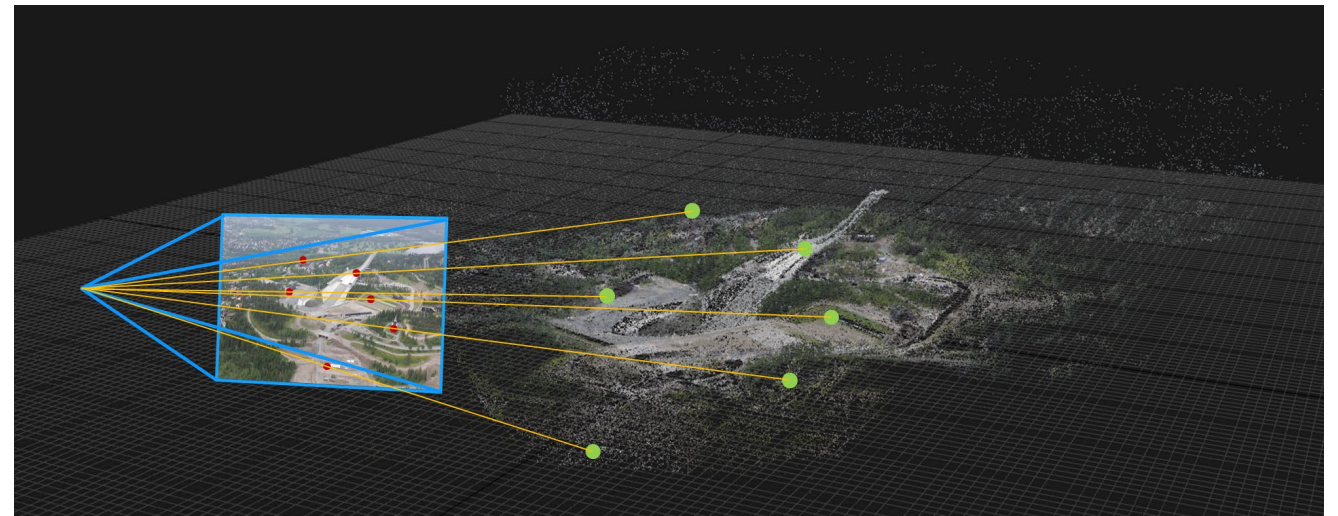


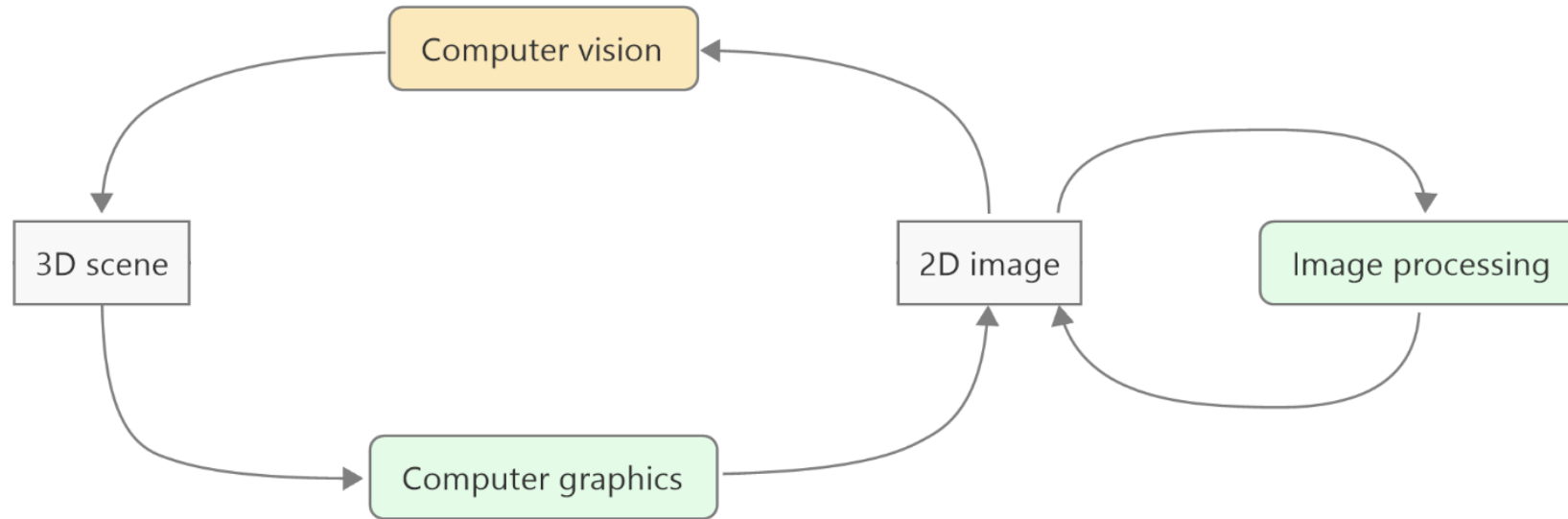
Estimating camera pose from a single image and a known map

