Inside-out (Visual) Tracking

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Content is largely borrowed from vSLAM tutorial by Prof. L. Freda (University of Rome)

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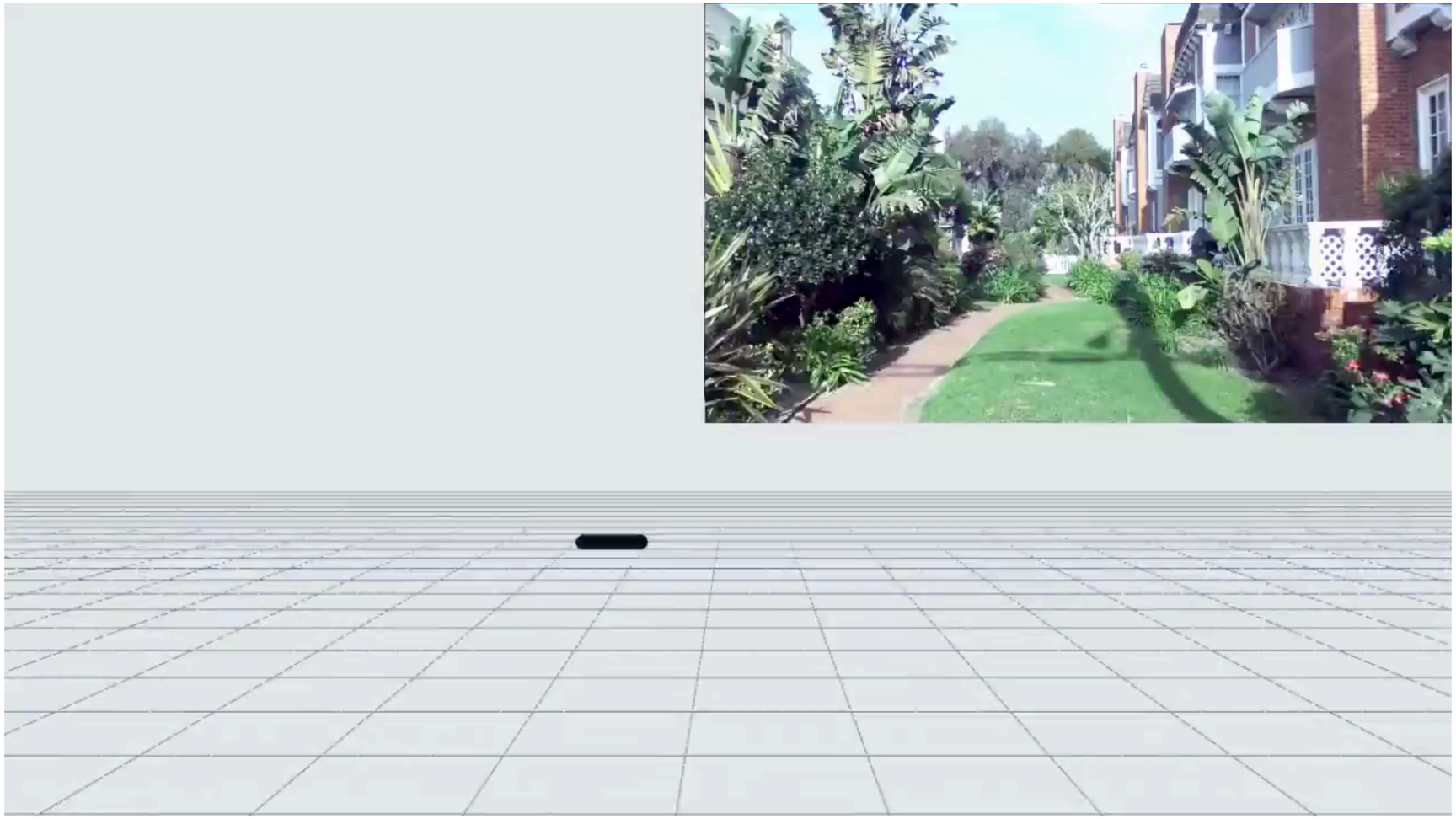
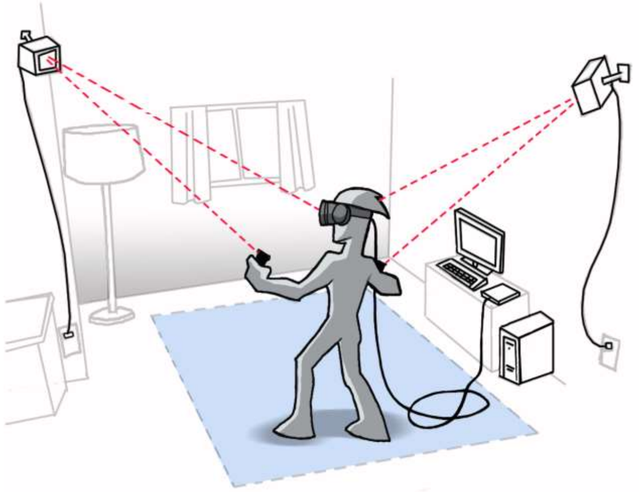
Positional Tracking



