Practical Course: Vision-based Navigation Summer Term 2015

Lecture 2: Visual Motion Estimation – Overview and Sparse Methods

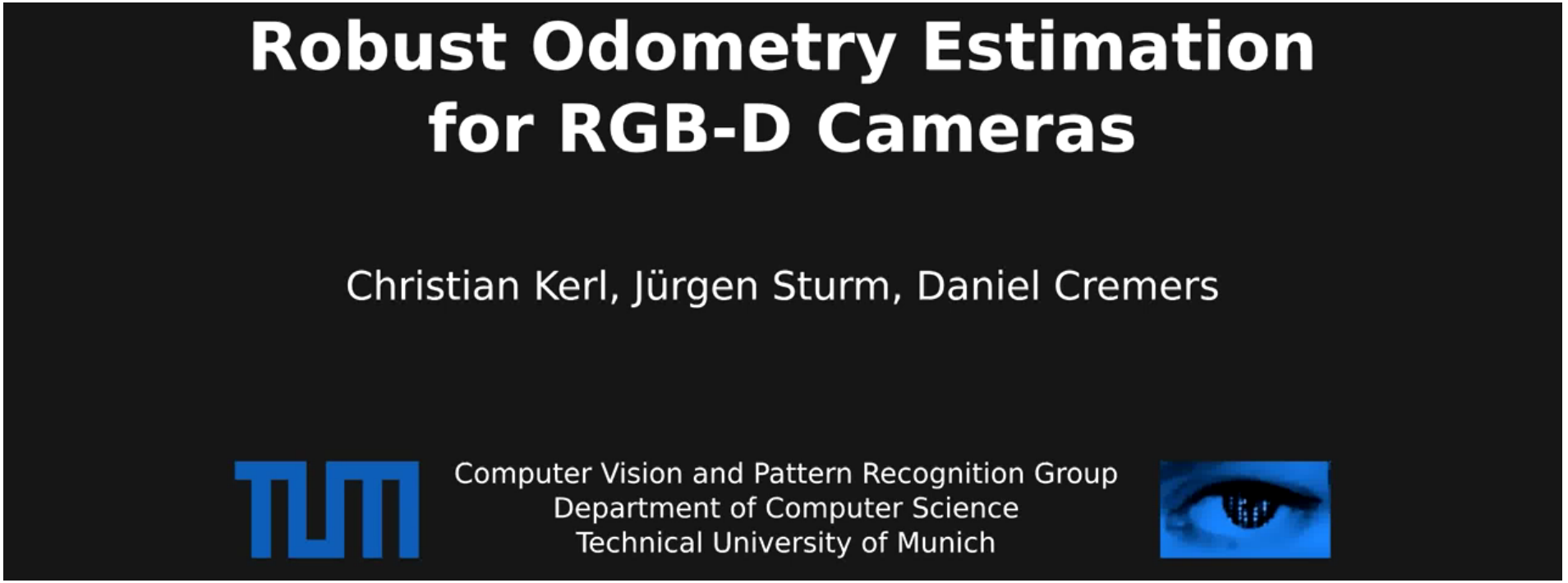
Dr. Jörg Stückler

What we will cover today

- Introduction to visual motion estimation approaches
  - Visual odometry (VO) vs. visual SLAM
  - Overview on VO approaches for monocular, stereo, RGB-D cameras
  - The notions of sparse, dense, and direct

- Sparse, keypoint-based visual odometry

Visual Motion Estimation a.k.a. Visual Odometry



Visual Motion Estimation a.k.a. Visual Odometry

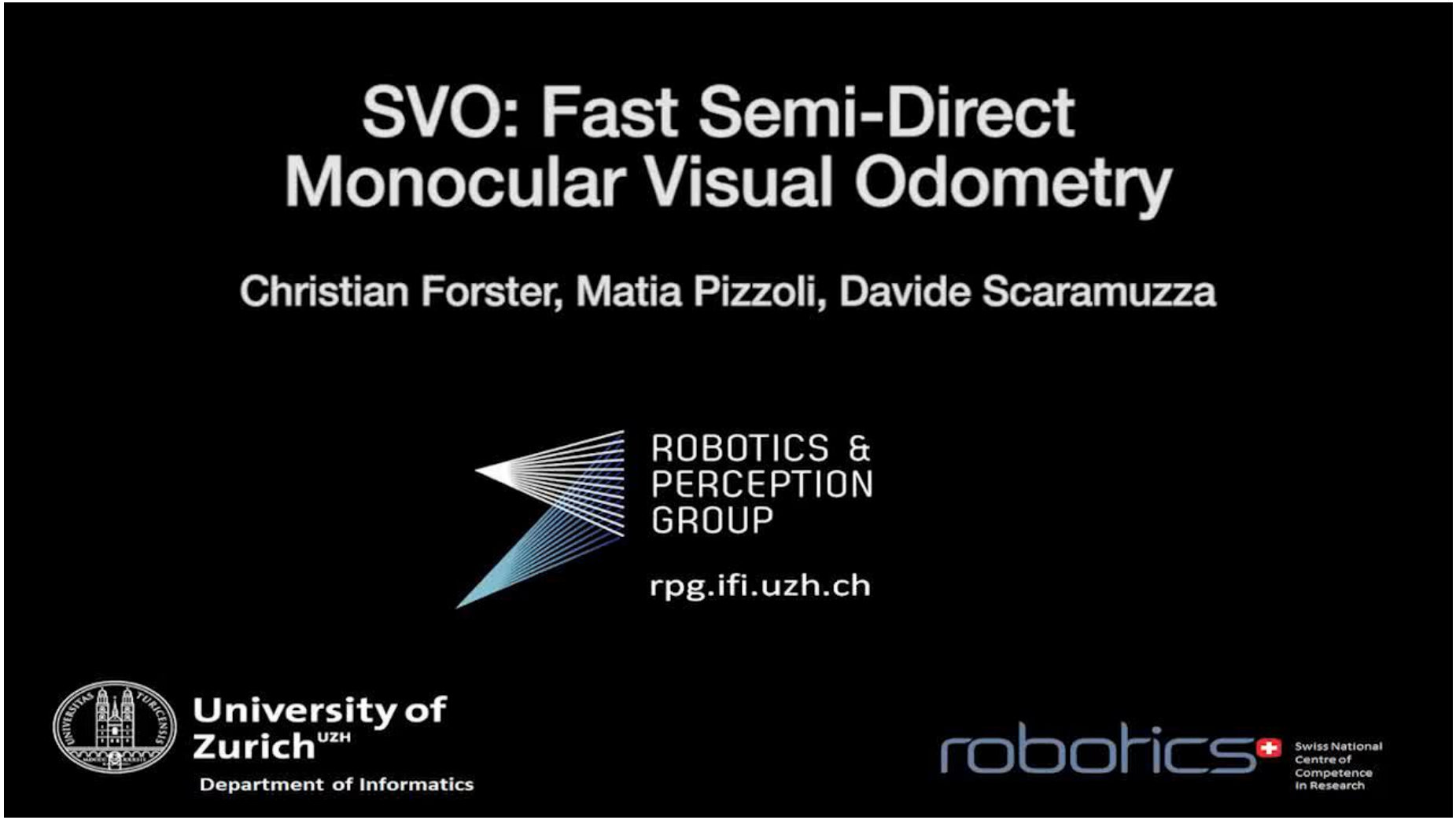
Semi-Dense Visual Odometry for AR on a Smartphone