Trym Vegard Haavardsholm

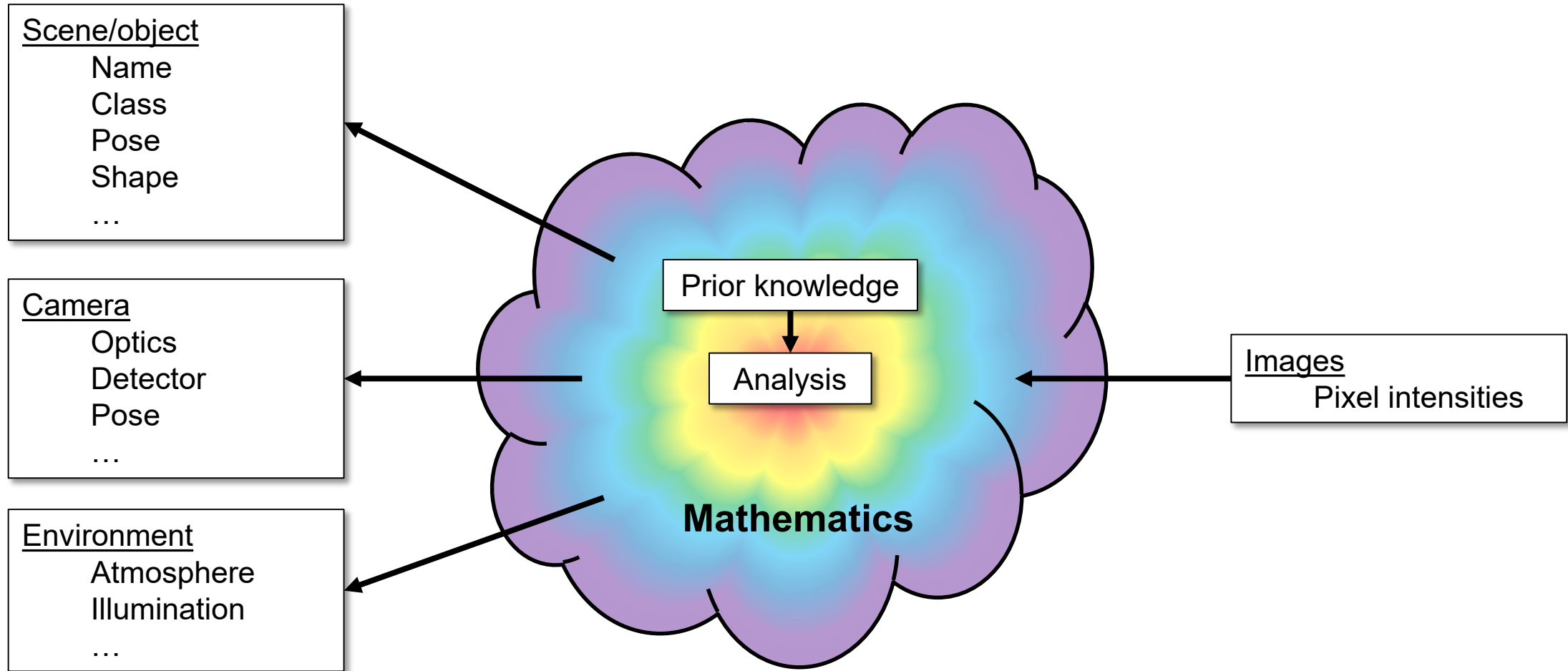
2023



Computer vision is an *inverse problem*!