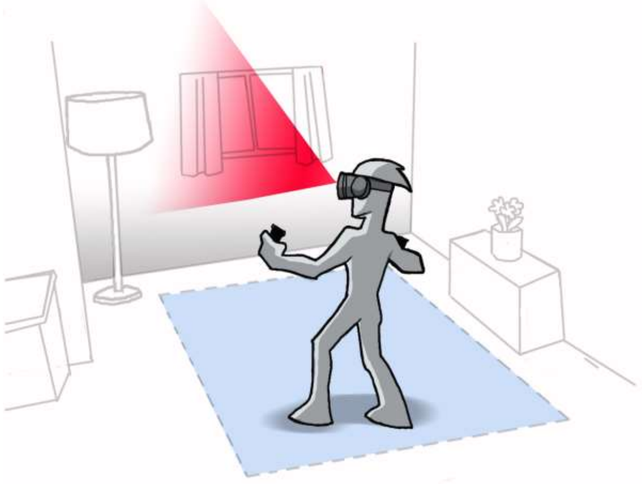
https://www.stereolabs.com/

Positional Tracking

- **Outside-in Tracking**: External sensors, cameras, or markers are required.



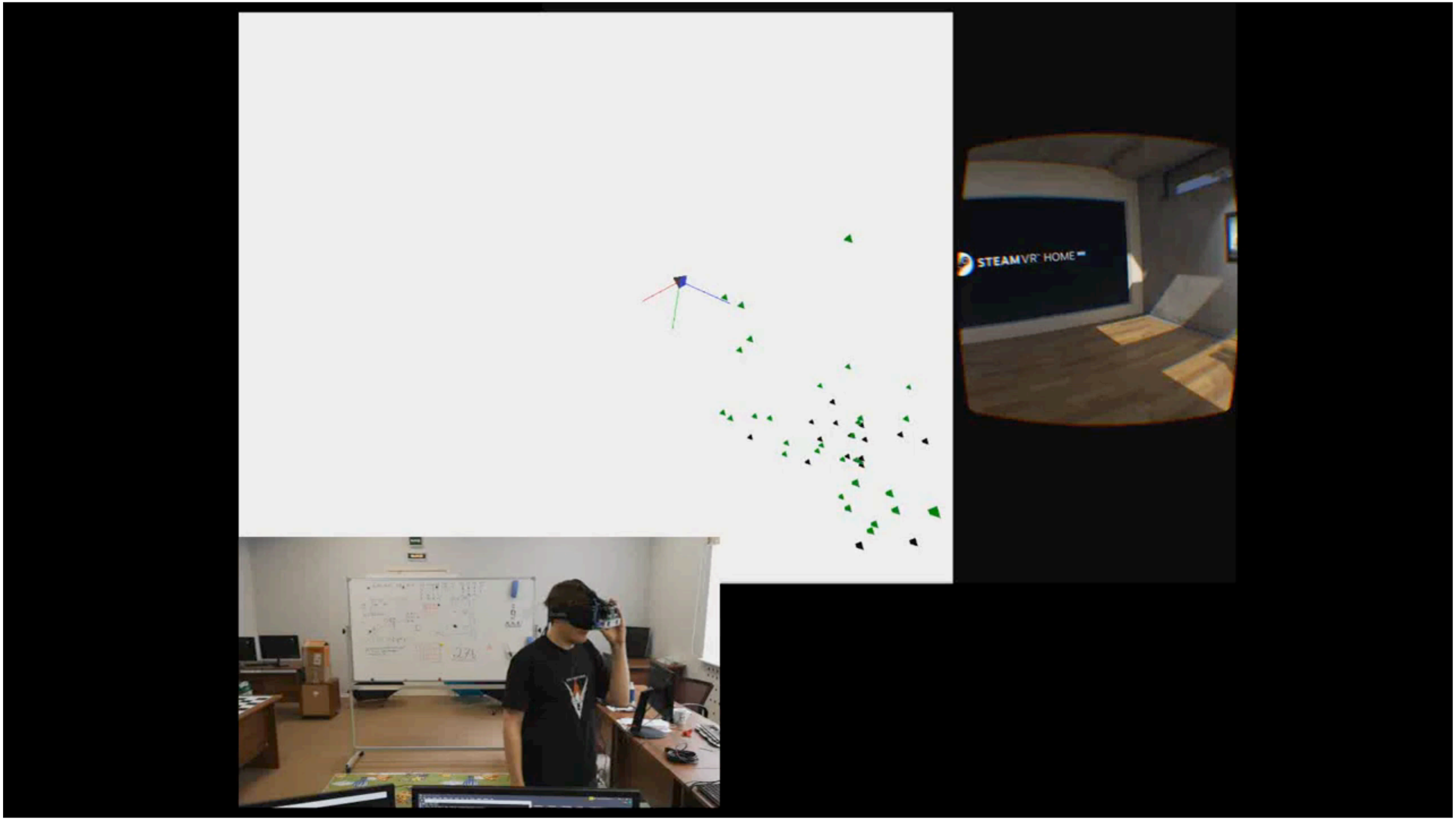
- **Inside-out Tracking**: Camera or sensor is located on HMD, no need for other external devices to do tracking.



Inside-out (Visual) Tracking

- **Unknown space**
- **Uncontrolled camera (6DoF motion)**
- **Real-time**
- **Drift-free**

https://www.youtube.com/watch?v=6S1la9SXntM



https://www.youtube.com/watch?v=6S1la9SXntM

Inside-out (Visual) Tracking

Two key steps:

1. **Mapping the unknown 3D world**
2. **Localizing the ego camera pose**

Doing it together:
“visual Simultaneous Localization and Mapping (vSLAM)”

vSLAM

Mapping – "What does the world look like?"
Integration of the information gathered with sensors into a given representation.