Thomas Schöps, Jakob Engel, Daniel Cremers

ISMAR 2014, Munich

Computer Vision Group
Department of Computer Science
Technical University of Munich

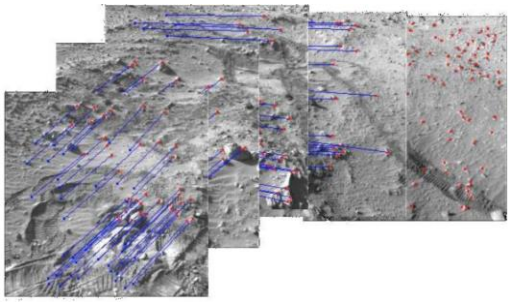
Visual Motion Estimation a.k.a. Visual Odometry



The Term "Visual Odometry"

- Odometry:
  - Greek: „hodos" – path, „metron" – measurement
  - Motion or position estimation from measurements or controls
  - Typical example: wheel encoders

- Visual Odometry (VO):
  - 1980-2004: Dominant research by NASA JPL for Mars exploration rovers (Spirit and Opportunity in 2004)
  - David Nister's „Visual Odometry" paper from 2004 about keypoint-based methods for monocular and stereo cameras



Visual Odometry

- VO is often used to complement other motion sensors
  - GPS
  - Inertial Measurement Units (IMUs)
  - Wheel odometry
  - etc.

- Important in GPS-denied environments (indoors, underwater, etc.)

- Relation to Visual Simultaneous Localization and Mapping (SLAM):
  - Local (VO) vs. global (VSLAM) consistency
  - VO: 3D reconstruction only at local scale (if at all)
  - VO: Real-time requirements

