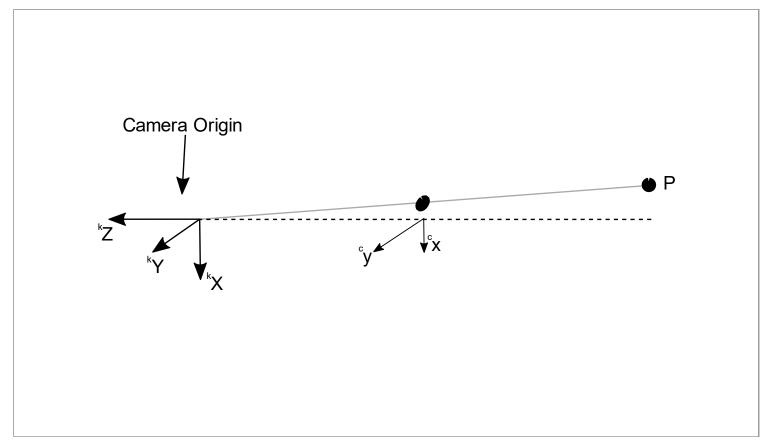


• Let's get rid of things we don't need



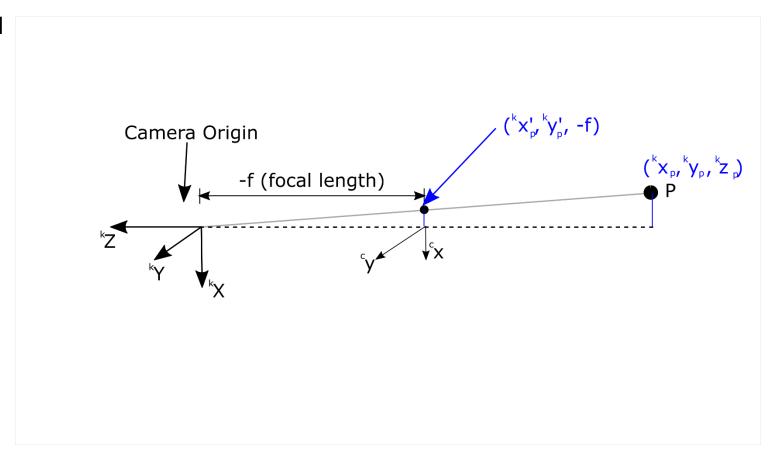


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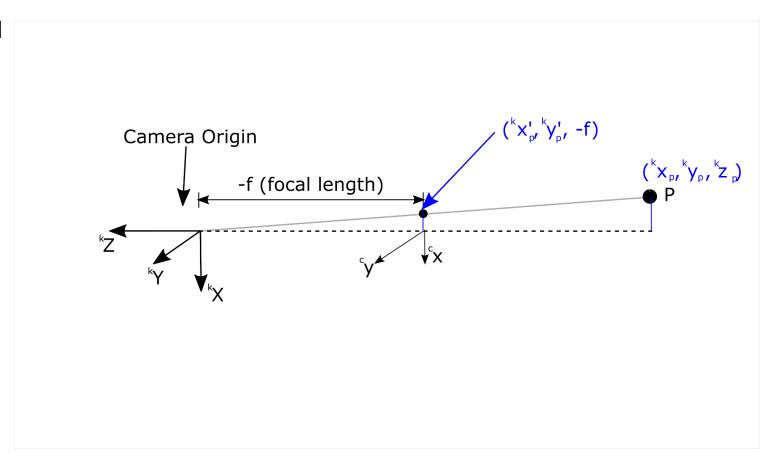