Localization – "Where am I?"
Estimation of the robot pose relative to a map. Typical problems:
(i) pose tracking, where the initial pose of the vehicle is known
(ii) global localization, where no a priori knowledge about the starting position is given.

Simultaneous localization and mapping (**SLAM**)
Build a map while at the same time localizing the robot within that map. The *chicken and egg problem*: A good map is needed for localization while an accurate pose estimate is needed to build a map.

Visual SLAM: SLAM by using *visual* sensors such as monocular cameras, stereo rigs, RGB-D cameras, DVS, etc

vSLAM System Overview

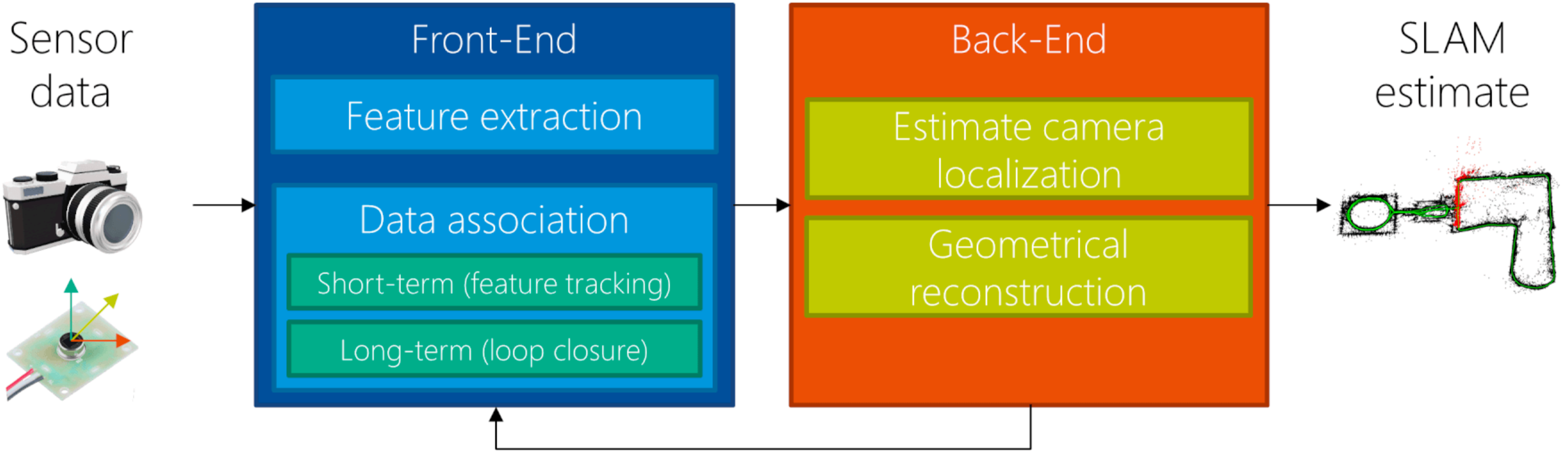


Diagram based on: Cadena, Cesar, et al. "Past, present, and future of simultaneous localization and mapping: Toward the robust-perception age." *IEEE Transactions on Robotics* 32.6 (2016): 1309-1332.
SLAM estimate: R. Mur-Artal, J. M. M. Montiel and J. D. Tardós, "ORB-SLAM: A Versatile and Accurate Monocular SLAM System," in *IEEE Transactions on Robotics*, vol. 31, no. 5, pp. 1147-1163, Oct. 2015.

vSLAM System Overview

1. **Sensor data:** Usually includes the camera, accelerometer and gyroscope. It might be augmented by other sensors like GPS, light sensor, depth sensors, etc.

2. **Front-End:** The first step is feature extraction. These features also need to be associated with landmarks – keypoints with a 3D position, also called *map points*. In addition, map points need to be tracked in a video stream.
   Long-term association reduces drift by recognizing places that have been encountered before (loop closure).

3. **Back-End:** Takes care of establishing the relationship between different frames, localizing the camera (pose model), as well as handling the overall geometrical reconstruction. Some algorithms create a sparse reconstruction (based on the keypoints). Others try to capture a dense 3D point cloud of the environment.

4. **SLAM estimate:** The result containing the tracked features, their locations & relations, as well as the camera position within the world.

vSLAM System Overview

Multi-Trajectory Pose Correspondences using Scale-Dependent Topological Analysis of Pose-Graphs

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Why vSLAM

Why using a camera?

- Vast information
- Extremely low Size, Weight, and Power (SWaP) footprint
- Cheap and easy to use
- Passive sensor

Challenge

- We need power efficiency for truly capable always-on tiny devices; or to do much more with larger devices

Question

- How does the human brain achieve always-on, dense, semantic vision with very limited power?