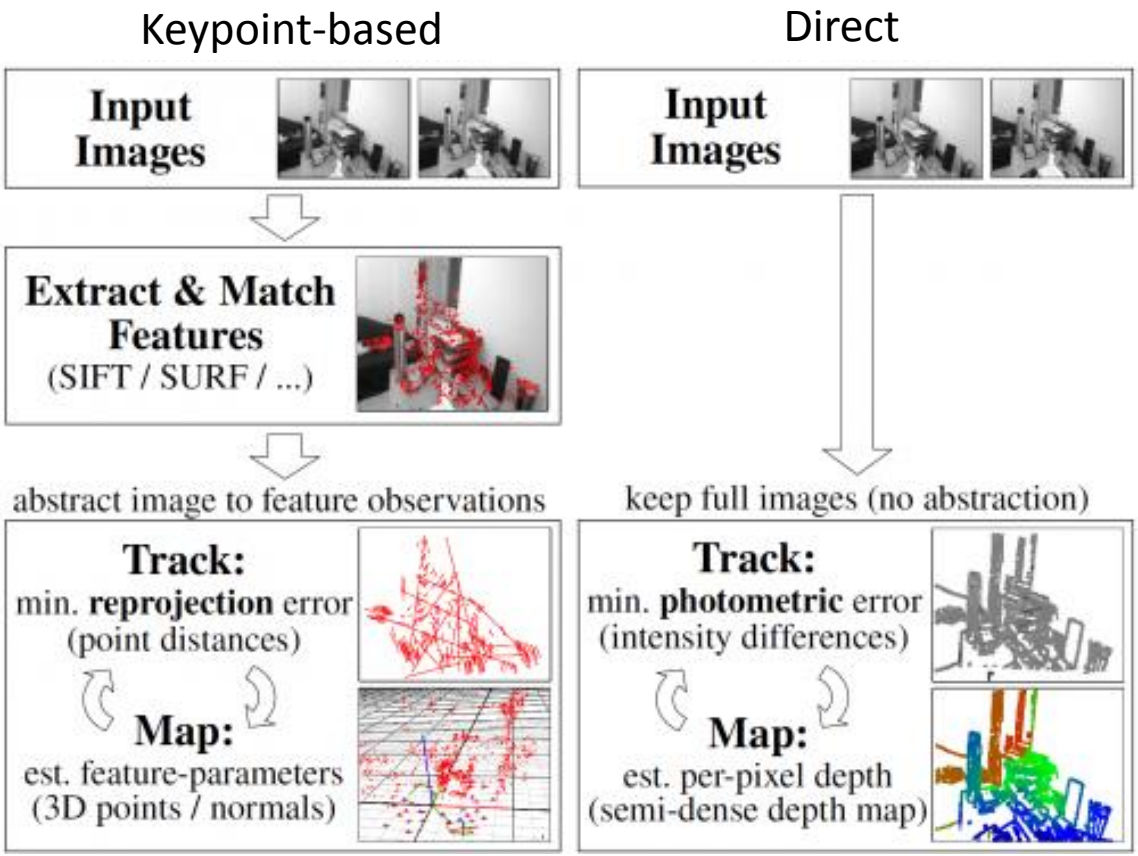
Sensors for Visual Odometry

- Monocular:
  - Pros: Low-power, light-weight, low-cost, simple to calibrate and use
  - Cons: requires motion parallax and textured scenes, scale not observable

- Stereo:
  - Pros: depth without motion, less power than active structured light
  - Cons: requires textured scenes, accuracy depends on baseline, requires extrinsic calibration of the cameras, synchronization of the cameras

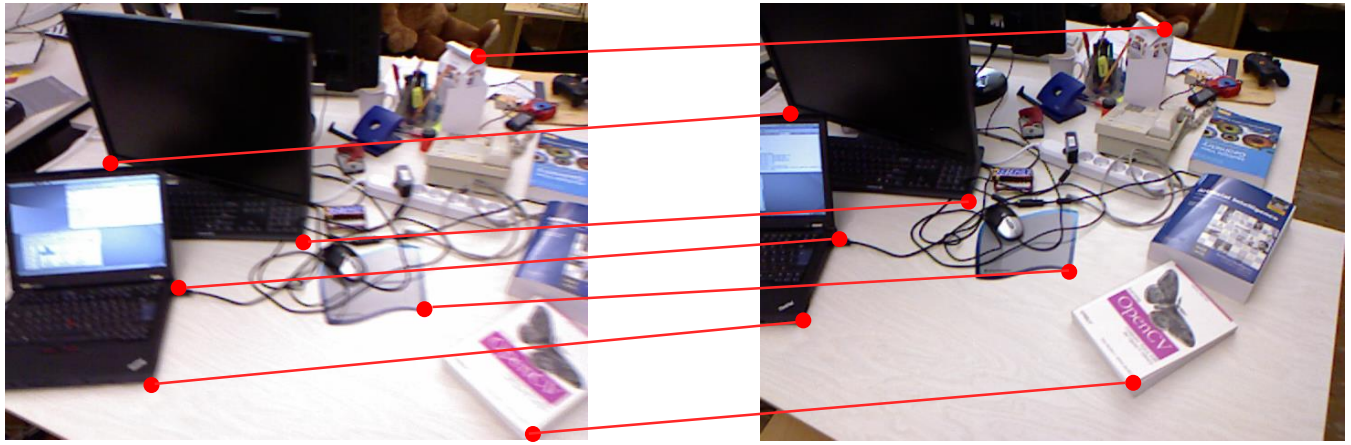
- Active RGB-D sensors:
  - Pros: also work in untextured scenes, similar to stereo processing
  - Cons: active sensing consumes power, blackbox depth estimation

Keypoints, Direct, Sparse, Dense

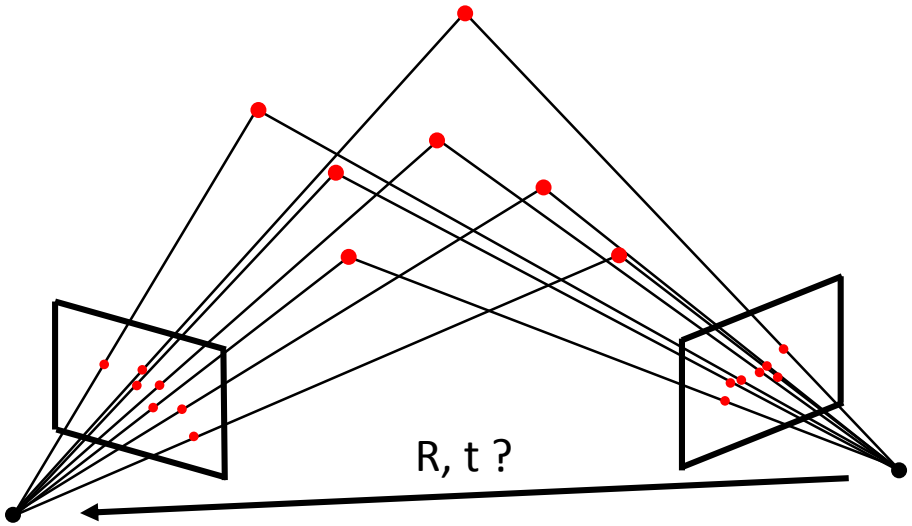


- Sparse: use a small set of selected pixels (keypoints)
- Dense: use all (valid) pixels