The *inverse* analysis process

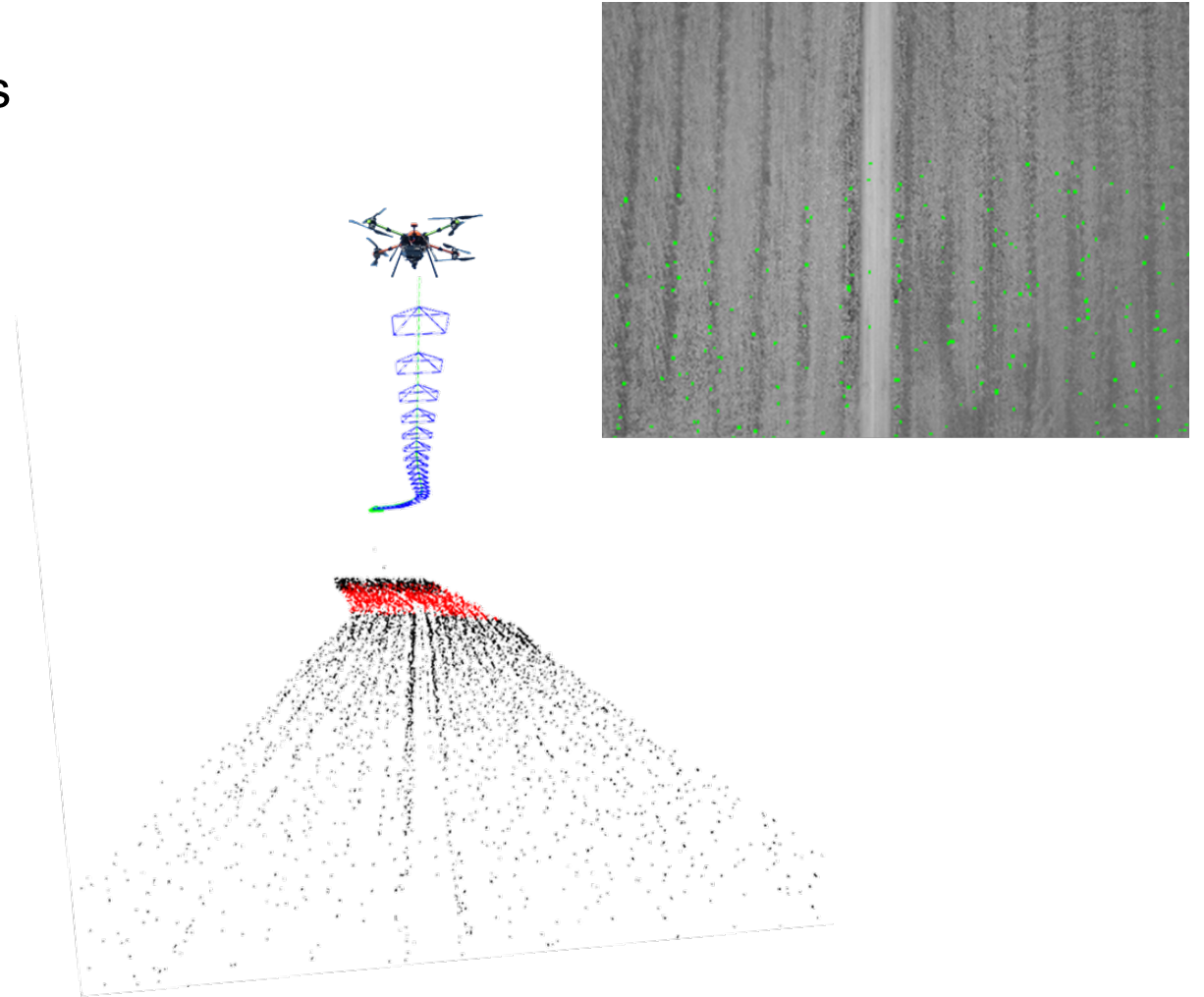


Localisation

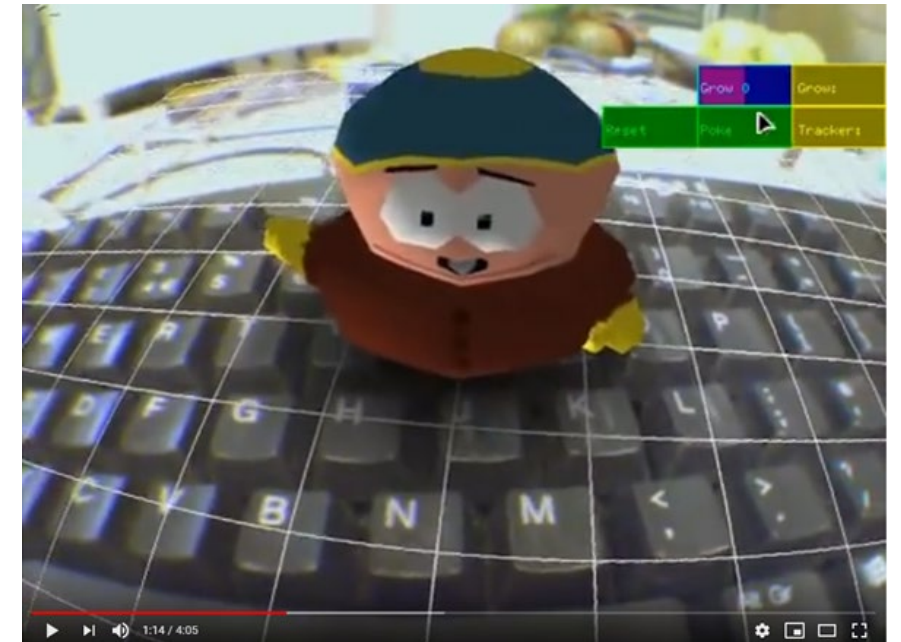
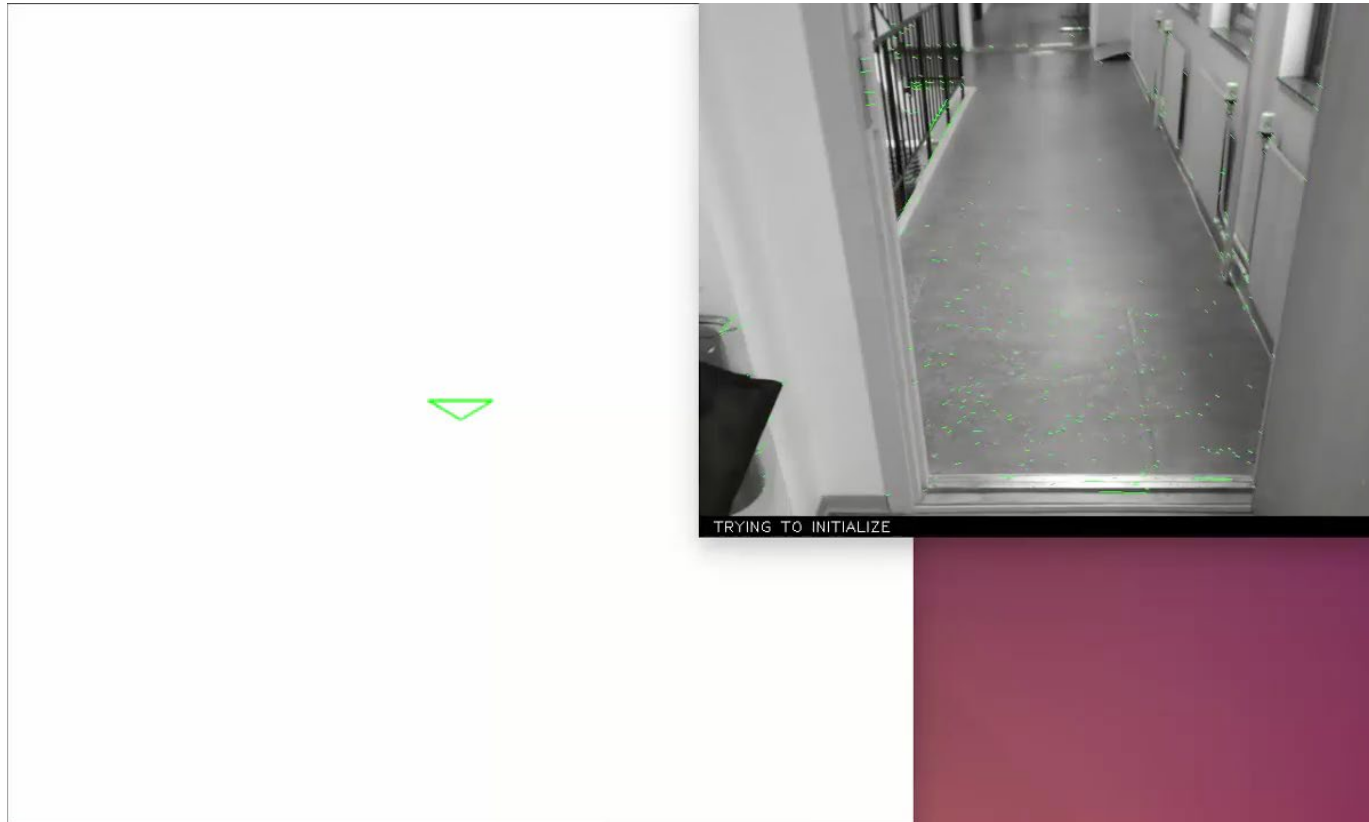
Pose estimation based on correspondences with a known map is called **localisation**

In **visual localisation**,
this is also sometimes called **tracking**

- Tracking the map in the image frames



Why learn about localisation?

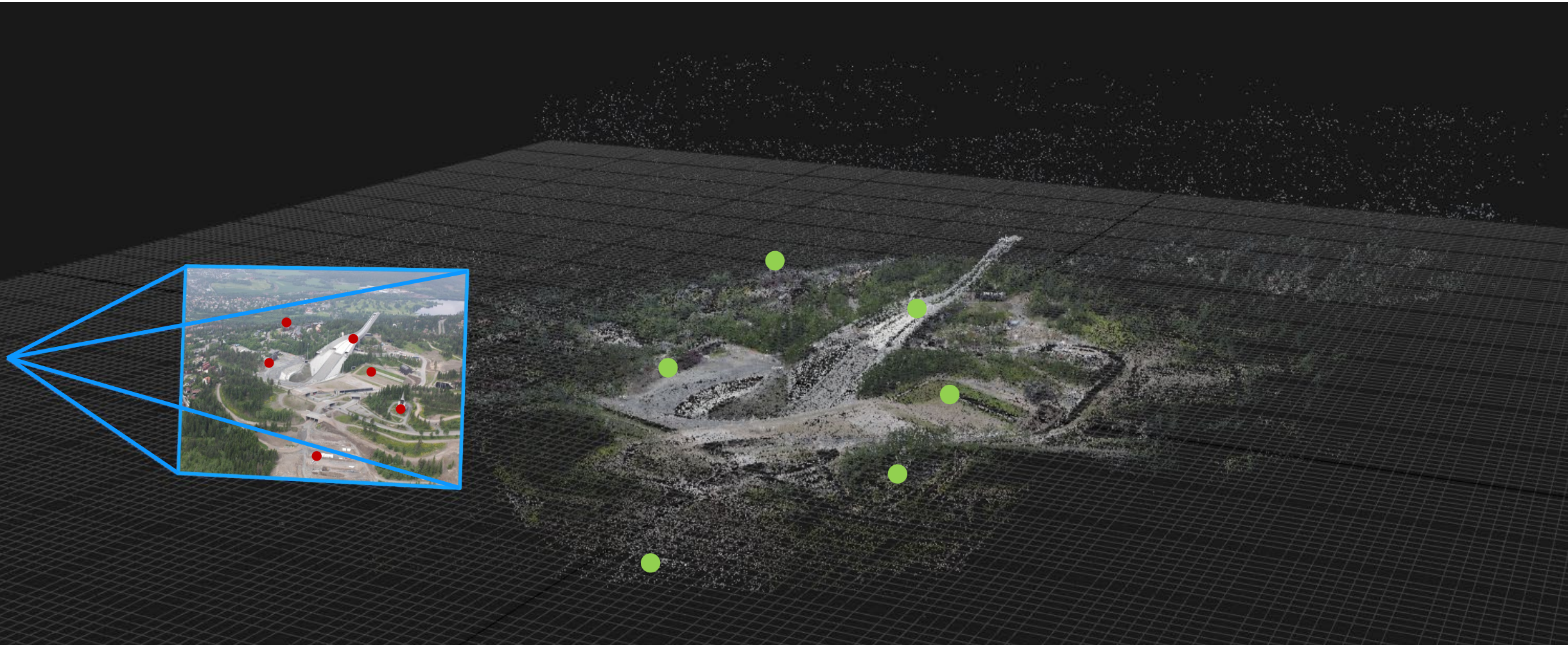


From PTAM by Georg Klein and David Murray (2007)
<https://www.youtube.com/watch?v=F3s3M0mokNc>