Visual Odometry (VO)

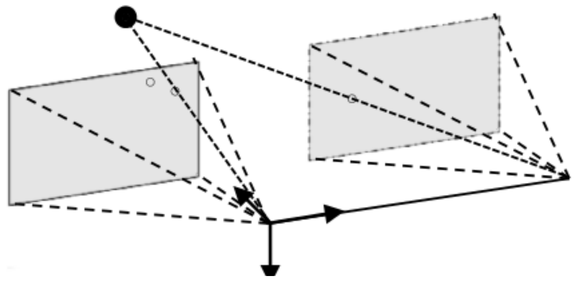
- An agent is moving through the environment and taking images with a rigidly-attached camera system at discrete times k
- In case of a **monocular system**, the set of images taken at times k is denoted by

$$I_{l,0:n} = \{I_0, ..., I_n\}$$

- In case of a **stereo system**, the set of images taken at times k is denoted by

$$I_{l,0:n} = \{I_{l,0}, ..., I_{l,n}\}$$
$$I_{r,0:n} = \{I_{r,0}, ..., I_{r,n}\}$$

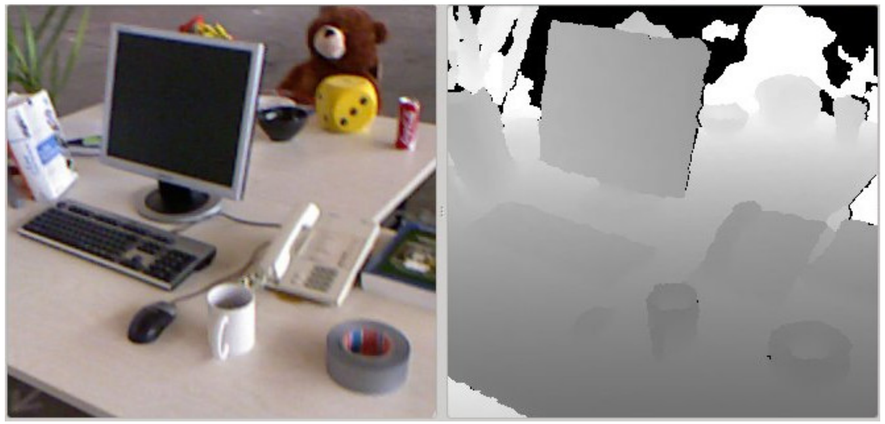
In this case, without loss of generality, the coordinate system of the left camera can be used as the origin



Visual Odometry (VO)

- In case of a **RGB-D camera**, the set of images taken at times k is denoted by

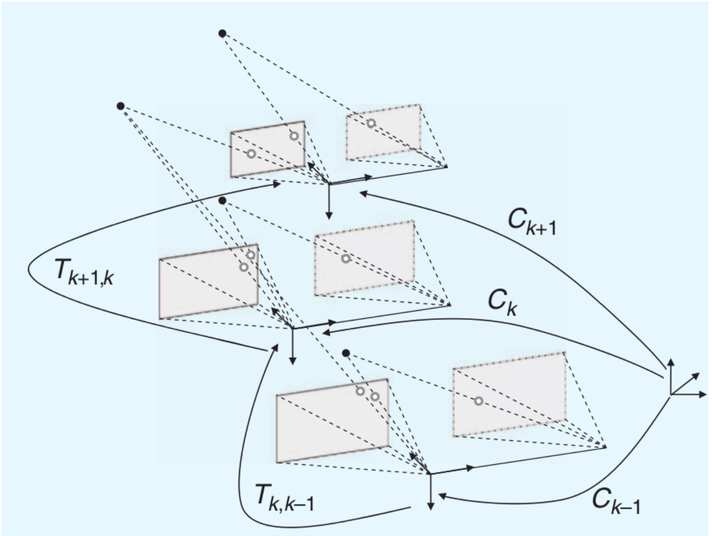
$$I_{0:n} = \{I_0, ..., I_n\}$$
$$D_{0:n} = \{D_0, ..., D_n\}$$



- Two camera positions at adjacent time istants $k-1$ and k are related by the rigid body transformation $T_k = \begin{bmatrix} R_{k-1,k} & t_{k-1,k} \\ 0 & 1 \end{bmatrix}$
- The set $T_{1:n} = \{T_1, ..., T_n\}$ contains all the subsequent motions

Visual Odometry (VO)

- The set of camera pose $C_{0:n} = \{C_0, ..., C_n\}$ contains the transformations of the camera w.r.t. the initial coordinate frame at $k = 0$



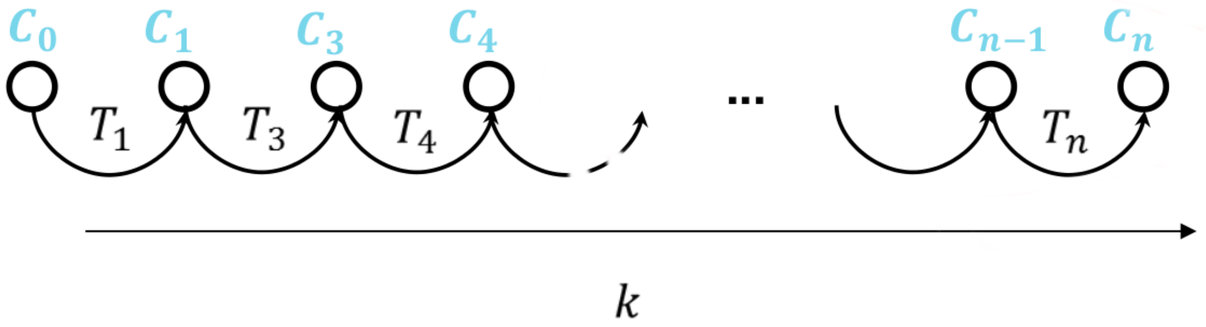
- The current camera pose C_n can be computed by concatenating all the transformations $T_{1:k}$, therefore

$$C_n = C_{n-1} T_n$$

with C_0 being the camera pose at the instant $k = 0$, which can be arbitrarily set by the user

Visual Odometry (VO)