Sparse Keypoint-based Visual Odometry



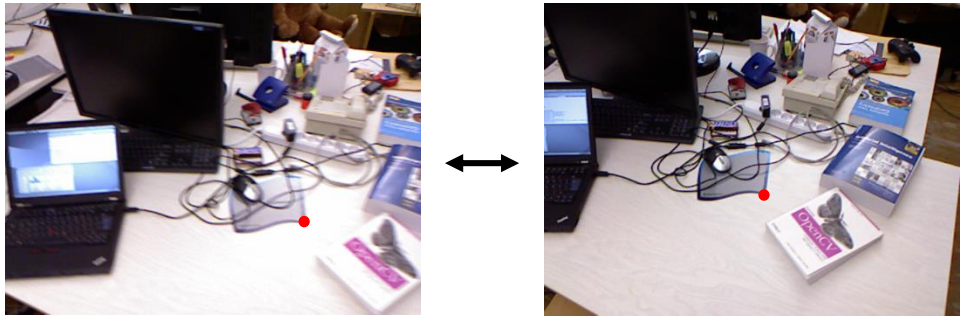
Extract and match keypoints



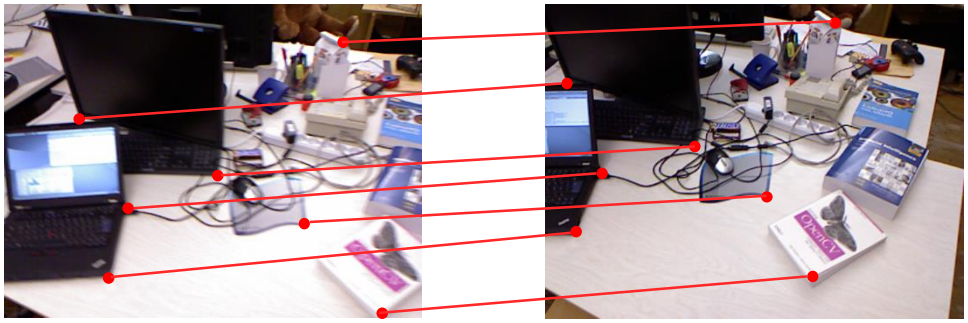
Determine relative camera pose (R, t) from keypoint matches

Keypoint Extraction

- Detection repeatability
  - We want to find the (accurate) image of the same 3D point from different view-points



- Descriptor distinctiveness
  - We want a descriptor that achieves (in the ideal case) a unique and correct association of corresponding keypoints



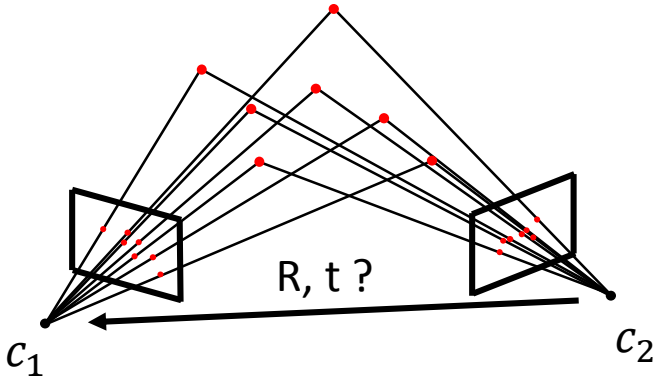
Keypoint Detectors and Descriptors

- Keypoint detection and description in images has been extensively studied
- Nowadays there is plenty of fast and repeatable detectors available, e.g.,
  - Harris corner variants
  - FAST corner variants (e.g. ORB detector)
  - DoG blob variants (SIFT, SURF)
  - Learning-based keypoints
- Many detectors come with a suitable descriptor, e.g.,
  - ORB (binary pixel comparisons locally around keypoint)
  - SIFT/SURF (grayscale gradient patterns locally around keypoint)

Monocular Keypoint-based Motion Estimation

- In the monocular case, we do not have depth available at keypoints

- If we knew the relative pose of the cameras and the 3D position of each keypoint match, we could directly compute to which pixels the keypoints should project in each camera image



- To find the unknown pose and 3D positions, we could formulate an optimization problem that minimizes the reprojection error of all keypoints

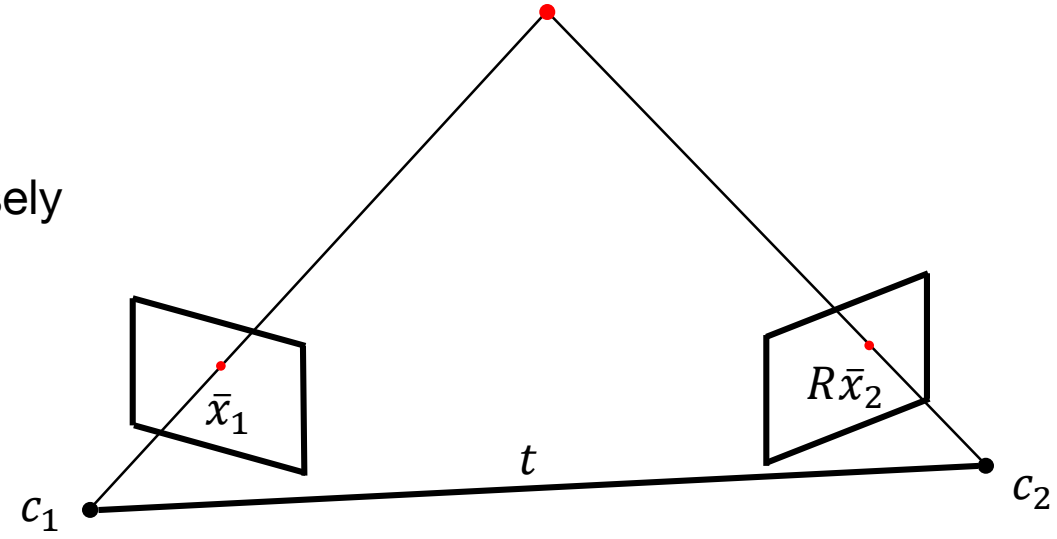
$$E(R,t,x_1,\dots,x_N) = \frac{1}{N}\sum_i \left\|z_{1,i} - \pi(x_i)\right\|_2^2 + \left\|z_{2,i} - \pi(Rx_i + t)\right\|_2^2$$

- Reprojection error: difference between measured and expected pixel position of a keypoint

Uniqueness?
Non-linear projection?