• Let's get rid of things we don't need



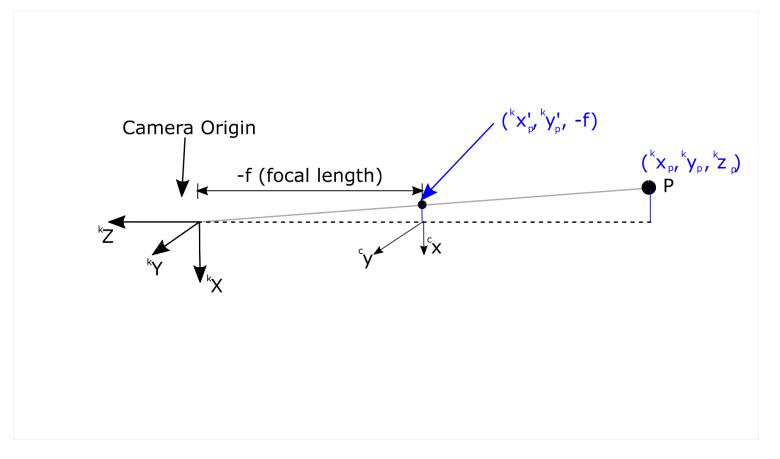


- Let's get rid of things we don't need
- So it is clear that the position of the projection on the image frame is dependent on the ratio x/z



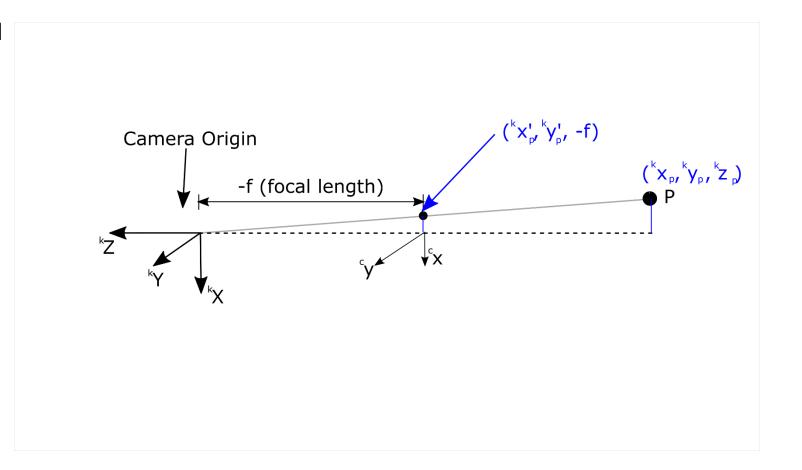


- Let's get rid of things we don't need
- So it is clear that the position of the projection on the image frame is dependent on the ratio x/z
- In fact ${}^{c}x_p = -f * {}^{k}x_p / {}^{k}z_p$ and ${}^{c}y_p = -f * {}^{k}y_p / {}^{k}z_p$





- Let's get rid of things we don't need
- So it is clear that the position of the projection on the image frame is dependent on the ratio x/z
- In fact ${}^cx_p = -f * {}^kx_p/{}^kz_p$ and ${}^cy_p = -f * {}^ky_p/{}^kz_p$
- Additionally we can add the transformation to the sensor frame



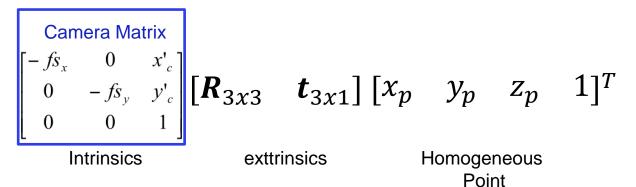


From the previous

$$\begin{bmatrix} {}^k x_p & {}^k y_p & {}^k z_p & 1 \end{bmatrix}^T = \begin{bmatrix} \boldsymbol{R}_{3x3} & \boldsymbol{0}_{3x3} \\ \boldsymbol{0}_{1x3} & 1 \end{bmatrix} \begin{bmatrix} \boldsymbol{I}_{3x3} & \boldsymbol{t}_{3x1} \\ \boldsymbol{0}_{1x3} & 1 \end{bmatrix} [x_p & y_p & z_p & 1]^T$$
rotation translation Homogeneous Point In World Coordinates

We get to the following

$$[^{s}x, ^{s}y, w]^{T} =$$



in World Coordinates

- · Where W is the scale
- This is the analytic version of the projection matrix



Projection Matrix

We can define the Projection Matrix as follows

$$\begin{bmatrix} \lambda x \\ \lambda y \\ \lambda \end{bmatrix} = \begin{bmatrix} P_{11} & P_{12} & P_{13} & P_{14} \\ P_{21} & P_{22} & P_{23} & P_{24} \\ P_{31} & P_{32} & P_{33} & P_{34} \end{bmatrix} \begin{bmatrix} X \\ Y \\ Z \\ 1 \end{bmatrix} \quad \text{sy}$$
Great news for Calibration!

