

3D VISION

Monocular POSE

Homography between Projective Planes



Systems Engineering and Automation

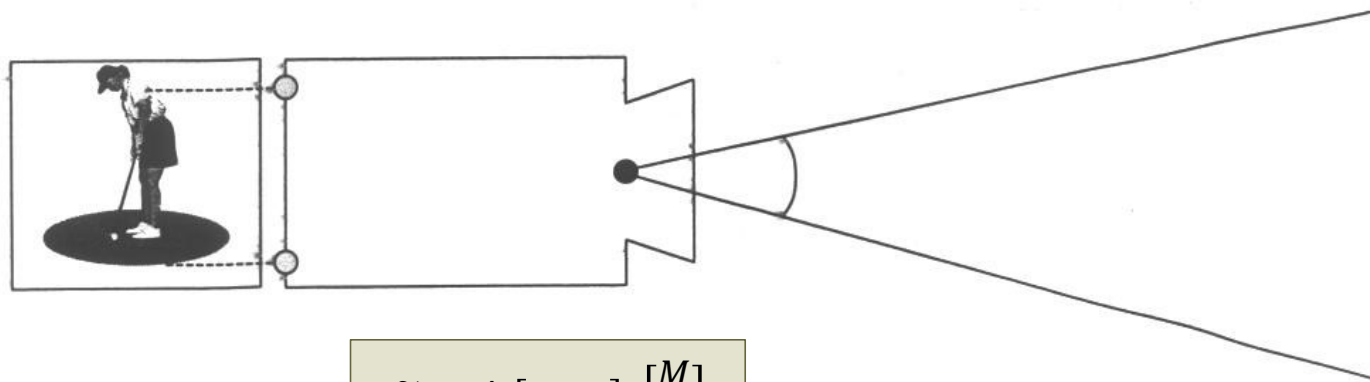
Miguel Hernández University

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Single-Image POSE Estimation

- Objectives
 - To what extent we can get information about the location of objects in the scene from a single view.
 - A camera measures angles, not distances
- Options:
 - Calibrated Camera
 - Not-Calibrated Camera



$$\tilde{m} \cong A \begin{bmatrix} R & t \end{bmatrix} \begin{bmatrix} M \\ 1 \end{bmatrix}$$

POSE Estimation

- Definition:
 - **Pose** (position and orientation) of an object from:
 - Knowledge of the structure of the object (e.g. Distances between marks on the object)
 - An image taken with a calibrated camera in which the marks can be identified
 - There are many algorithms depending on the information and structure of the object.

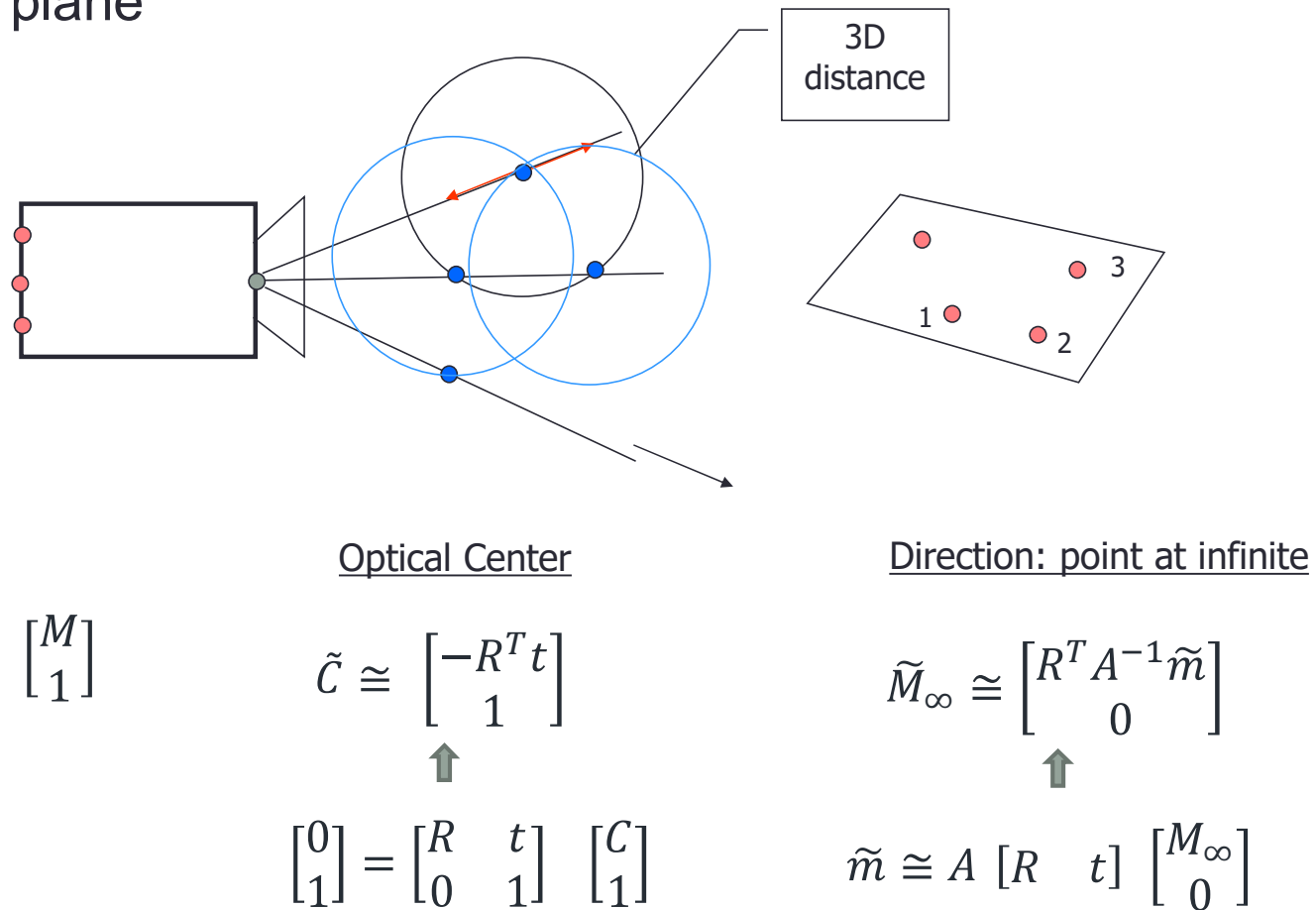
POSE Estimation

- **'Pose'** estimation of an object using artificial marks (points):
 - We know the camera matrix (intrinsic parameters) $\mathbf{A}$ ($[\mathbf{R}, \mathbf{t}]$ allow to set an absolute reference)
 - 6 dof (3 Position, 3 Orientation)
 - Each mark (point) provides two restrictions
- At least 3 marks are required (distances between them)