Motion from Epipolar Geometry

- An alternative is to examine epipolar geometry more closely



- The rays from each camera to the keypoint and the baseline t are coplanar!

$$\bar{x}_1^T(t \times R\bar{x}_2) = 0 \leftrightarrow \bar{x}_1^T[t]_\times R\bar{x}_2 = 0$$

- The essential matrix $E = [t]_\times R$ captures the relative camera pose
- Each keypoint match provides an „epipolar constraint“
- 8 matches suffice to determine E (8-point algorithm)
- In the uncalibrated case, the camera calibration needs to be subsumed into the so-called fundamental matrix $F = K^{-T}EK^{-1}$

8-Point Algorithm (Longuet-Higgins, 1981)

- Find approximation to essential matrix:
  - Construct matrix $A = (a_1, a_2, \ldots, a_N)^T$ with $a_i = \bar{x}_{1,i} \times \bar{x}_{2,i}$.
  - Apply a singular value decomposition (SVD) on $\mathrm{A} = \mathrm{U}SV^T$ and unstack the 9th column vector of V into $\tilde{E}$
  - Project the approximate $\tilde{E}$ into the (normalized) essential space:
    Determine the SVD of $\tilde{E} = U\ \mathrm{diag}(\sigma_1, \sigma_2, \sigma_3)\ V^T$ and replace the singular values $\sigma_1, \sigma_2, \sigma_3$ with 1,1,0 to find $E = U\ \mathrm{diag}(1,1,0)\ V^T$
  - Determine one of the following 4 possible solutions that intersect the points in front of both cameras:

$$R = U\ R_Z^T\left(\pm\frac{\pi}{2}\right)V^T$$

$$[t]_\times = U\ R_Z\left(\pm\frac{\pi}{2}\right)\mathrm{diag}(1,1,0)V^T$$

$$\text{with}\quad R_Z^T\left(\pm\frac{\pi}{2}\right) = \begin{pmatrix} 0 & \pm 1 & 0 \\ \mp 1 & 0 & 0 \\ 0 & 0 & 1 \end{pmatrix}$$

3D Keypoint-based Motion Estimation

- In the stereo case, rotation and translation between the left and right image are known
- We can first match keypoints between the left and right image, and triangulate their 3D positions
- To estimate motion between two stereo image pairs, we could use the 8-point algorithm as well on the keypoints in the left images and recover scale from the triangulated stereo depth

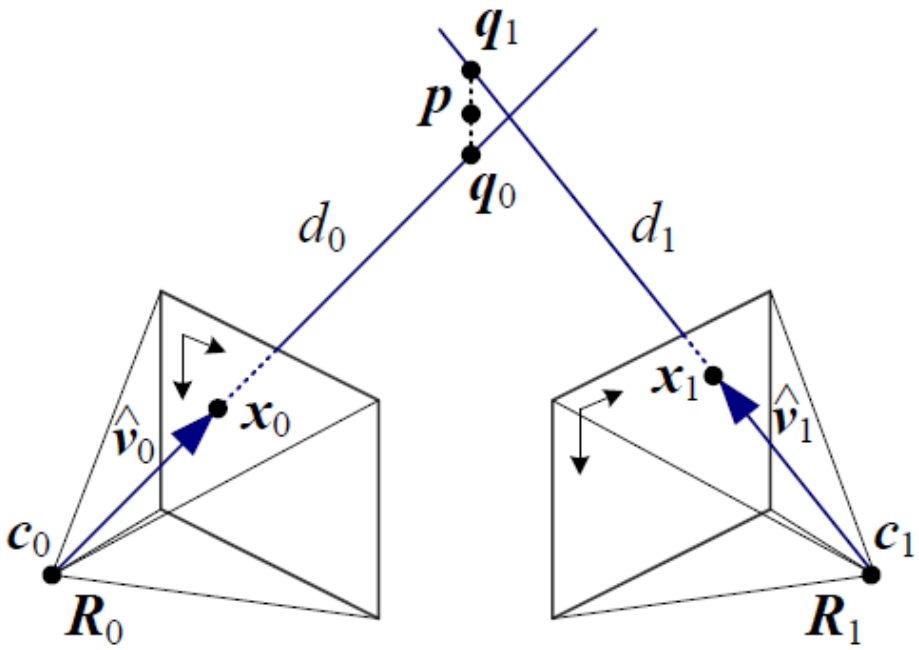
- Alternatively, least-squares optimization of the reprojection error is now simpler, since we know the 3D positions of the keypoints

$$E(R,t) = \frac{1}{N}\sum_i \left\| z_{1,i} - \pi(R^T x_i - R^T t) \right\|_2^2 + \left\| z_{2,i} - \pi(R x_i + t) \right\|_2^2$$

Triangulation

- **Given:** n cameras $\{M_j = K_j(R_j \; \mathbf{t}_j)\}$

  Point correspondence $\mathbf{x}_0, \mathbf{x}_1$
- **Wanted:** Corresponding 3D point $\mathbf{p}$



Triangulation

- Where do we expect to see $\mathbf{p} = (X \; Y \; Z \; W)^\top$?

$$\hat{x} = \frac{m_{11}X + m_{12}Y + m_{13}Z + m_{14}W}{m_{31}X + m_{32}Y + m_{33}Z + m_{34}W} \qquad \hat{y} = \frac{m_{21}X + m_{22}Y + m_{23}Z + m_{24}W}{m_{31}X + m_{32}Y + m_{33}Z + m_{34}W}$$

- Minimize the residuals

$$\mathbf{p}^* = \arg\min_{\mathbf{p}} \sum_j d(\mathbf{x}_j, \hat{\mathbf{x}}_j)^2$$