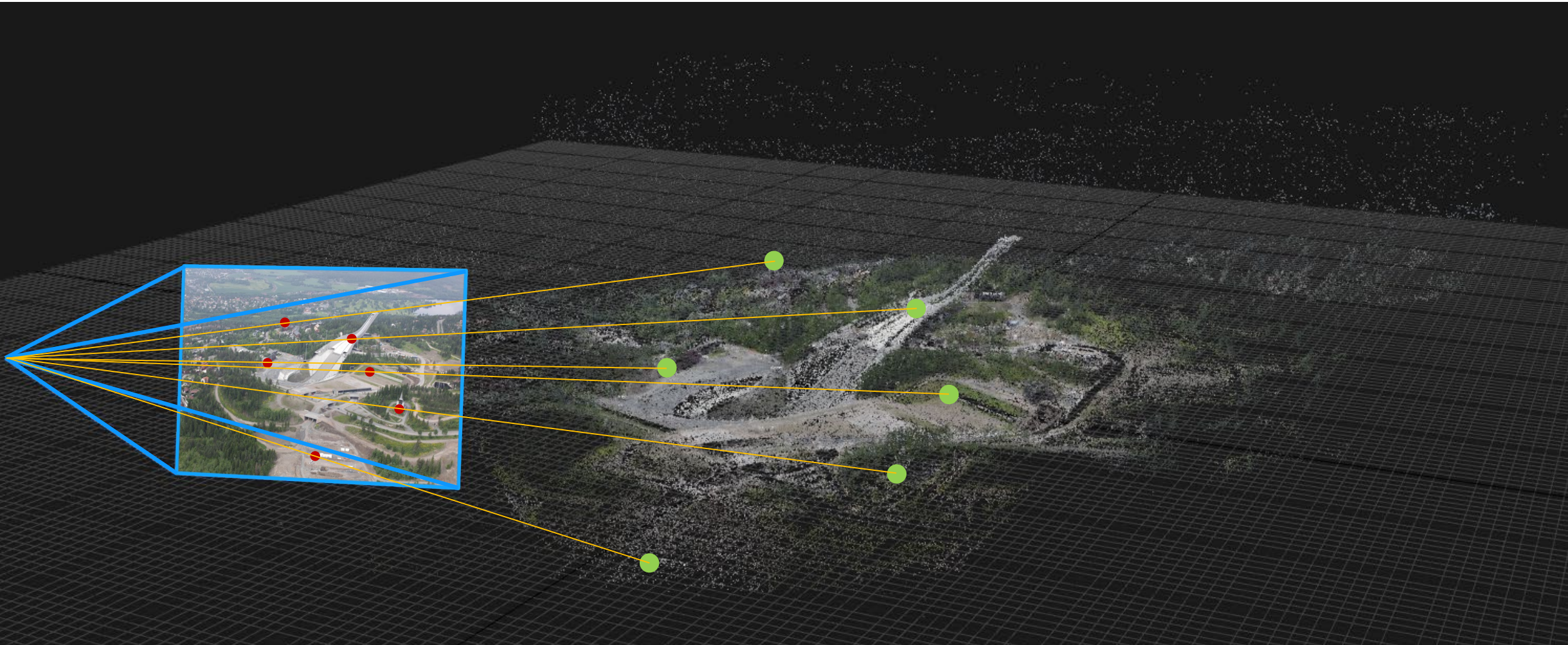
How can we track a map with a camera?



Pose from 2D correspondences with known 3D points



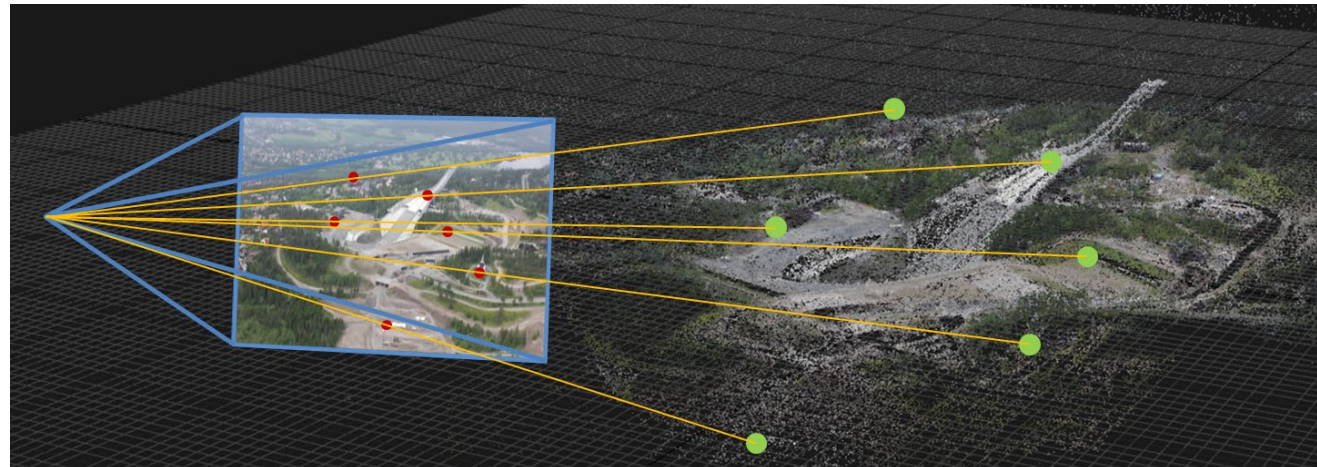
Pose from 2D correspondences with known 3D points



Pose from 2D correspondences with known 3D points

Minimise geometric error

$$\mathbf{T}_{wc}^* = \operatorname{argmin}_{\mathbf{T}_{wc}} \sum_i \left\| \pi(\mathbf{T}_{wc}^{-1} \cdot \mathbf{x}_i^w) - \mathbf{u}_i \right\|^2$$