POSE Estimation: 3 points on a plane

- 3 points on a plane



POSE Estimation: 3 points on a plane

- Analytical Solution:
 - Equation of the projection rays:

$$\tilde{Q}_i \cong \begin{bmatrix} -R^T t \\ 1 \end{bmatrix} + \lambda_i \begin{bmatrix} R^T A^{-1} \tilde{m}_i \\ 0 \end{bmatrix} = \begin{bmatrix} -R^T t + \lambda_i R^T A^{-1} \tilde{m}_i \\ 1 \end{bmatrix} = \begin{bmatrix} Q_i \\ 1 \end{bmatrix}$$

$$\begin{aligned} d_{12}^2 &= \|\lambda_1 R^T A^{-1} \tilde{m}_1 - \lambda_2 R^T A^{-1} \tilde{m}_2\|^2 \\ d_{13}^2 &= \|\lambda_1 R^T A^{-1} \tilde{m}_1 - \lambda_3 R^T A^{-1} \tilde{m}_3\|^2 \\ d_{23}^2 &= \|\lambda_2 R^T A^{-1} \tilde{m}_2 - \lambda_3 R^T A^{-1} \tilde{m}_3\|^2 \end{aligned}$$

- 3 quadratic equations with three unknowns
 - $2^3=8$ solutions if the projections are non-coplanar (the plane does not pass through the optical center)
 - 4 in front of the camera
 - Unique solution: Use a 4th point

Perspective-n-Point (PnP): Plane Homography

- POSE calculation the from a set of 2D-3D matched points on a plane (linear method):

$$\tilde{m} \cong A[R \quad t]\tilde{M} = \tilde{P} \tilde{M} \quad \text{Si } \tilde{M} \cong \begin{bmatrix} X \\ Y \\ 0 \\ 1 \end{bmatrix} \in \Pi \Rightarrow \tilde{m} \cong A \cdot \begin{bmatrix} r_{11} & r_{12} & t_x \\ r_{21} & r_{22} & t_y \\ r_{31} & r_{32} & t_z \end{bmatrix} \begin{bmatrix} X \\ Y \\ 1 \end{bmatrix}$$

$\bar{\mathbf{r}}_1 \quad \bar{\mathbf{r}}_2 \quad \bar{\mathbf{t}} \quad \bar{\mathbf{r}}_3$

$$\begin{bmatrix} \rho \cdot u \\ \rho \cdot v \\ \rho \end{bmatrix} = \begin{bmatrix} h_{11} & h_{12} & h_{13} \\ h_{21} & h_{22} & h_{23} \\ h_{31} & h_{32} & h_{33} \end{bmatrix} \begin{bmatrix} X \\ Y \\ 1 \end{bmatrix} \Rightarrow \begin{aligned} (h_{31}X + h_{32}Y + h_{33}) \cdot u &= h_{11}X + h_{12}Y + h_{13} \\ (h_{31}X + h_{32}Y + h_{33}) \cdot v &= h_{21}X + h_{22}Y + h_{23} \end{aligned}$$

$\bar{\mathbf{r}}_1 \times \bar{\mathbf{r}}_2$

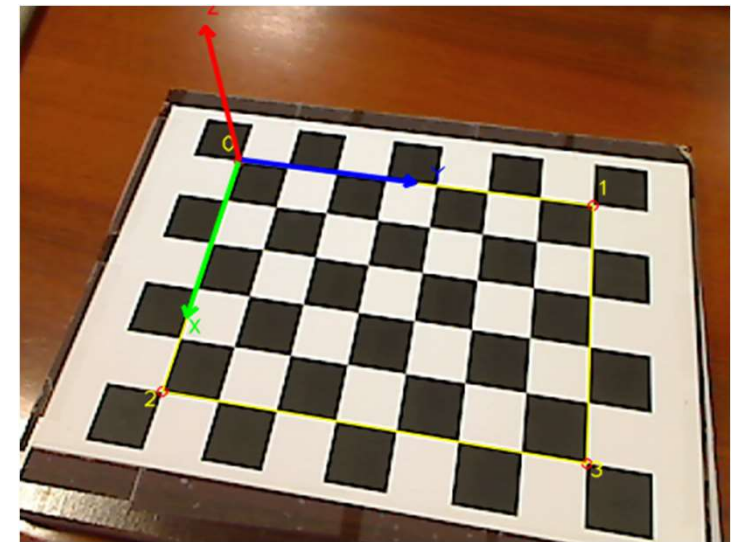
At least 4 points are needed:

$$\mathbf{A}_{xy} = \begin{bmatrix} -X^{(1)} & -Y^{(1)} & -1 & 0 & 0 & 0 & X^{(1)}u^{(1)} & Y^{(1)}u^{(1)} & u^{(1)} \\ 0 & 0 & 0 & -X^{(1)} & -Y^{(1)} & -1 & X^{(1)}v^{(1)} & Y^{(1)}v^{(1)} & v^{(1)} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \end{bmatrix}$$

$$\mathbf{h} = [h_{11}, h_{12}, h_{13}, h_{21}, h_{22}, h_{23}, h_{31}, h_{32}, h_{33}]^T$$

$$\mathbf{A}_{xy} \cdot \mathbf{h} = 0 \quad \min_{\mathbf{h}} [(\mathbf{A}_{xy}\mathbf{h})^2]$$

$$\text{SVD}(\mathbf{A}_{xy}) \rightarrow \mathbf{A}_{xy} = \mathbf{U}\mathbf{D}\mathbf{V}^T \Rightarrow \mathbf{h} = \mathbf{v}_9$$



Perspective-n-Point (PnP): Plane Homography

- Homography Calculation:

- Non-homogeneous solution (Euclidean): we assume $(h_{33} \neq 0)$ $H = \lambda A[\bar{\mathbf{r}}_1 \quad \bar{\mathbf{r}}_2 \quad \bar{\mathbf{t}}]$

$$\begin{bmatrix} \rho \cdot u \\ \rho \cdot v \\ \rho \end{bmatrix} = \begin{bmatrix} h_{11}/h_{33} & h_{12}/h_{33} & h_{13}/h_{33} \\ h_{21}/h_{33} & h_{22}/h_{33} & h_{23}/h_{33} \\ h_{31}/h_{33} & h_{32}/h_{33} & 1 \end{bmatrix} \begin{bmatrix} X \\ Y \\ 1 \end{bmatrix} \quad h_{33} \cong t_z \quad \text{Distance between planes}$$

$$\begin{bmatrix} \rho \cdot u \\ \rho \cdot v \\ \rho \end{bmatrix} = \begin{bmatrix} h'_{11} & h'_{12} & h'_{13} \\ h'_{21} & h'_{22} & h'_{23} \\ h'_{31} & h'_{32} & 1 \end{bmatrix} \begin{bmatrix} X \\ Y \\ 1 \end{bmatrix} \Rightarrow \begin{aligned} (h'_{31}X + h'_{32}Y + 1) \cdot u &= h'_{11}X + h'_{12}Y + h'_{13} \\ (h'_{31}X + h'_{32}Y + 1) \cdot v &= h'_{21}X + h'_{22}Y + h'_{23} \end{aligned}$$

$$\mathbf{A}_{xy} = \begin{bmatrix} -x^{(1)} & -y^{(1)} & -1 & 0 & 0 & 0 & x^{(1)}x'^{(1)} & y^{(1)}x'^{(1)} \\ 0 & 0 & 0 & -x^{(1)} & -y^{(1)} & -1 & x^{(1)}y'^{(1)} & y^{(1)}y'^{(1)} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \end{bmatrix} \quad \mathbf{b} = \begin{bmatrix} -u^{(1)} \\ -v^{(1)} \\ \vdots \end{bmatrix}^T$$

$$\mathbf{h} = [h'_{11}, h'_{12}, h'_{13}, h'_{21}, h'_{22}, h'_{23}, h'_{31}, h'_{32}]^T$$