- The main task of VO is to compute the relative transformations T_k from images I_k and I_{k-1} and then to concatenate these transformation to recover the full trajectory $C_{0:n}$ of the camera
- This means that VO recovers the path incrementally, pose after pose



Visual Odometry (VO)

Usual assumptions about the environment

- Sufficient illumination in the environment
- Dominance of static scene over moving objects
- Enough texture to allow apparent motion to be extracted
- Sufficient scene overlap between consecutive frames

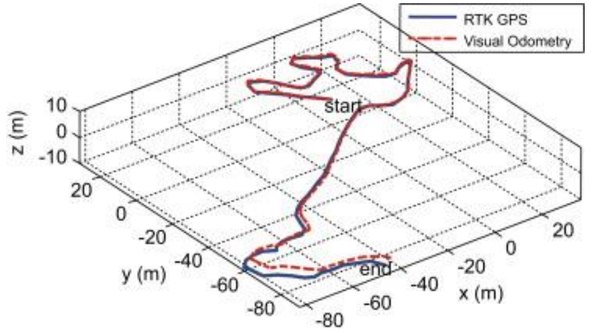
Are these examples OK?



Visual Odometry (VO)

Advantages of Visual odometry

- Contrary to wheel odometry, VO is not affected by wheel slip in uneven terrain or other adverse conditions.
- More accurate trajectory estimates compared to wheel odometry (relative position error 0.1% 2%)
- VO can be used as a complement to wheel odometry
  - GPS
  - inertial measurement units (IMUs)
  - laser odometry
- In GPS-denied environments, such as underwater and aerial, VO has utmost importance