Triangulation

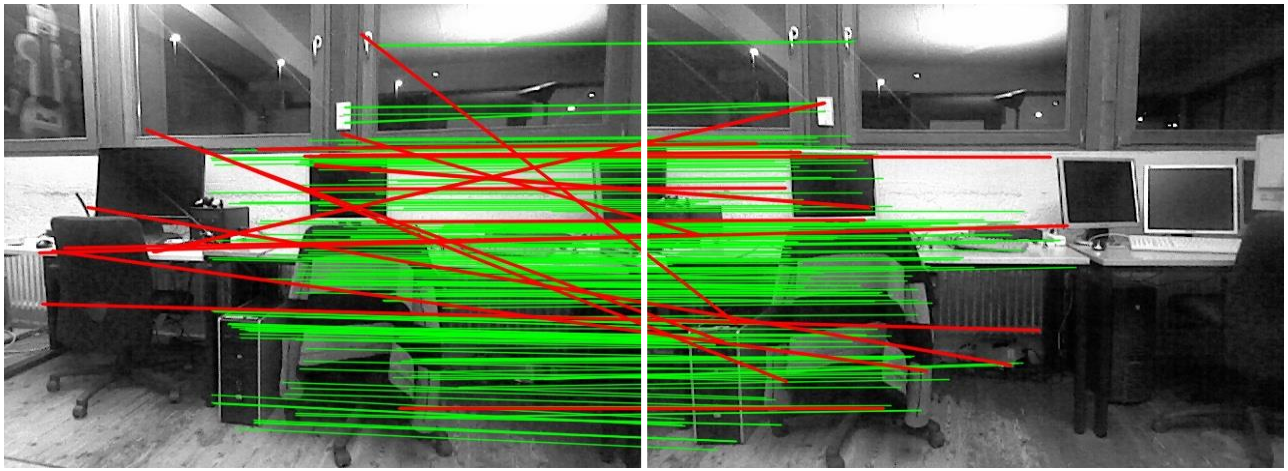
- Multiply with denominator gives

$$0 = (x_j m_{31} - m_{11})X + (x_j m_{32} - m_{12})Y + (x_j m_{33} - m_{13})Z + (x_j m_{34} - m_{14})W$$
$$0 = (y_j m_{31} - m_{21})X + (y_j m_{32} - m_{22})Y + (y_j m_{33} - m_{23})Z + (y_j m_{34} - m_{24})W$$

Solve for $\mathbf{p} = (X\ Y\ Z\ W)^\top$ using:

- Linear least squares with W=1
- Linear least squares using SVD
- Non-linear least squares of the residuals (most accurate)

Robust Keypoint Matching



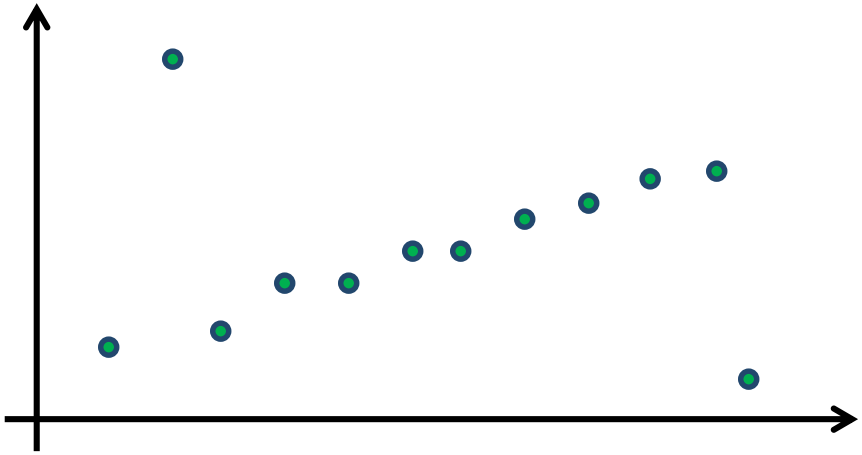
- Keypoint detectors and descriptors are not perfect
- Pose estimation can be very sensitive to wrong correspondences (especially when using the 8-point algorithm)

- What can we do?
- Idea: try out different combinations of 8 matches until we find a good fit for most of the overall keypoints

- Random Sample Consensus (RANSAC) algorithm

Robust Estimation

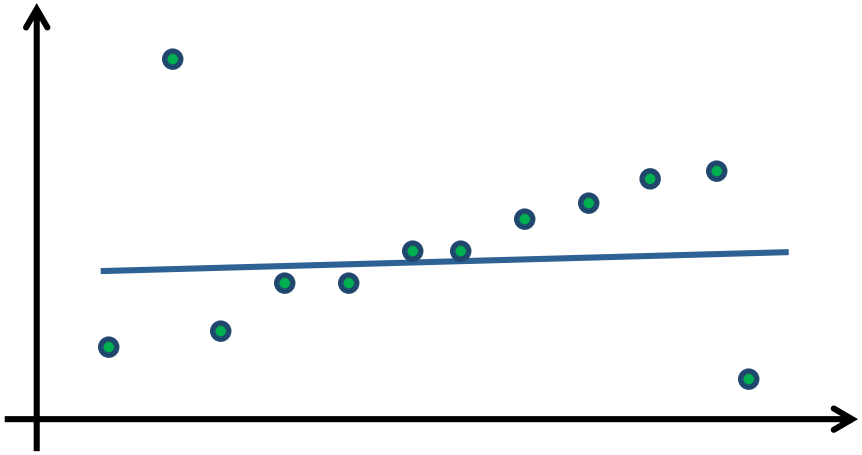
Example: Fit a line to 2D data containing outliers



- Input data is a mixture of
  - Inliers (perturbed by Gaussian noise)
  - Outliers (unknown distribution)
- Let's fit a line using least squares…

Robust Estimation

Example: Fit a line to 2D data containing outliers



- Input data is a mixture of
  - Inliers (perturbed by Gaussian noise)
  - Outliers (unknown distribution)
- Least squares fit gives poor results!