- Least Squares:

$$\mathbf{A}_{xy} \cdot \mathbf{h} = \mathbf{b} \quad \min_{\mathbf{h}} [(\mathbf{A}_{xy}\mathbf{h} - \mathbf{b})^2] \quad \longrightarrow \quad \mathbf{h} = (\mathbf{A}_{xy}^T \mathbf{A}_{xy})^{-1} \cdot \mathbf{A}_{xy}^T \cdot \mathbf{b}$$

Data Normalization

- More robust estimation against noise

- Equation System better conditioned

- Specify a transformation

- The center of gravity of all points is the origin
- The mean distance to origin is $\sqrt{2}$
- Applies to image and space points
-

$$\left. \begin{aligned} \tilde{\tilde{m}}_w &= T \cdot \tilde{m}_w \\ \tilde{\tilde{m}} &= T' \cdot \tilde{m} \end{aligned} \right\} \longrightarrow \boxed{\tilde{\tilde{m}} \cong \hat{H} \cdot \tilde{\tilde{m}}_w} \quad \boxed{H \cong T'^{-1} \cdot \hat{H} \cdot T}$$

$$T = \begin{bmatrix} 1/\sigma_x & 0 & -\mu_x/\sigma_x \\ 0 & 1/\sigma_y & -\mu_y/\sigma_y \\ 0 & 0 & 1 \end{bmatrix}$$

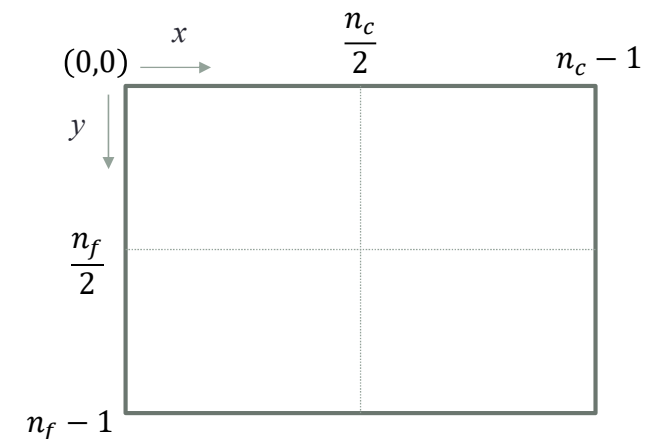
- Using simpler transformations

- All the points between -1 y 1

$$T = \begin{bmatrix} 2/n_c & 0 & -1 \\ 0 & 2/n_f & -1 \\ 0 & 0 & 1 \end{bmatrix}$$

- All the points between 0 y 2

$$T = \begin{bmatrix} 2/n_c & 0 & 0 \\ 0 & 2/n_f & 0 \\ 0 & 0 & 1 \end{bmatrix}$$



Perspective-n-Point (PnP): Plane Homography

- POSE calculation the from a set of 2D-3D matched points on a plane (linear method):
 - Due to the noise in the data we cannot directly assign the rotation vectors from the homography (they are not orthonormal)

$$A \cdot \begin{bmatrix} r_{11} & r_{12} & t_x \\ r_{21} & r_{22} & t_y \\ r_{31} & r_{32} & t_z \end{bmatrix} = \lambda \cdot \begin{bmatrix} h_{11} & h_{12} & h_{13} \\ h_{21} & h_{22} & h_{23} \\ h_{31} & h_{32} & h_{33} \end{bmatrix} \quad \begin{bmatrix} \bar{\mathbf{r}}_1 & \bar{\mathbf{r}}_2 & \bar{\mathbf{t}} \end{bmatrix} = \lambda \cdot A^{-1} [\bar{\mathbf{h}}_1 \quad \bar{\mathbf{h}}_2 \quad \bar{\mathbf{h}}_3]$$

$$\|\bar{\mathbf{r}}_1\| = 1 \Rightarrow \lambda = 1/\|A^{-1}\bar{\mathbf{h}}_1\|$$

$$\bar{\mathbf{r}}_1 = A^{-1}\bar{\mathbf{h}}_1/\|A^{-1}\bar{\mathbf{h}}_1\|; \quad \bar{\mathbf{r}}_2 = A^{-1}\bar{\mathbf{h}}_2/\|A^{-1}\bar{\mathbf{h}}_1\|; \quad \bar{\mathbf{r}}_3 = \bar{\mathbf{r}}_1 \times \bar{\mathbf{r}}_2; \quad \bar{\mathbf{t}} = A^{-1}\bar{\mathbf{h}}_3/\|A^{-1}\bar{\mathbf{h}}_1\|$$

- Robust procedure:
 - We calculate $\mathbf{H}$ from 2D-3D correspondences
 - A first estimation of $\mathbf{R}^*$ is calculated considering $\lambda=1$
 - We adjust the rotation matrix so that its vectors are orthoormal $\rightarrow \mathbf{R}$
 - We calculate the scale factor λ as the inverse of the biggest singular value $1/\sigma_1$
 - We calculate the translation vector with the scale factor λ y $\mathbf{h}_3$

$$R^* = [A^{-1}\bar{\mathbf{h}}_1 \quad A^{-1}\bar{\mathbf{h}}_2 \quad (A^{-1}\bar{\mathbf{h}}_1 \times A^{-1}\bar{\mathbf{h}}_2)]$$

$$SVD(R^*) \rightarrow R^* = U \cdot D \cdot V^T$$

$$D = \text{diag}(\sigma_1, \sigma_2, \sigma_3)$$

$$R = U \cdot \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & |U \cdot V^T| \end{bmatrix} \cdot V^T$$

± 1

$$\lambda = 1/\sigma_1$$

$$\bar{\mathbf{t}} = A^{-1}\bar{\mathbf{h}}_3/\sigma_1$$

Perspective-n-Point (PnP): General Disposition

- POSE calculation the from a set of 2D-3D matched points in a general disposition (linear method):
 - Problem similar to calibration but in this case we know **A**

$$\tilde{m} \cong A[R \quad t]\tilde{M} = \tilde{P} \tilde{M}$$

$$\begin{cases} p_{31}X_w u + p_{32}Y_w u + p_{33}Z_w u + p_{34}u - p_{11}X_w - p_{12}Y_w - p_{13}Z_w - p_{14} = 0 \\ p_{31}X_w v + p_{32}Y_w v + p_{33}Z_w v + p_{34}v - p_{21}X_w - p_{22}Y_w - p_{23}Z_w - p_{24} = 0 \end{cases}$$

$$\begin{bmatrix} \rho u \\ \rho v \\ \rho \end{bmatrix} = \begin{bmatrix} p_{11} & p_{12} & p_{13} & p_{14} \\ p_{21} & p_{22} & p_{23} & p_{24} \\ p_{31} & p_{32} & p_{33} & p_{34} \end{bmatrix} \begin{bmatrix} X_w \\ Y_w \\ Z_w \\ 1 \end{bmatrix} \quad \mathbf{A}_{xy} = \begin{bmatrix} -X_w^{(1)} & -Y_w^{(1)} & -Z_w^{(1)} & -1 & 0 & 0 & 0 & 0 & X_w^{(1)}u^{(1)} & Y_w^{(1)}u^{(1)} & Z_w^{(1)}u^{(1)} & u^{(1)} \\ 0 & 0 & 0 & 0 & -X_w^{(1)} & -Y_w^{(1)} & -Z_w^{(1)} & -1 & X_w^{(1)}v^{(1)} & Y_w^{(1)}v^{(1)} & Z_w^{(1)}v^{(1)} & v^{(1)} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \end{bmatrix}$$

$$\bar{\mathbf{p}} = [p_{11}, p_{12}, p_{13}, p_{14}, p_{21}, p_{22}, p_{23}, p_{24}, p_{31}, p_{32}, p_{33}, p_{34}]$$