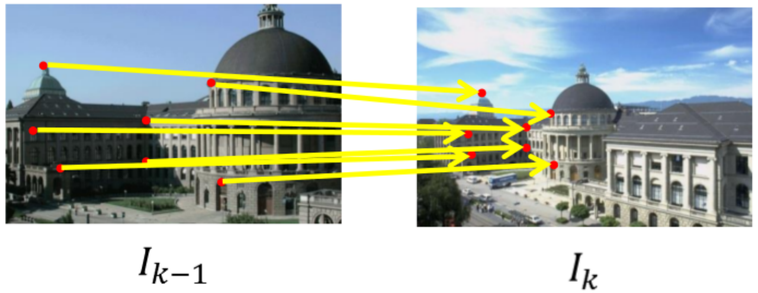


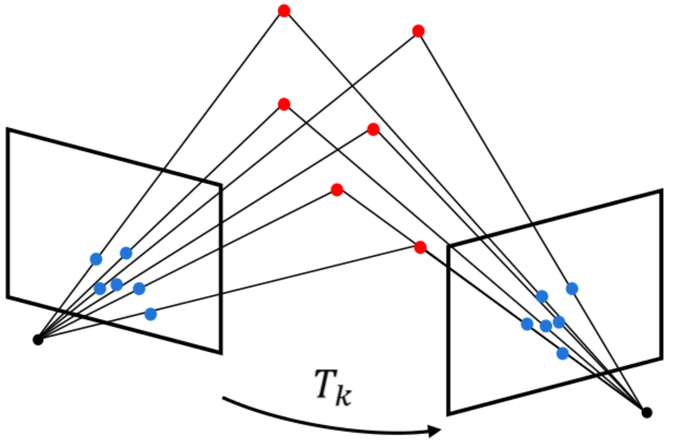
Visual Odometry Pipeline

Visual odometry (VO) feature-based

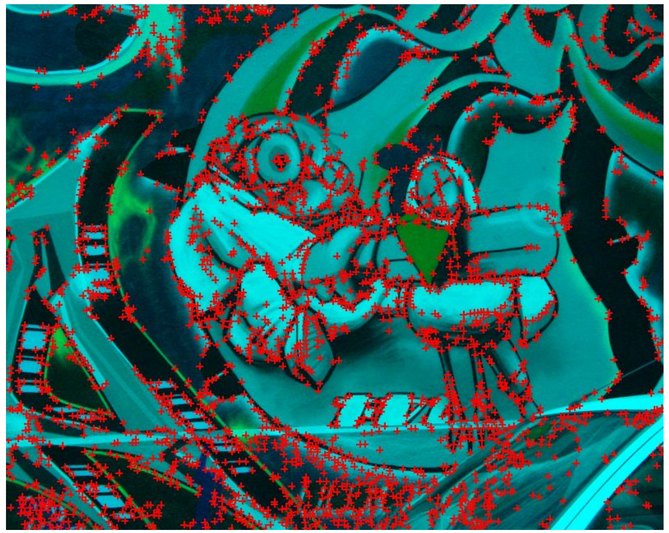
Overview

1. Feature detection
2. Feature matching/tracking
3. Motion estimation
4. Local optimization



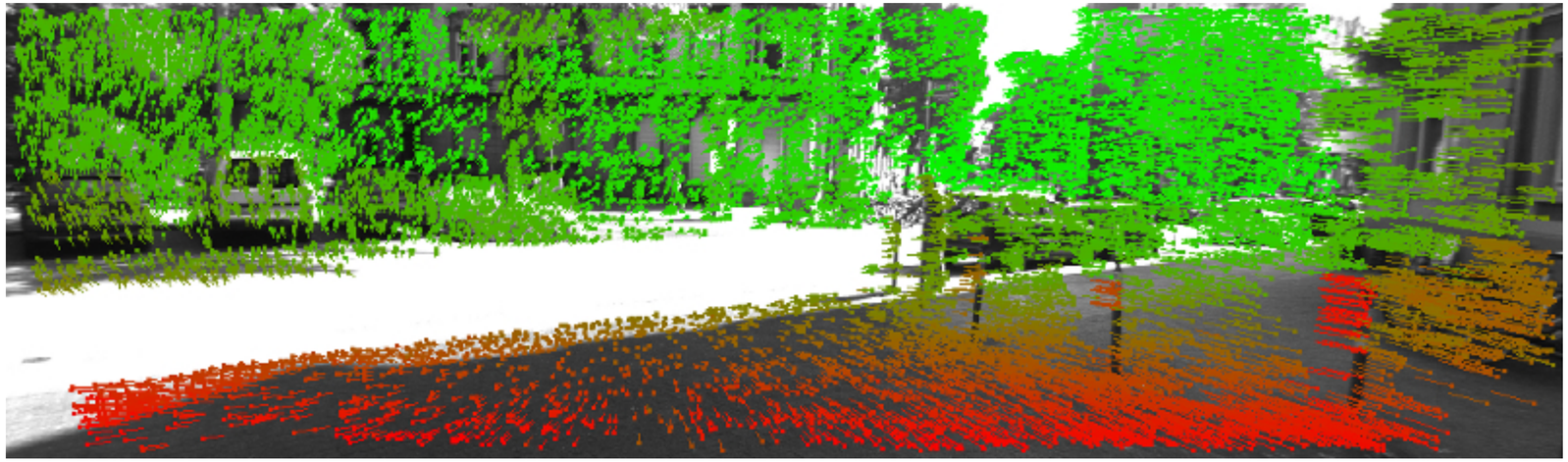


Visual Odometry Pipeline



Visual odometry (VO) feature-based
Assumption: camera is well calibrated

1. **Feature detection**:
   Detect a set of features f_k at time k
   (General idea: extract high-contrast areas in the image)



2. **Feature matching/Feature tracking**
   Find correspondences between set of features f_{k-1} , f_k
   - tracking: locally search each feature (e.g. by prediction and correlation)
   - matching: independently detect features in each image and find correspondences on the basis of a similarity metric (exploit descriptors such SURF, SIFT, ORB, etc)

Visual Odometry Pipeline

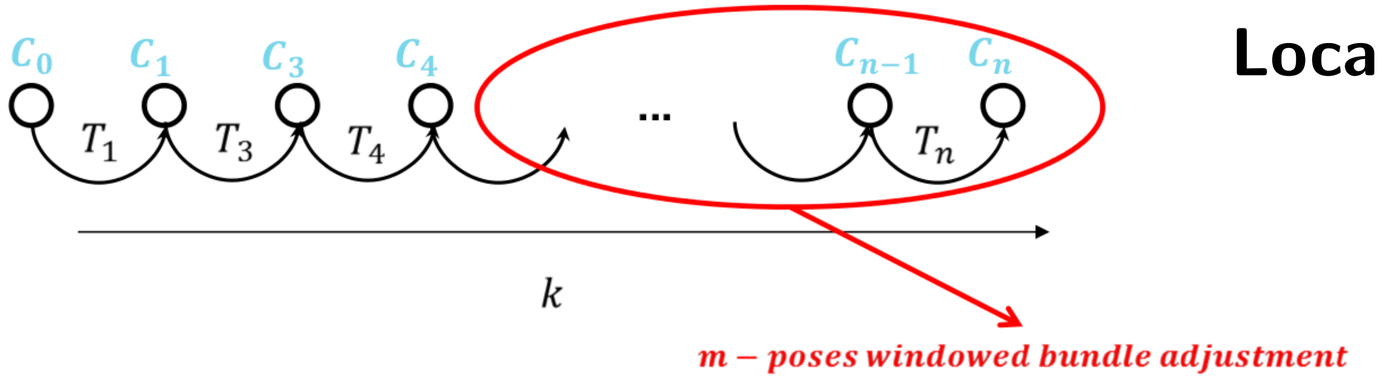
3. **Motion estimation**
   Compute transformation T_k between two images I_{k-1} and I_k from two sets of corresponding features f_{k-1} , f_k.
   Different algorithms depending on available sensor data:

   - *2-D to 2-D*: works on f_{k-1} , f_k specified in 2-D image coords
   - *3-D to 3-D*: works on X_{k-1} , X_k, sets of 3D points corresponding to f_{k-1} , f_k
   - *3-D to 2-D*: works on X_{k-1}, set of 3D points corresponding to f_{k-1}, and on f_k their corresponding 2-D reprojections on the image I_k

Type of correspondences	Monocular	Stereo
2D–2D	X	X
3D–3D		X
3D–2D	X	X

Visual Odometry Pipeline

4. An iterative refinement over last m poses can be **optionally** performed after motion estimation to obtain a more accurate estimate of the **local** trajectory



Local optimization

One has to minimize the following image reprojection error

$$T_k = \begin{bmatrix} R_{k-1,k} & t_{k-1,k} \\ 0 & 1 \end{bmatrix} = \arg\min_{X^i, C_k} \sum_{i,k} \|p_k^i - g(X^i, C_k)\|$$

where p_i^k is the i-th image point of the 3D landmark X_i measured in the k-th image and $g(X_i, C_k)$ is its image reprojection according to the current camera pose C_k