RANdom SAmple Consensus (RANSAC) [Fischler and Bolles, 1981]

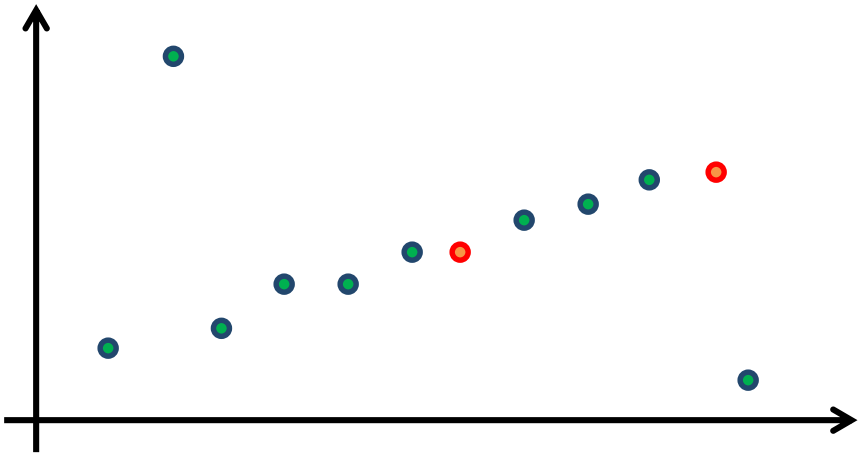
Goal: Robustly fit a model to a data set S which contains outliers

Algorithm:

1. Randomly select a (minimal) subset
2. Instantiate the model from it
3. Using this model, classify all data points as inliers or outliers
4. Repeat 1-3 for N iterations
5. Select the largest inlier set, and re-estimate the model from all points in this set

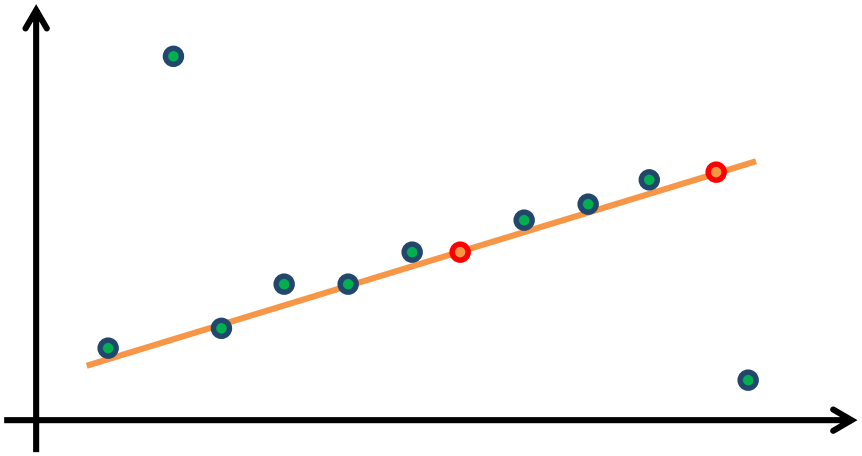
Example

- Step 1: Sample a random subset



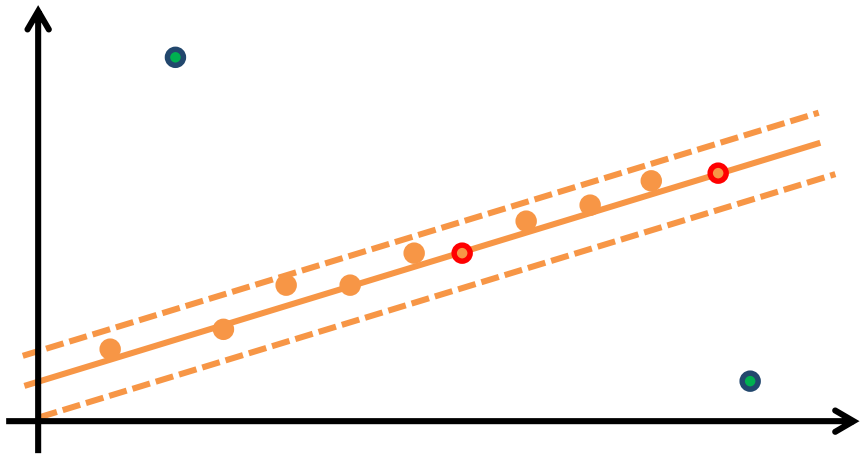
Example

- Step 2: Fit a model to this subset



Example

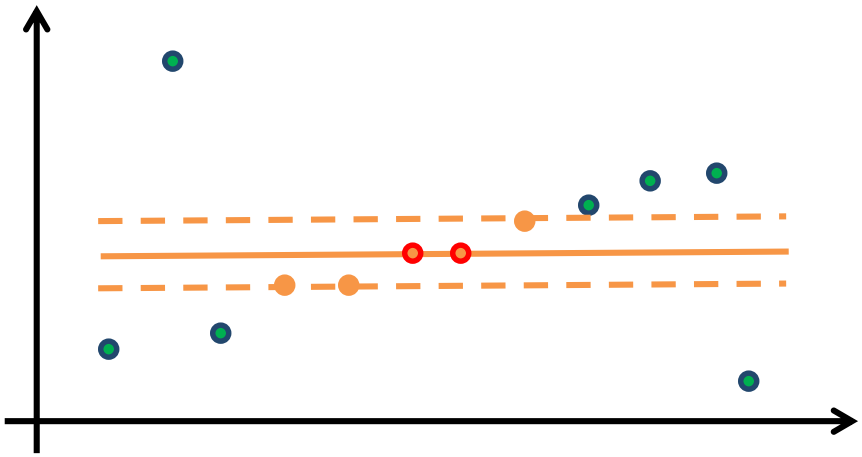
- Step 3: Classify points as inliers and outliers (e.g., using a threshold distance)