At least 6 points are needed:

$$\mathbf{A}_{xy} \cdot \mathbf{p} = 0$$

$$SVD(\mathbf{A}_{xy}) \rightarrow \mathbf{A}_{xy} = \mathbf{U}\mathbf{D}\mathbf{V}^T \Rightarrow \mathbf{p} = \mathbf{v}_{12}$$

- Once calculated matrix **P** we can identify **R**, **t**

$$[R \quad t] = \lambda \cdot A^{-1}\tilde{P} \Rightarrow [\bar{\mathbf{r}}_1 \quad \bar{\mathbf{r}}_2 \quad \bar{\mathbf{r}}_3 \quad \bar{\mathbf{t}}] = \lambda \cdot A^{-1}[\bar{\mathbf{p}}_1 \quad \bar{\mathbf{p}}_2 \quad \bar{\mathbf{p}}_3 \quad \bar{\mathbf{p}}_4]$$

$$R^* = A^{-1}[\bar{\mathbf{p}}_1 \quad \bar{\mathbf{p}}_2 \quad \bar{\mathbf{p}}_3]$$

$$SVD(R^*) \rightarrow R^* = U \cdot D \cdot V^T$$

$$D = \text{diag}(\sigma_1, \sigma_2, \sigma_3)$$

$$R = U \cdot \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & |U \cdot V^T| \end{bmatrix} \cdot V^T$$

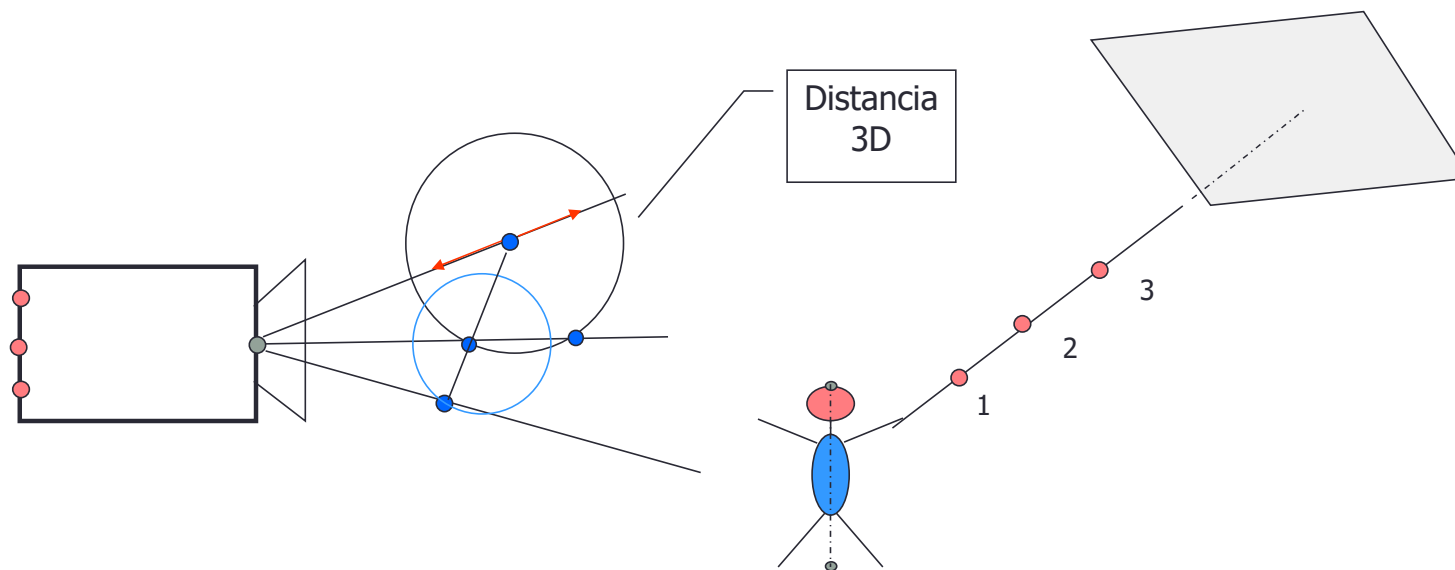
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$$\lambda = 1/\sigma_1$$

$$\bar{\mathbf{t}} = A^{-1}\bar{\mathbf{p}}_4/\sigma_1$$

POSE Estimation: 3 aligned points

- Example: POSE Estimation of a bar with 3 marks:
 - We know the distance between marks and the calibration matrix
 - 5 dof (3 Position of the 3 marks + 2 Rotation)



POSE Estimation: 3 aligned points

- Analytical Solution:
 - Equation of the projection rays:

$$\tilde{Q}_i \cong \begin{bmatrix} -R^T t \\ 1 \end{bmatrix} + \lambda_i \begin{bmatrix} R^T A^{-1} \tilde{m}_i \\ 0 \end{bmatrix} = \begin{bmatrix} -R^T t + \lambda_i R^T A^{-1} \tilde{m}_i \\ 1 \end{bmatrix} = \begin{bmatrix} Q_i \\ 1 \end{bmatrix}$$

distances

$$d_{12}^2 = \|\lambda_1 R^T A^{-1} \tilde{m}_1 - \lambda_2 R^T A^{-1} \tilde{m}_2\|^2$$

$$d_{13}^2 = \|\lambda_1 R^T A^{-1} \tilde{m}_1 - \lambda_3 R^T A^{-1} \tilde{m}_3\|^2$$

3 aligned points

$$Q_3 \cong Q_1 + \lambda (Q_2 - Q_1)$$

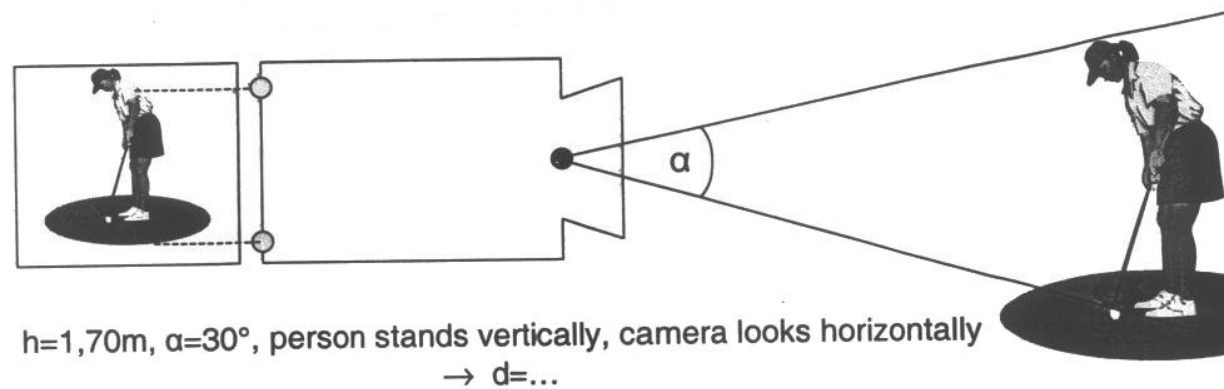
$$R^T A^{-1} (\lambda_3 \tilde{m}_3 - \lambda_1 \tilde{m}_1) = R^T A^{-1} \lambda (\lambda_2 \tilde{m}_2 - \lambda_1 \tilde{m}_1)$$

$$\lambda_3 \tilde{m}_3 - \lambda_1 \tilde{m}_1 = \lambda (\lambda_2 \tilde{m}_2 - \lambda_1 \tilde{m}_1)$$