- This is great news for Calibration!
- It means that our problem is a system of linear equations
- How many unknowns?
- 11: (5 + 6) Intrinsic+Extrinsic



Calibration – Known 3D positions

We defined our camera projection as follows:

$$\begin{bmatrix} \lambda x \\ \lambda y \\ \lambda \end{bmatrix} = \begin{bmatrix} P_{11} & P_{12} & P_{13} & P_{14} \\ P_{21} & P_{22} & P_{23} & P_{24} \\ P_{31} & P_{32} & P_{33} & P_{34} \end{bmatrix} \begin{bmatrix} X \\ Y \\ Z \\ 1 \end{bmatrix}$$

If we "sample" a set of points in 3D and 2D: [X, Y, Z] → [x,y]
we get the following analytic equations:

$$\lambda x = P_{11}X + P_{12}Y + P_{13}Z + P_{14}$$
$$\lambda y = P_{21}X + P_{22}Y + P_{23}Z + P_{24}$$
$$\lambda = P_{31}X + P_{32}Y + P_{33}Z + P_{34}$$

However, λ is used for scale and therefore does not provide a 3rd equation



Calibration – Known 3D positions

• So for every 3D to 2D correspondence we get 2 equations:

$$(P_{31}X + P_{32}Y + P_{33}Z + P_{34})x = P_{11}X + P_{12}Y + P_{13}Z + P_{14}$$
$$(P_{31}X + P_{32}Y + P_{33}Z + P_{34})y = P_{21}X + P_{22}Y + P_{23}Z + P_{24}$$

- How many points do we need?
- 6 Points x 2 equations



For every point we get the following

$$0 = p_{11}X + p_{12}Y + p_{13}Z + p - p_{31}xX - p_{32}xY - p_{33}xZ - p_{34}x$$
$$0 = p_{21}X + p_{22}Y + p_{23}Z + p_{24} - p_{31}yX - p_{32}yY - p_{33}yZ - p_{34}y$$

We can format all the linear equations in a single matrix: Ap=0

$$\begin{bmatrix} X_1 & Y_1 & Z_1 & 1 & 0 & 0 & 0 & 0 & -x_1X_1 & -x_1Y_1 & -x_1Z_1 & -x_1 \\ 0 & 0 & 0 & 0 & X_1 & Y_1 & Z_1 & 1 & -y_1X_1 & -y_1Y_1 & -y_1Z_1 & -y_1 \\ \vdots & & & & \vdots & & & & & \\ X_n & Y_n & Z_n & 1 & 0 & 0 & 0 & 0 & -x_nX_n & -x_nY_n & -x_nZ_n & -x_n \\ 0 & 0 & 0 & 0 & X_n & Y_n & Z_n & 1 & -y_nX_n & -y_nY_n & -x_nZ_n & -x_n \end{bmatrix} \begin{bmatrix} r_{11} \\ p_{12} \\ p_{13} \\ p_{21} \\ p_{22} \\ p_{23} \\ p_{24} \\ p_{31} \\ p_{32} \\ p_{33} \\ p_{34} \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ \vdots \\ 0 \\ 0 \end{bmatrix}$$



Calibration – Known 3D positions

- The solution is given by the following process which is itself called DLT:
 - Calculate the Singular Value decomposition (SVD)

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SVD : A = UDV^T
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Get the last column of V

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P = V_{smallest} (column of V corr. to smallest singular value)
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-Reshape into the P matrix



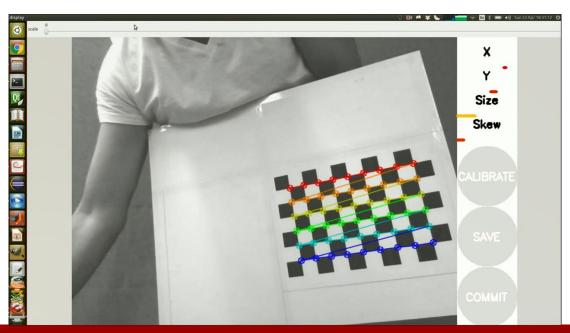
≅ Calibration – Known 3D positions

- To summarize:
 - Get min 6 3D 2D correspondences
 - Form matrix A (AP=0)
 - Calculate SVD
 - Get Last column of V which corresponds to the values of P