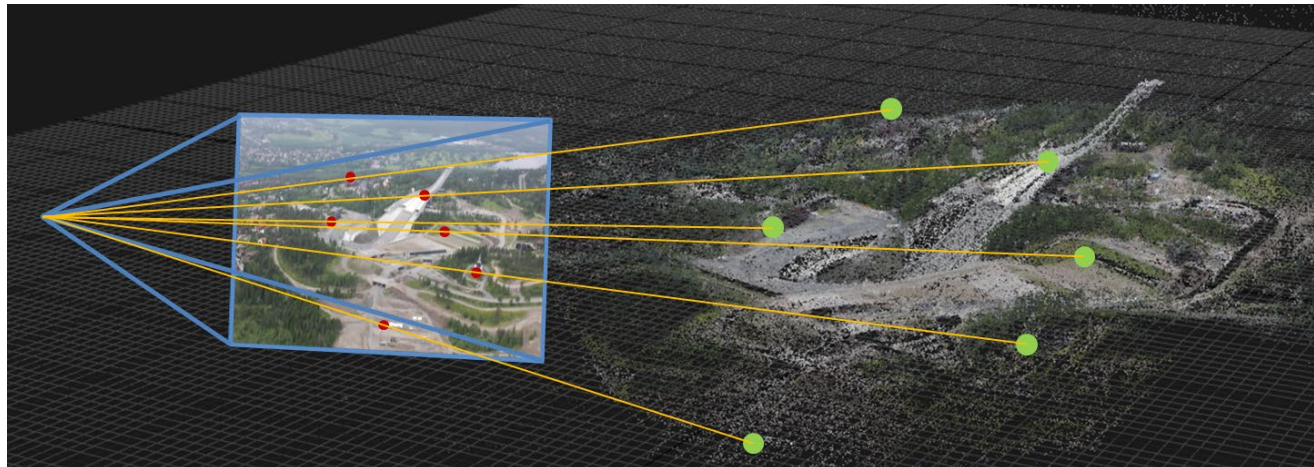


Pose from 2D correspondences with known 3D points

Minimise **geometric error**

$$\mathbf{T}_{wc}^* = \operatorname{argmin}_{\mathbf{T}_{wc}} \sum_i \left\| \pi(\mathbf{T}_{wc}^{-1} \cdot \mathbf{x}_i^w) - \mathbf{u}_i \right\|^2$$

also called **reprojection error**



Pose estimation

We will solve the indirect tracking problem

$$\mathbf{T}_{wc}^* = \operatorname{argmin}_{\mathbf{T}_{wc}} \sum_i \left\| \pi(\mathbf{T}_{wc}^{-1} \cdot \mathbf{x}_i^w) - \mathbf{u}_i \right\|^2$$

in the next few videos.

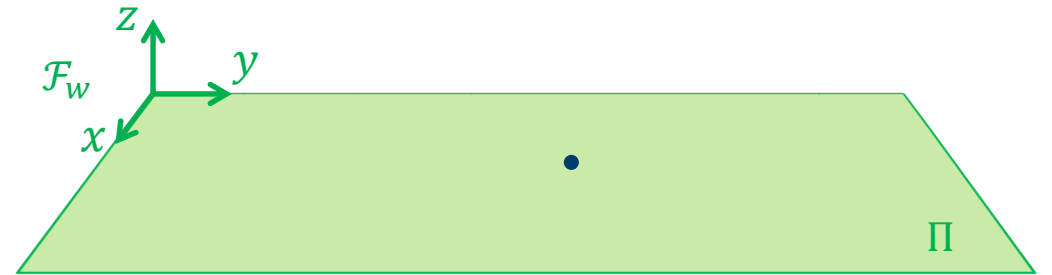
But lets first solve a simpler problem,
when we can assume that the world is planar!



Pose estimation relative to a world plane

Choose the world coordinate system so that the xy -plane corresponds to a plane Π in the scene

$$\mathbf{x}_{\Pi}^w = \begin{bmatrix} x \\ y \\ 0 \end{bmatrix} \quad \mathbf{x}^{\Pi} = \begin{bmatrix} x \\ y \end{bmatrix}$$

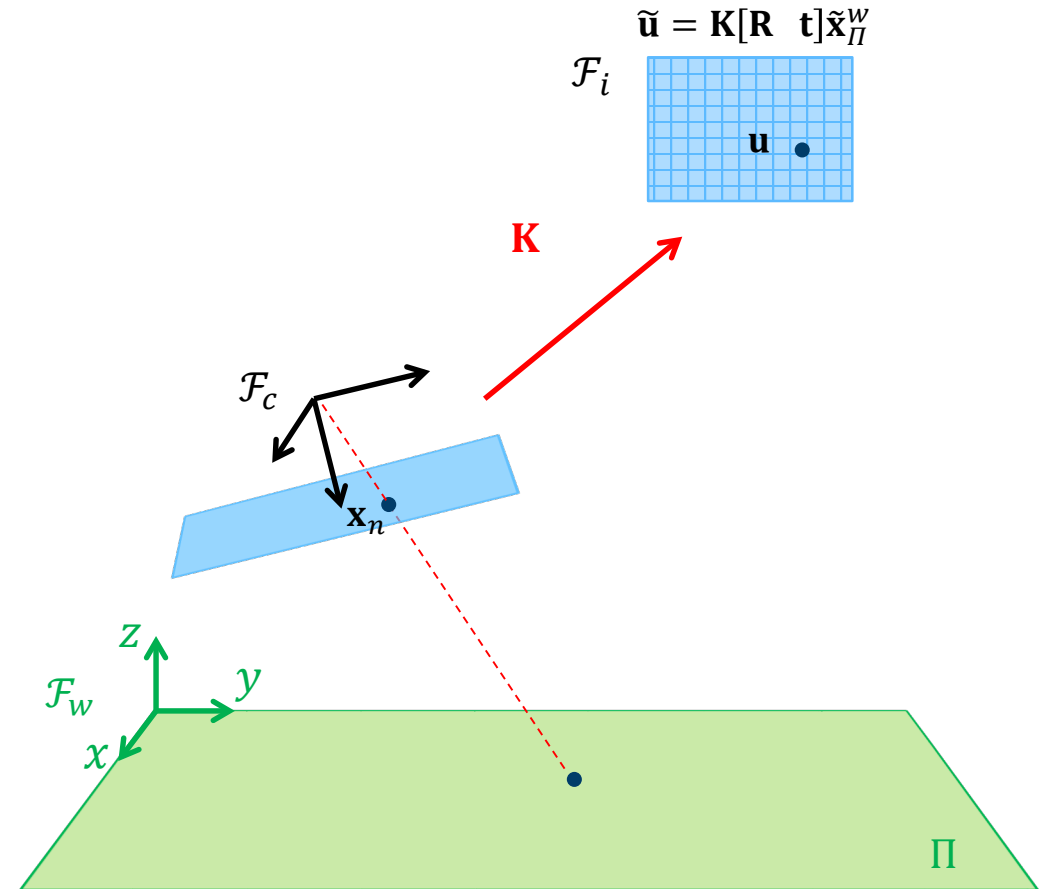


Pose estimation relative to a world plane

We can map points on the world plane into image coordinates by using the perspective camera model

$$\tilde{\mathbf{u}} = \mathbf{K} [\mathbf{R} \ \mathbf{t}] \tilde{\mathbf{x}}_{\Pi}^w$$

$$\mathbf{T}_{cw} = \begin{bmatrix} \mathbf{R} & \mathbf{t} \\ \mathbf{0} & 1 \end{bmatrix}$$