- Unique solution in front of the camera

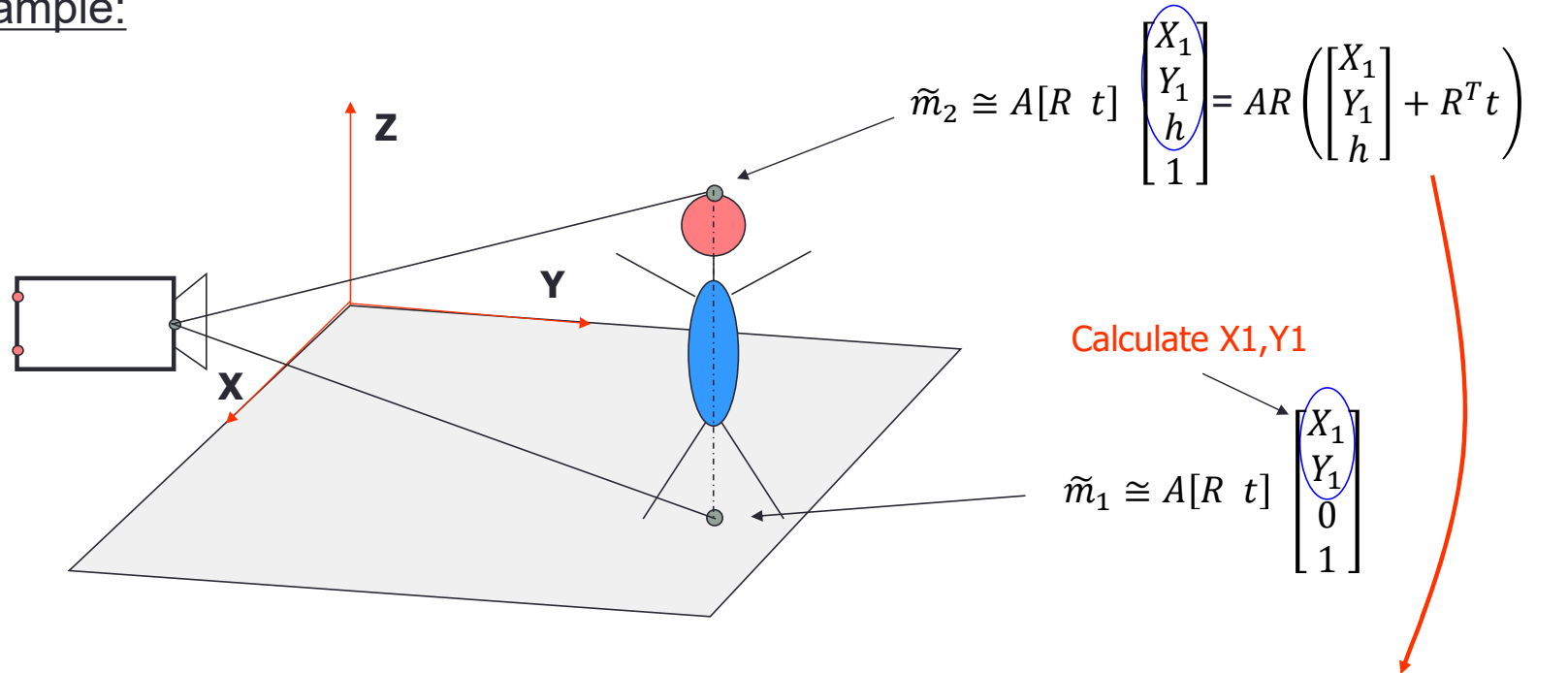
POSE Estimation: height on a plane

- Height of an object sitting on a plane (floor)



POSE Estimation: height on a plane

- Example:

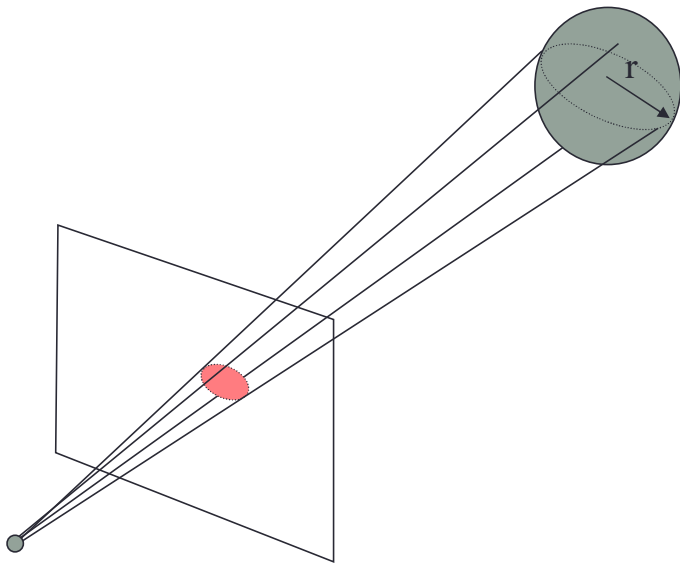


$$A = \begin{bmatrix} 1000 & 0 & 200 \\ 0 & 1000 & 200 \\ 0 & 0 & 1 \end{bmatrix}, R = \begin{bmatrix} 1/\sqrt{2} & 0 & -1/\sqrt{2} \\ 0 & 1 & 0 \\ 1/\sqrt{2} & 0 & 1/\sqrt{2} \end{bmatrix}, t = \begin{bmatrix} -3.5355 \\ -5.0000 \\ -42.4264 \end{bmatrix}$$

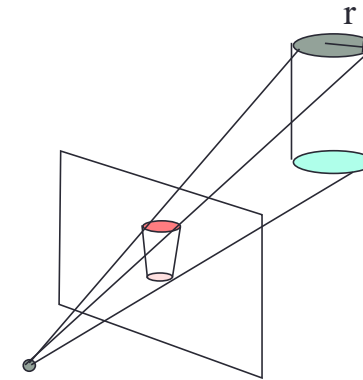
$$m_1 = [181.48 \quad 121.43]^T, m_2 = [219.23 \quad 118.41]^T$$