Calibration in real world

- In Real World we do not have 3D points.
- Or do we?
- What if we could use some sort of predefined setup which would allow us to know the relative position of 3D points?
- It turns out that if we have a calibration pattern we can know their relative positions of all points as they are on a known configuration





• Since Z = 0 we lose one degree of freedom:

$$\begin{bmatrix} x \\ y \\ 1 \end{bmatrix} \equiv \begin{bmatrix} P_{11} & P_{12} & P_{13} & P_{14} \\ P_{21} & P_{22} & P_{23} & P_{24} \\ P_{31} & P_{32} & P_{33} & P_{34} \end{bmatrix} \begin{bmatrix} X \\ Y \\ 0 \\ 1 \end{bmatrix}$$

- We can then redefine our P as: $\begin{bmatrix} P_{11} & P_{12} & P_{14} \\ P_{21} & P_{22} & P_{24} \\ P_{31} & P_{32} & P_{34} \end{bmatrix} \begin{bmatrix} X \\ Y \\ 1 \end{bmatrix}$
 - This is called homography and allows us to project points from one plane to another



How to calculate the homography:

$$\mathbf{x}' = \mathbf{H}\mathbf{x}$$
 $\mathbf{x}' = \begin{bmatrix} w'x' \\ w'y' \\ w' \end{bmatrix}$ $\mathbf{H} = \begin{bmatrix} h_1 & h_2 & h_3 \\ h_4 & h_5 & h_6 \\ h_7 & h_8 & h_9 \end{bmatrix}$

- The homography has 9 elements. However, similar to before due to the scale there are only 8 unknowns
- Therefore, we need minimum 4 correspondences to setup the problem as a DLT

$$\begin{bmatrix} -x & -y & -1 & 0 & 0 & 0 & xx' & xx' & x' \\ 0 & 0 & 0 & -x & -y & -1 & yx' & yy' & y' \end{bmatrix} \begin{bmatrix} h_1 \\ h_2 \\ h_3 \\ h_4 \\ h_5 \\ h_6 \\ h_7 \\ h_8 \\ h_9 \end{bmatrix} = \mathbf{0}$$



Steps

- With a static camera move the pattern and get images.
 - Make sure to not present only one orientation, as there will be a problem with the estimation of the homography
- Calculate correspondences using the pattern
- Solve using Normalized DLT
 - Normalize coordinates for each image
 - Translate for zero mean
 - Scale so that average distance to origin is ~sqrt(2)
 - Form Matrix A
 - Solve using SVD
 - Calculate SVD
 - Use last column of V to get the homography.
 - Denormalize



- However the DLT solution is known to be prone to outliers.
- Other approaches exist to solving the calibration:
 - Nonlinear least squares
 - RANSAC
- RANSAC:
- 1. Choose number of samples *N*
- 2. Choose 4 random potential matches
- 3. Compute **H** using normalized DLT
- 4. Project points from **x** to **x**' for each potentially matching pair:
- 5. Count points with projected distance < t
- 6. Repeat steps 2-5 *N* times

Choose **H** with most inliers



• Ok, but still, What about the lens Distortion?



Barrel



Pincushion



Fisheye



• So how do we model it:



- So how do we model it:
- Usually a quartic (biquadratic) polynomial is used:

$$\hat{x}_{c} = x_{c}(1 + \kappa_{1}r_{c}^{2} + \kappa_{2}r_{c}^{4})$$

$$\hat{y}_{c} = y_{c}(1 + \kappa_{1}r_{c}^{2} + \kappa_{2}r_{c}^{4})$$

OR higher order

30

30



- So how do we model it:
- Usually a quartic (biquadratic) polynomial is used:



Distorted



Undistorted



- How to calibrate for the distortion coefficients:
 - First do DLT for the Projection Matrix
 - Then form a non linear least square problem that includes both the linear projection and the non-linear distortion using the Levenberg Marquardt algorithm.



• What did we learn?



Perception for Autonomous Systems 31392:

Camera Matrix and Camera Calibration

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