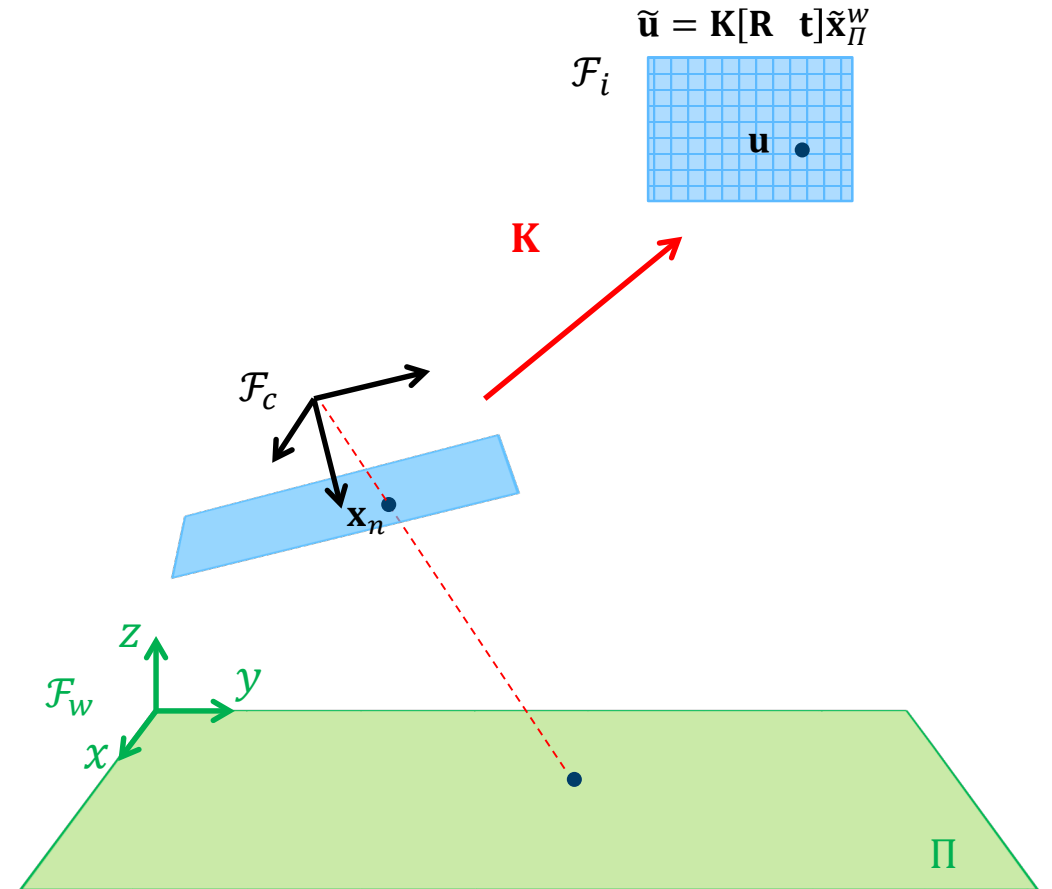
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$$\tilde{\mathbf{u}} = \mathbf{K} [\mathbf{R} \ \mathbf{t}] \tilde{\mathbf{x}}_{\Pi}^w$$

$$= \mathbf{K} [\mathbf{r}_1, \mathbf{r}_2, \mathbf{r}_3, \mathbf{t}] \begin{bmatrix} x \\ y \\ 0 \\ 1 \end{bmatrix}$$

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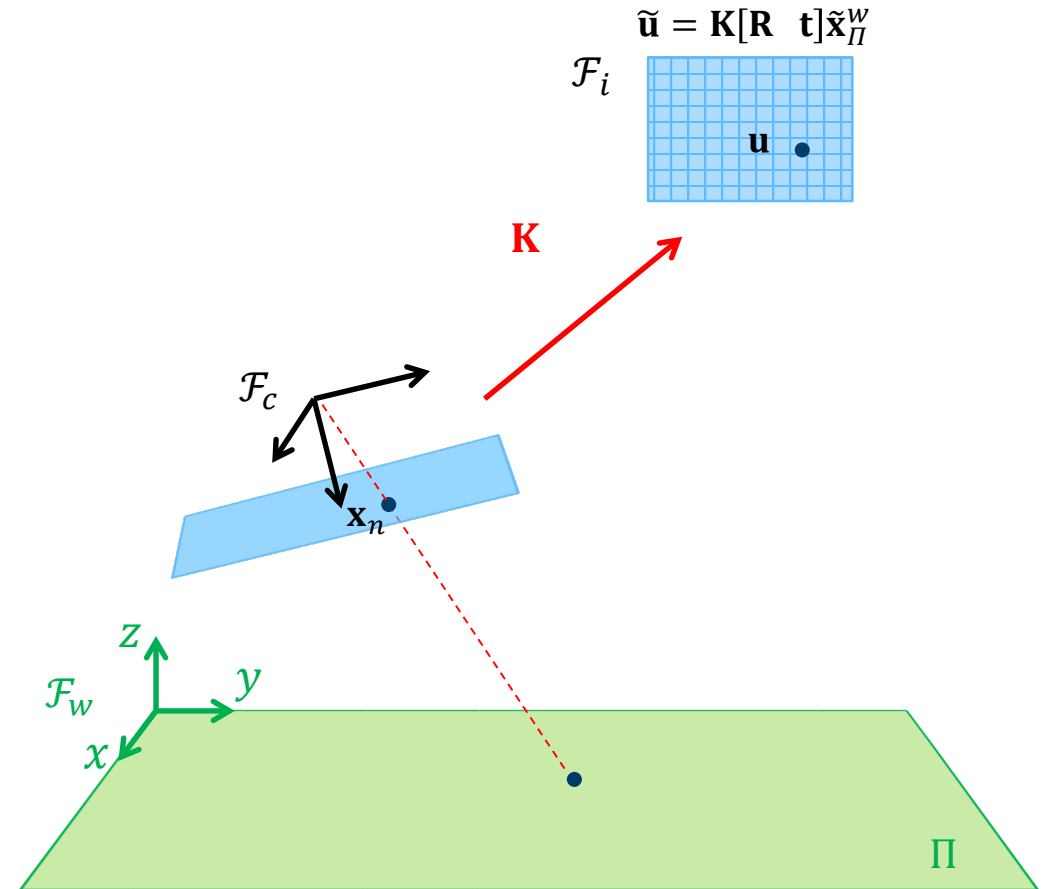
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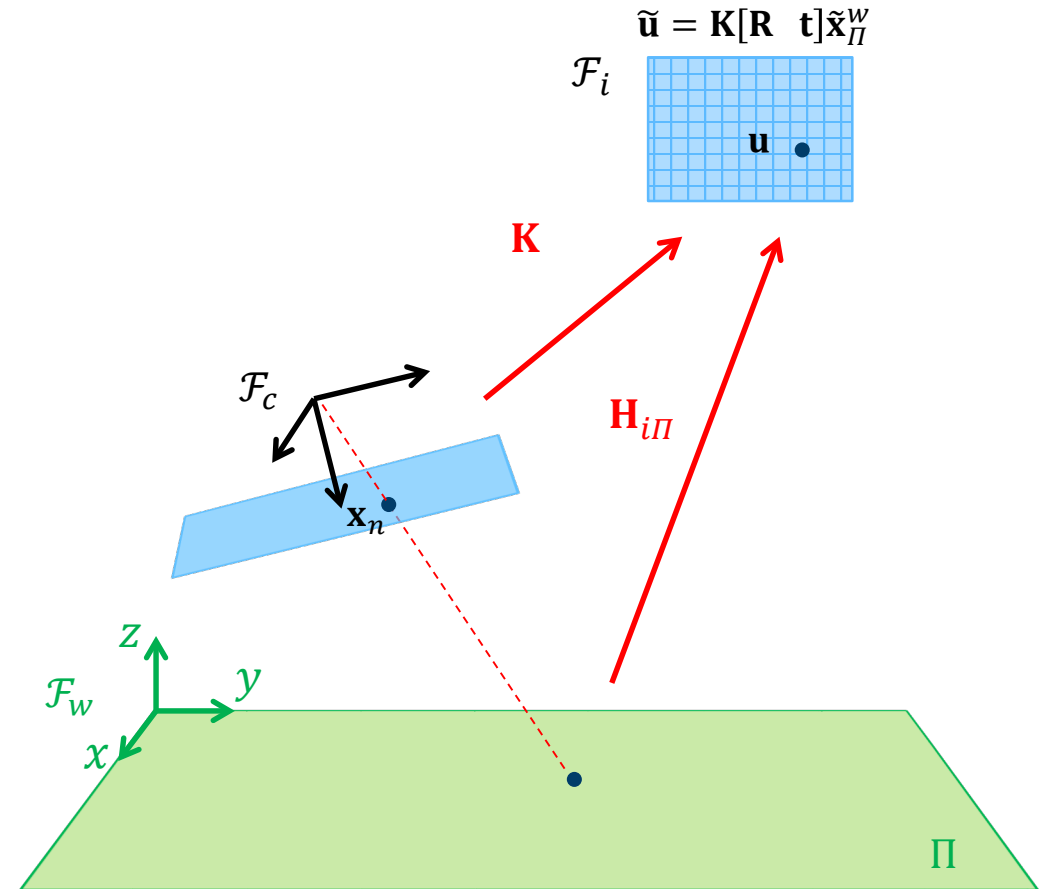
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$$= \mathbf{H}_{i\Pi} \tilde{\mathbf{x}}^{\Pi}$$