POSE Estimation: other examples

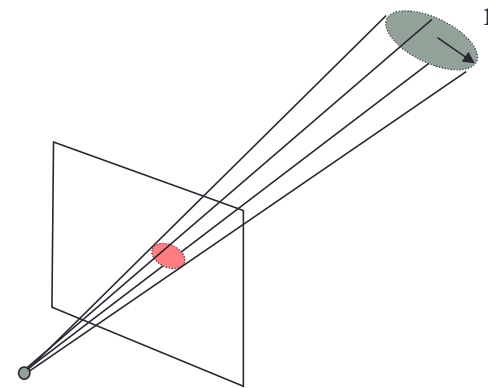
- Pose knowing the radius of a sphere



- Pose knowing the radius of a cylinder



- Pose knowing the radius of a disc

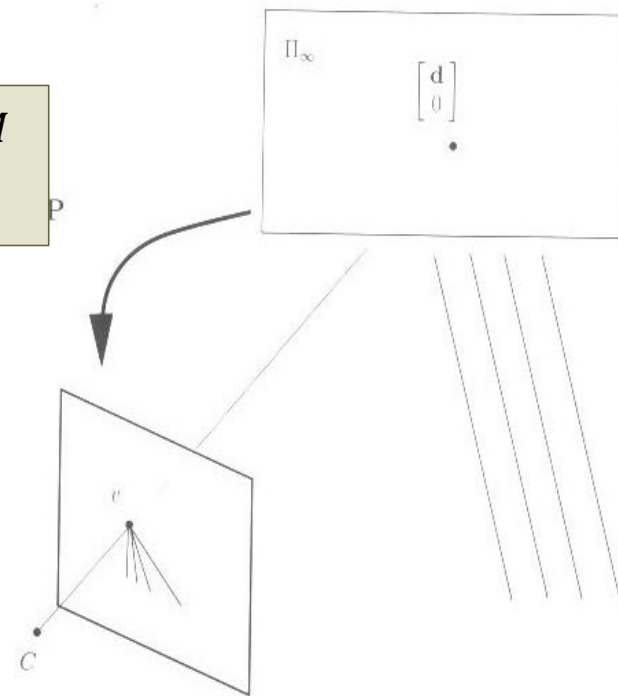


POSE Estimation: Vanishing Points

- An Homography can be calculated between the **plane at infinity** and the image plane (Allows to calculate the orientation **R**)
 - Vanishing Points: projection of infinity points (intersection point of two parallel lines)

$$\tilde{m} \cong A[R \quad t] \tilde{M}$$

$$\text{if } \tilde{M} \cong \begin{bmatrix} M \\ 0 \end{bmatrix} \in \Pi_{\infty} \Rightarrow \begin{cases} \tilde{m} \cong AR \ M = \tilde{H}_{\infty} M \\ M \cong \tilde{H}_{\infty}^{-1} \tilde{m} \end{cases}$$



POSE Estimation: Vanishing Points

- Calculation of Orientation **R**:
 - Find the projection of points in infinity (directions)
 - Vanishing Points: intersection point of two parallel lines to the axis Z,X

$$\text{Si } \tilde{M} \cong \begin{bmatrix} M \\ 0 \end{bmatrix} \in \Pi_{\infty} \Rightarrow \tilde{m} \cong A[R \ t] \begin{bmatrix} M \\ 0 \end{bmatrix} = ARM = \tilde{H}_{\infty} M$$

$$\tilde{m}_{\infty}^{(x)} \cong A[\bar{\mathbf{r}}_1 \ \bar{\mathbf{r}}_2 \ \bar{\mathbf{r}}_3 \ \bar{\mathbf{t}}] \begin{bmatrix} 1 \\ 0 \\ 0 \\ 0 \end{bmatrix} = A \cdot \bar{\mathbf{r}}_1$$

$$\tilde{m}_{\infty}^{(z)} \cong A[\bar{\mathbf{r}}_1 \ \bar{\mathbf{r}}_2 \ \bar{\mathbf{r}}_3 \ \bar{\mathbf{t}}] \begin{bmatrix} 0 \\ 0 \\ 1 \\ 0 \end{bmatrix} = A \cdot \bar{\mathbf{r}}_3$$

$$\bar{\mathbf{r}}_1 = A^{-1} \tilde{m}_{\infty}^{(x)} / \|A^{-1} \tilde{m}_{\infty}^{(x)}\|$$

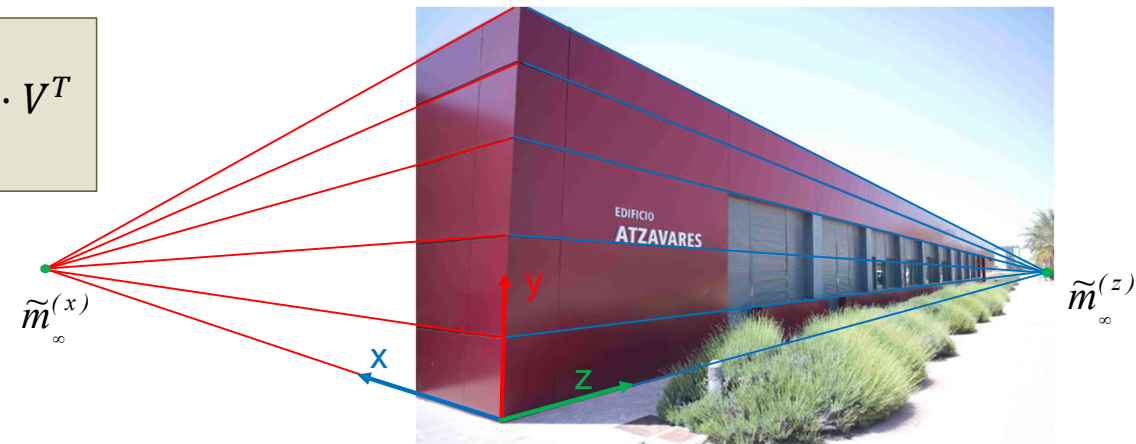
$$\bar{\mathbf{r}}_3 = A^{-1} \tilde{m}_{\infty}^{(z)} / \|A^{-1} \tilde{m}_{\infty}^{(z)}\|$$

$$\bar{\mathbf{r}}_2 = \bar{\mathbf{r}}_3 \times \bar{\mathbf{r}}_1$$

$$R^* = [\bar{\mathbf{r}}_1 \ \bar{\mathbf{r}}_2 \ \bar{\mathbf{r}}_3]$$

$$SVD(R^*) \rightarrow R^* = U \cdot D \cdot V^T$$

$$R = U \cdot \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & |U \cdot V^T| \end{bmatrix} \cdot V^T$$



POSE Estimation: Vanishing Points

- Application:
 - Tracking road lines
 - Vanishing Point: intersection point of two parallel lines (Z-axis)
 - Considering that the vehicle moves on a plane we only have an angular degree of freedom