Visual Odometry Pipeline

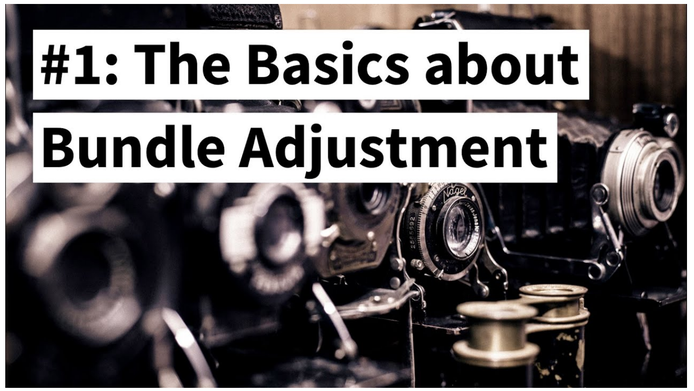
Bundle Adjustment

Least squares approach to estimating camera poses and 3D points

Key idea:

- Start with an initial guess
- Project the estimated 3D points into the estimated camera images
- Compare locations of the projected 3D points with measured (2D) ones
- Adjust to minimize error in the images

By Cyrill Stachniss

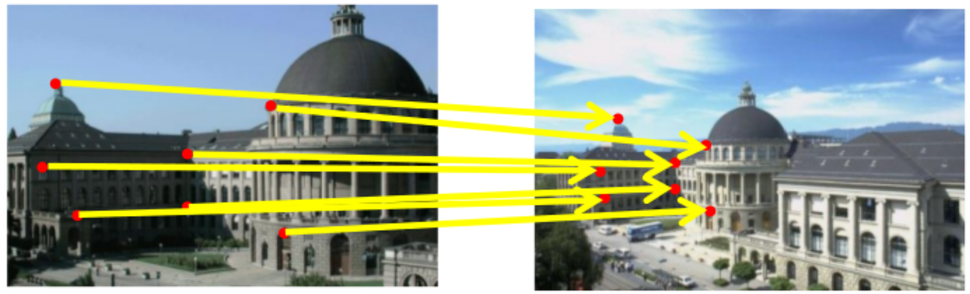


https://www.youtube.com/watch?v=sobyKHwgB0Y

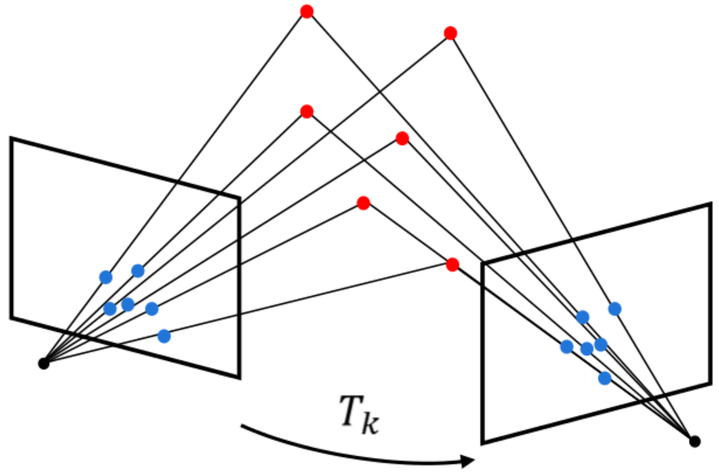
Visual Odometry Pipeline

VO from 2-D to 2-D (feature-based)

1. Capture new frame I_k
2. Extract and match features between I_{k-1} and I_k
3. Compute essential matrix for image pair I_{k-1} , I_k
4. Decompose essential matrix into R_k and t_k , and form T_k
5. Compute relative scale and rescale t_k accordingly
6. Concatenate transformation by computing $C_k = C_{k-1} T_k$
7. Repeat from 1).



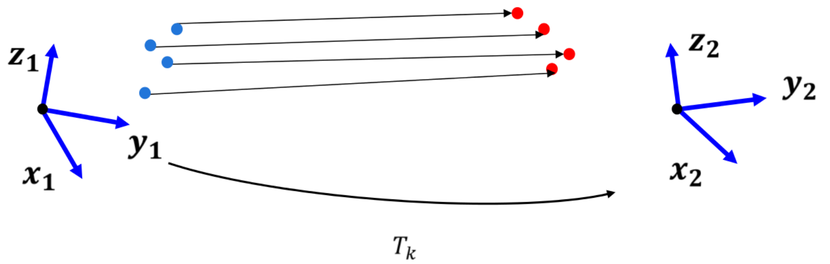
I_{k-1} I_k



$$T_k = \begin{bmatrix} R_{k,k-1} & t_{k,k-1} \\ 0 & 1 \end{bmatrix} = \arg\min_{X^i, C_k} \sum_{i,k} \| p_k^i - g(X^i, C_k) \|^2$$

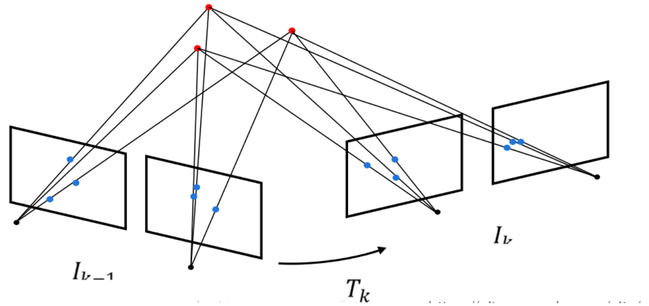
NOTE: The minimal-case solution involves 5-point correspondences