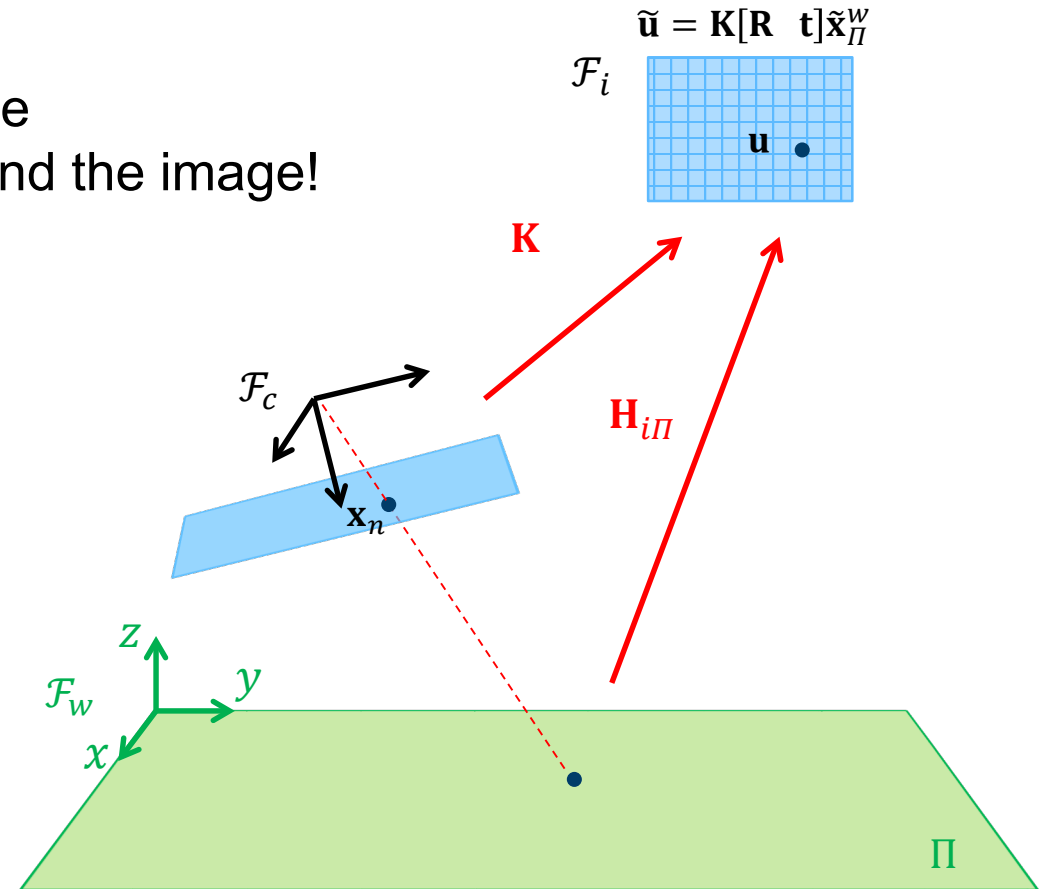
$$\mathbf{T}_{cw} = \begin{bmatrix} \mathbf{R} & \mathbf{t} \\ \mathbf{0} & 1 \end{bmatrix}$$



Pose estimation relative to a world plane

⇒ For a calibrated camera,
we have a relationship between the camera pose
and the homography between the world plane and the image!