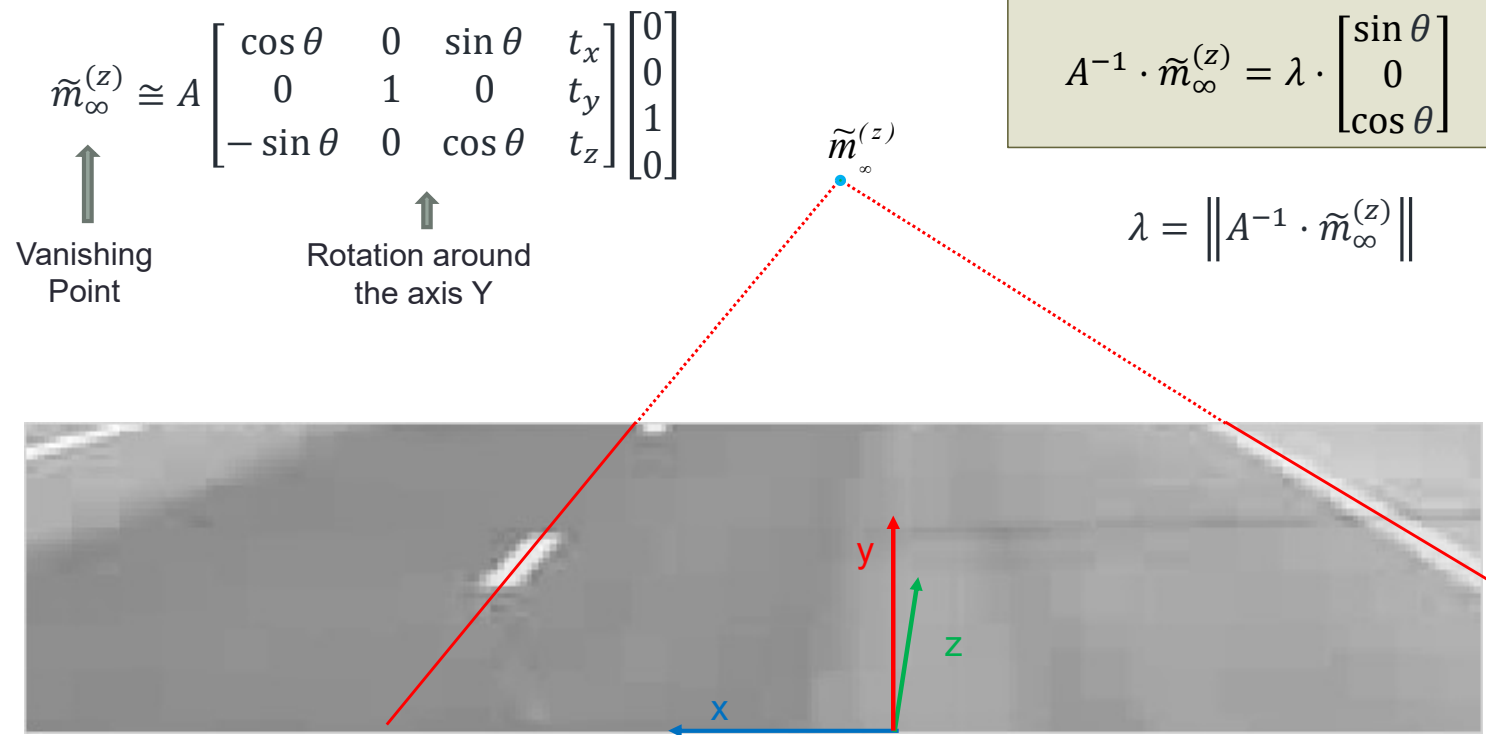


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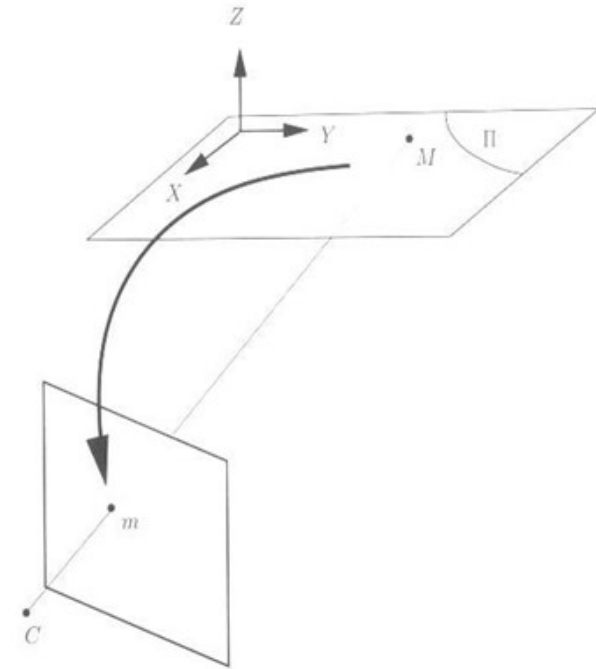
Homographies between Projective Planes

- **Plane – Image**
 - NOT-calibrated camare
 - The Plane Π does not contains the optical center $\mathbf{C}$
 - *Points on the plane:*

$$\tilde{m} \cong \tilde{P} \tilde{M} = [P \quad p] \tilde{M}$$

$$\text{if } \tilde{M} \cong \begin{bmatrix} X \\ Y \\ 0 \\ 1 \end{bmatrix} \in \Pi \Rightarrow \tilde{m} \cong \begin{bmatrix} P_{11} & P_{12} & P_{14} \\ P_{21} & P_{22} & P_{24} \\ P_{31} & P_{32} & P_{34} \end{bmatrix} \begin{bmatrix} X \\ Y \\ 1 \end{bmatrix}$$

$$\tilde{m} \cong H_{3 \times 3} \tilde{M}_{\Pi}, \quad \tilde{M}_{\Pi} \cong H^{-1}_{3 \times 3} \tilde{m}$$



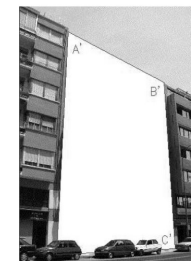
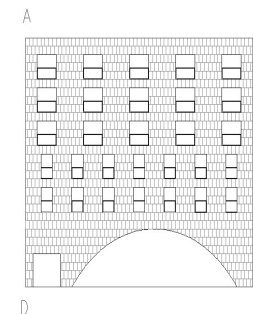
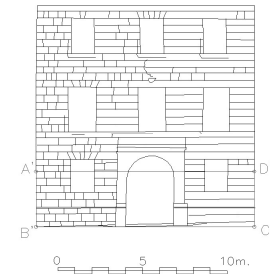
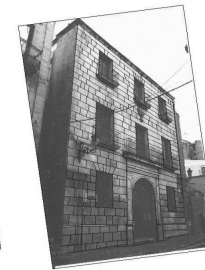
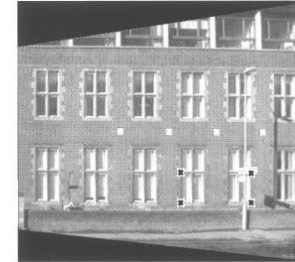
- **Calculation of $\mathbf{H}$:** 4 points of the plane projected into the image
 - Non collinear taken in threes

Homographies between Projective Planes

- Examples:
 - Projective insertion of one projective plane into another
 - Camera NOT Calibrated
 - Recognition of projective patterns
 - Camera NOT Calibrated