→ 10 inliers, 2 outliers

Example

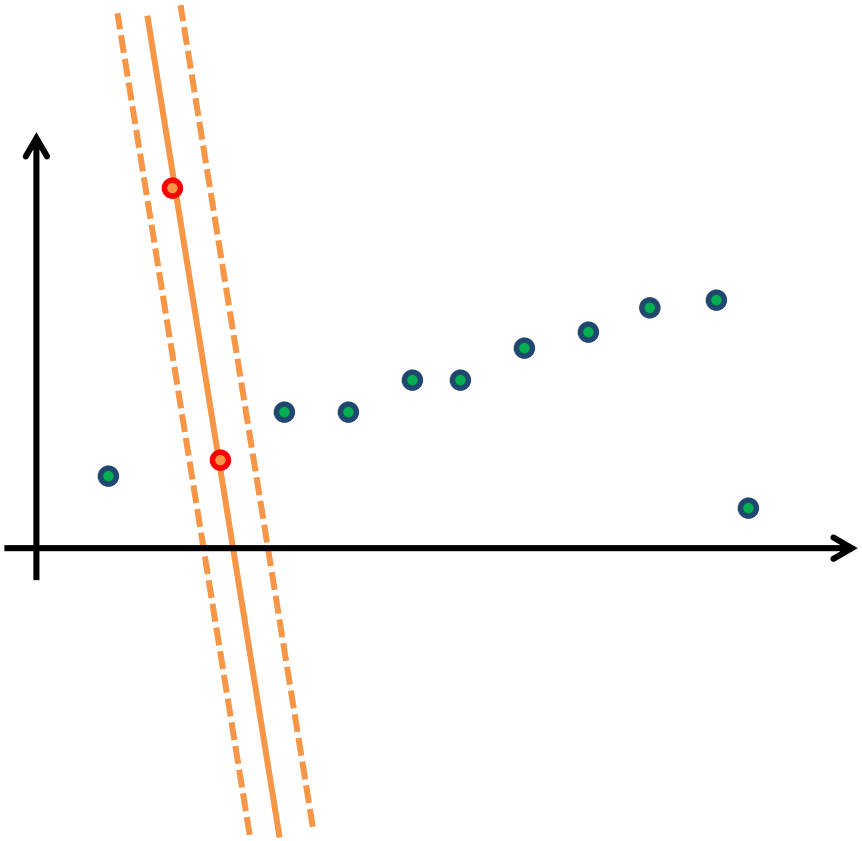
- Step 4: Repeat steps 1-3 for N iterations



Iteration 2:
→ 5 inliers, 7 outliers

Example

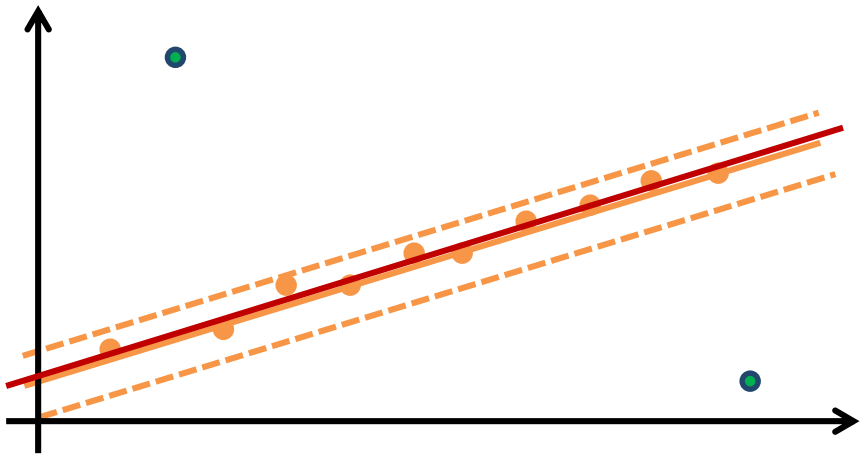
- Step 4: Repeat steps 1-3 for N iterations



Iteration 3:
→ 2 inliers, 10 outliers

Example

- Step 5: Select the best model (most inliers), then re-fit model using all inliers



Best model:
Iteration 1
(10 inliers, 2 outliers)

How Many Iterations Do We Need?

- For a probability of success p, we need

$$N = \frac{\log(1-p)}{\log(1-(1-\epsilon)^s)}$$ iterations

  for subset size s and outlier ratio ϵ

- E.g., for p=0.99:

	Required points s	Outlier ratio ε						
		10 %	20 %	30 %	40 %	50 %	60 %	70 %
Line	2	3	5	7	11	17	27	49
Plane	3	4	7	11	19	35	70	169
Essential matrix	8	9	26	78	272	1177	7025	70188

Summary on RANSAC

- Efficient algorithm to estimate a model from noisy and outlier-contaminated data
- RANSAC is used today very widely
- Often used in feature matching / visual motion estimation
- Many improvements/variants (e.g., PROSAC, MLESAC, …)

Lessons Learned Today

- Overview on visual odometry and SLAM
- How to estimate motion from keypoints from monocular images using the 8-point algorithm
- How to use the 8-point algorithm for stereo and RGB-D
- How to triangulate keypoint matches given the camera pose
- How to separate inliers from outliers using RANSAC

Questions ?