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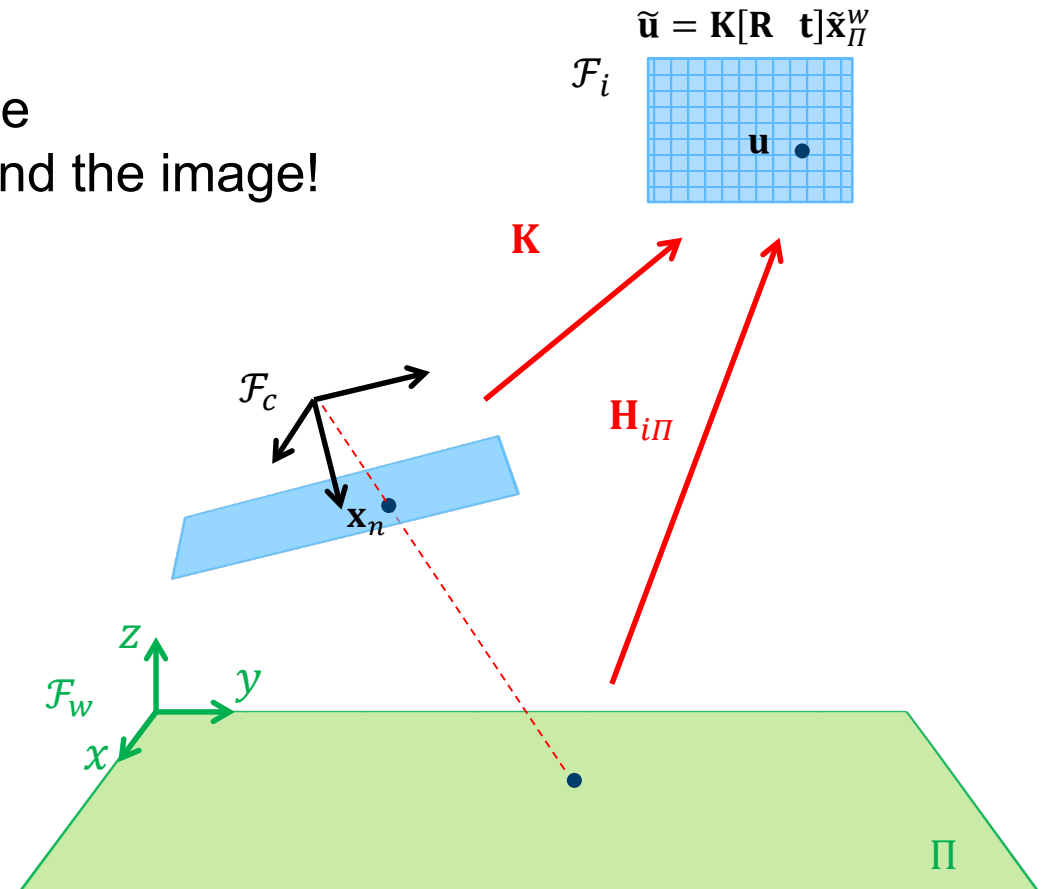


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How can we use this to
estimate camera pose
given a homography?



Pose estimation relative to a world plane

Assume a perfect, noise-free homography between the world plane and the image:

$$\mathbf{H}_{i\Pi} = \mathbf{K}[\mathbf{r}_1, \mathbf{r}_2, \mathbf{t}]$$

Pose estimation relative to a world plane

Assume a perfect, noise-free homography between the world plane and the image:

$$\mathbf{H}_{i\Pi} = \mathbf{K}[\mathbf{r}_1, \mathbf{r}_2, \mathbf{t}]$$

Then, because of scale ambiguity:

$$[\mathbf{r}_1, \mathbf{r}_2, \mathbf{t}] \sim \mathbf{K}^{-1}\mathbf{H}_{i\Pi} = \mathbf{M}$$

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Since the columns of rotation matrices have unit norm, we find a scale factor λ so that the first two columns of \mathbf{M} also get unit norm. We then have the two possible solutions:

$$[\hat{\mathbf{r}}_1, \hat{\mathbf{r}}_2, \hat{\mathbf{t}}] = \pm\lambda\mathbf{M}$$

Pose estimation relative to a world plane

Assume a perfect, noise-free homography between the world plane and the image:

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The last column in $\hat{\mathbf{R}}$ is given by the cross product of the two first columns:

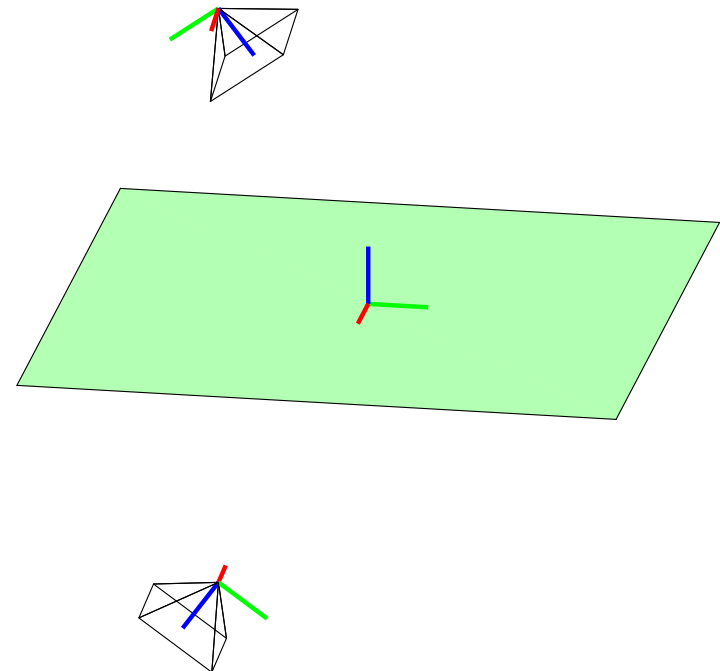
$$\hat{\mathbf{r}}_3 = \pm (\hat{\mathbf{r}}_1 \times \hat{\mathbf{r}}_2), \text{ where the sign is chosen so that } \det(\hat{\mathbf{R}}) = 1$$

Pose estimation relative to a world plane

We are now able to reconstruct the camera pose in the world coordinate system for each of the two solutions:

$$\hat{\mathbf{T}}_{wc} = \hat{\mathbf{T}}_{cw}^{-1} = \begin{bmatrix} \hat{\mathbf{R}}^T & -\hat{\mathbf{R}}^T \hat{\mathbf{t}} \\ \mathbf{0} & 1 \end{bmatrix} \quad \text{where} \quad \hat{\mathbf{R}} = [\hat{\mathbf{r}}_1, \hat{\mathbf{r}}_2, \hat{\mathbf{r}}_3]$$

It is easy to find the correct solution in practice because only one side of the plane is typically visible



Pose estimation with planar correspondences

With a homography estimated from point correspondences, this approach will typically not give proper rotation matrices because of noise

$$\hat{\mathbf{R}} \notin SO(3)$$

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But it is possible to find the closest rotation matrix with SVD!

$$\hat{\mathbf{R}} \rightarrow \hat{\mathbf{R}}^* \in SO(3)$$

Pose estimation with planar correspondences

Let $\bar{\mathbf{M}}$ be the matrix with the two first columns of \mathbf{M} :

$$\bar{\mathbf{M}} = [\mathbf{m}_1, \mathbf{m}_2]$$

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The corresponding scale λ can be computed as:

$$\lambda = \frac{\text{trace}(\bar{\mathbf{R}}^{*T} \bar{\mathbf{M}})}{\text{trace}(\bar{\mathbf{M}}^T \bar{\mathbf{M}})} = \frac{\sum_{i=1}^3 \sum_{j=1}^2 r_{ij}^* m_{ij}}{\sum_{i=1}^3 \sum_{j=1}^2 m_{ij}^2}$$

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With $\bar{\mathbf{R}}^*$ and λ , we can now compute the pose with ambiguity as we did in the error-free case

Summary

2D-3D pose estimation:

- Homography-based method

$$\mathbf{H}_{i\Pi} = \mathbf{K} [\mathbf{r}_1, \mathbf{r}_2, \mathbf{t}]$$

- Minimising geometric/reprojection error

$$\mathbf{T}_{wc}^* = \operatorname{argmin}_{\mathbf{T}_{wc}} \sum_i \left\| \pi(\mathbf{T}_{wc}^{-1} \cdot \mathbf{x}_i^w) - \mathbf{u}_i \right\|^2$$