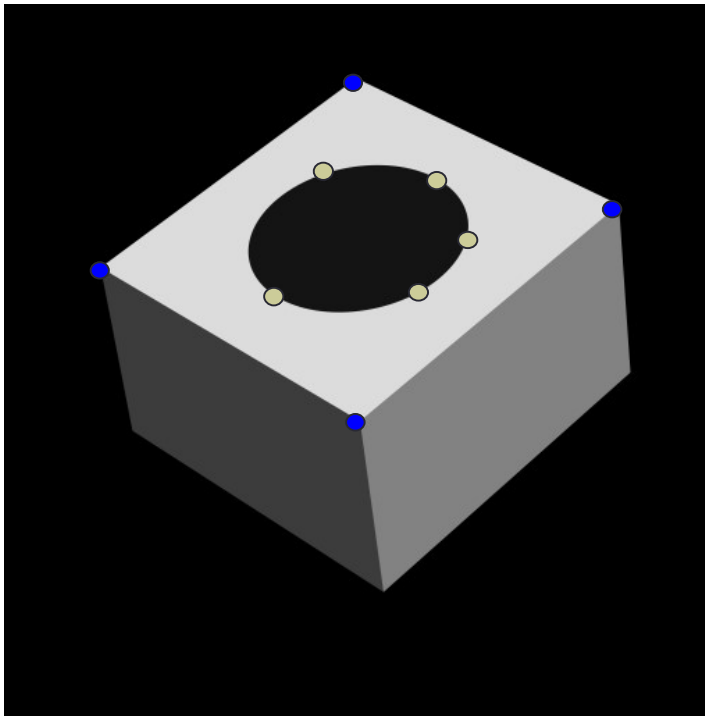
Homographies between Projective Planes

- Allows:
 - To know the projection of any point contained in the plane (outside the boundaries of the image)
 - To check if a point belongs to a plane
 - To know the 3D position on the plane from the projection in a single camera (2D)
 - Rectification: remove projective distortion in 2D vision
 - Photogrammetry:

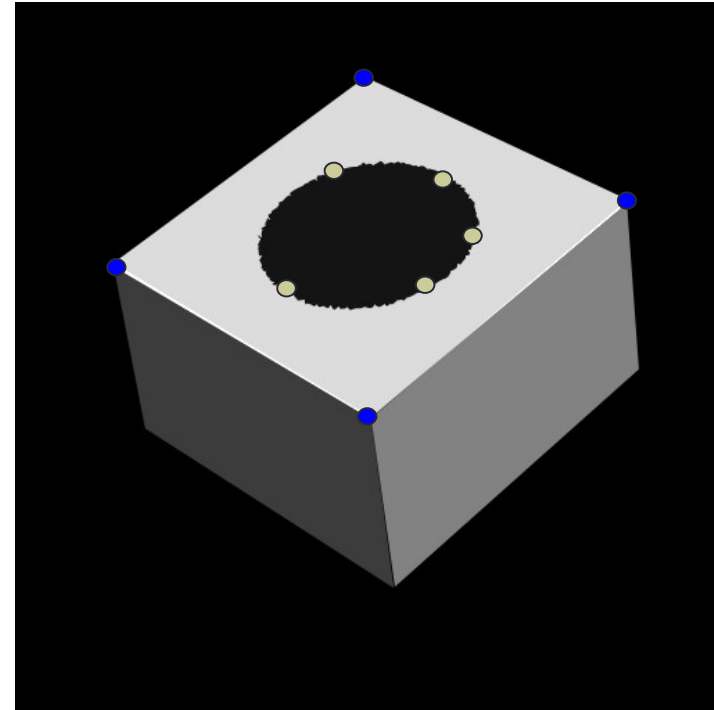


Homographies between Projective Planes

- Quality control in projective views



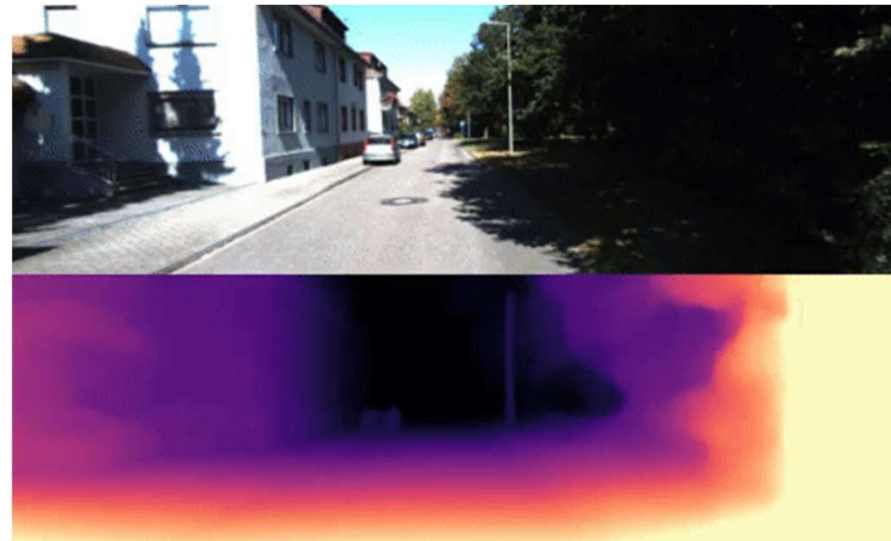
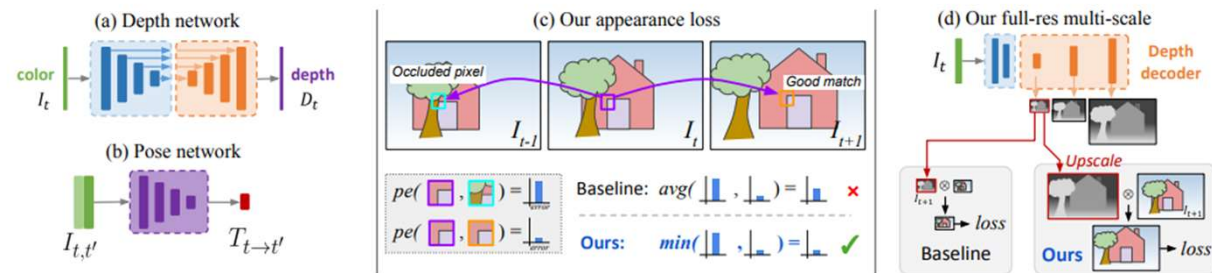
Correct Drill



Defective Drill

Advanced Monocular Techniques: CNN

- Monodepth2: Self-Supervised Monocular Depth Estimation
 - U-Net CNN



“Digging into Self-Supervised Monocular Depth Prediction” Clément Godard, Oisin Mac Aodha, Michael Firman and Gabriel J. Brostow, (2019) The International Conference on Computer Vision (ICCV), www.github.com/nianticlabs/monodepth2

Advanced Monocular Techniques: CNN

Depth Anything: Unleashing the Power of Large-Scale Unlabeled Data

Lihe Yang¹ Bingyi Kang^{2†} Zilong Huang² Xiaogang Xu^{3,4} Jiashi Feng² Hengshuang Zhao^{1†}

¹The University of Hong Kong ²TikTok ³Zhejiang Lab ⁴Zhejiang University

† corresponding authors

<https://depth-anything.github.io>



Figure 1. Our model exhibits impressive generalization ability across extensive unseen scenes. **Left two columns:** COCO [35]. **Middle two:** SA-1B [27] (a hold-out unseen set). **Right two:** photos captured by ourselves. Our model works robustly in low-light environments (1st and 3rd column), complex scenes (2nd and 5th column), foggy weather (5th column), and ultra-remote distance (5th and 6th column), etc.

Summary

- Monocular POSE
- Homography between Projective Planes
- Next step is the use of more than one point of view: Stereo Vision
 - 3D Reconstruction