Visual Odometry Pipeline



VO from 3-D to 3-D (feature-based)

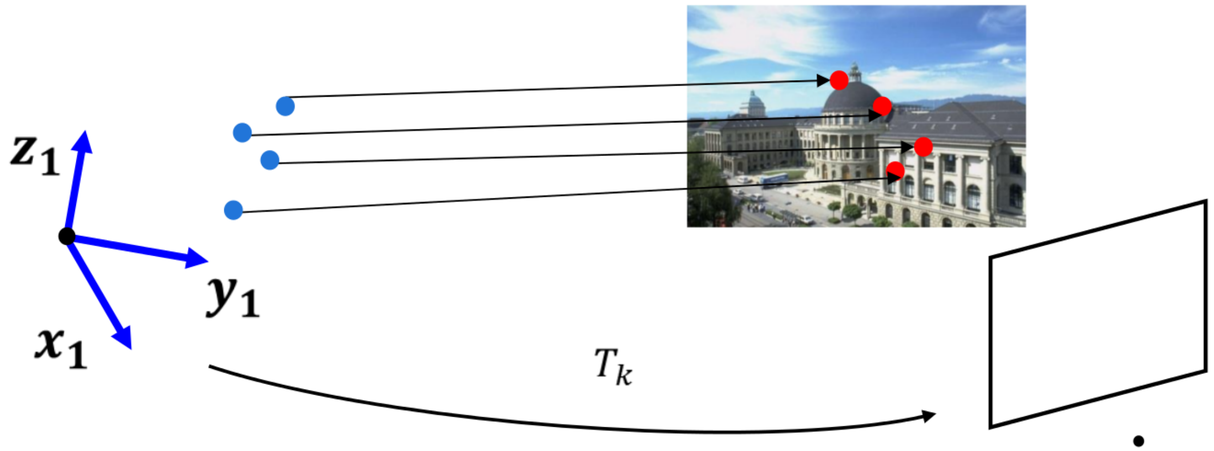
1. Capture two stereo image pairs $I_{l,k-1}$,$I_{r,k-1}$ and $I_{l,k}$,$I_{r,k}$
2. Extract and match features between $I_{l,k-1}$,$I_{l,k}$
3. Triangulate matched features for each stereo pair. Hence:
   $I_{l,k-1}$, $I_{r,k-1} \Rightarrow X_{k-1}$
   $I_{l,k}$, $I_{r,k} \Rightarrow X_k$
4. Compute T_k from 3-D features X_{k-1} and X_k
5. Concatenate transformation by computing $C_k = C_{k-1}T_k$
6. Repeat from 1).



$$T_k = \begin{bmatrix} R_{k,k-1} & t_{k,k-1} \\ 0 & 1 \end{bmatrix} = \arg\min_{T_k} \sum_i ||\tilde{X}_k^i - T_k \tilde{X}_{k-1}^i||$$

NOTE: The minimal-case solution involves 3 non-collinear correspondences

Visual Odometry Pipeline



VO from 3-D to 2-D (feature-based)

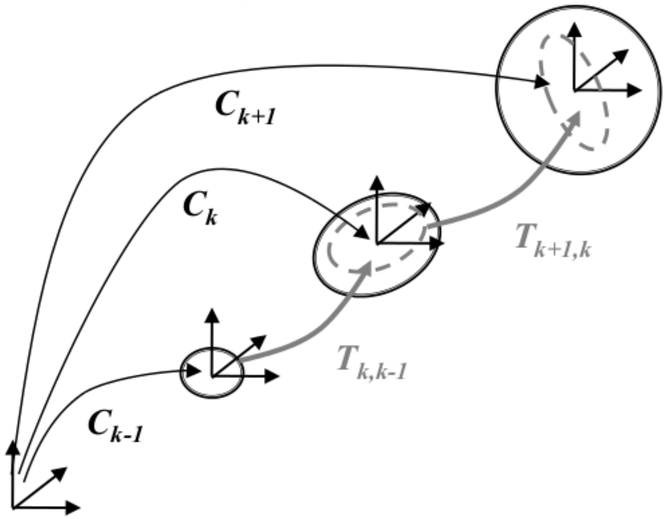
1. Do only once:
   - 1.1 Capture two frames I_{k-2} , I_{k-1}
   - 1.2 Extract and match features between them
   - 1.3 Triangulate features from I_{k-2} , I_{k-1} and get X_{k-1}
2. Do at each iteration:
   - 2.1 Capture new frame I_k
   - 2.2 Extract features and match with previous frame I_{k-1}
   - 2.3 Compute camera pose (PnP) from 3-D-to-2-D matches (between f_k and X_{k-1})
   - 2.4 Triangulate all new features between I_{k-1} and I_k and get X_k
   - 2.5 Iterate from 2.1

$$T_k = \begin{bmatrix} R_{k,k-1} & t_{k,k-1} \\ 0 & 1 \end{bmatrix} = \arg\min_{T_k} \sum_i \| p_k^i - \hat{p}_{k-1}^i \|^2$$

Visual Odometry (VO)

VO drift

1. The errors introduced by each new frame-to-frame motion accumulate over time
2. This generates a drift of the estimated trajectory from the real one



NOTE: the uncertainty of the camera pose at C_k is a combination of the uncertainty at C_{k-1} (black solid ellipse) and the uncertainty of the transformation $T_{k,k-1}$ (gray dashed ellipse)

VO vs SfM

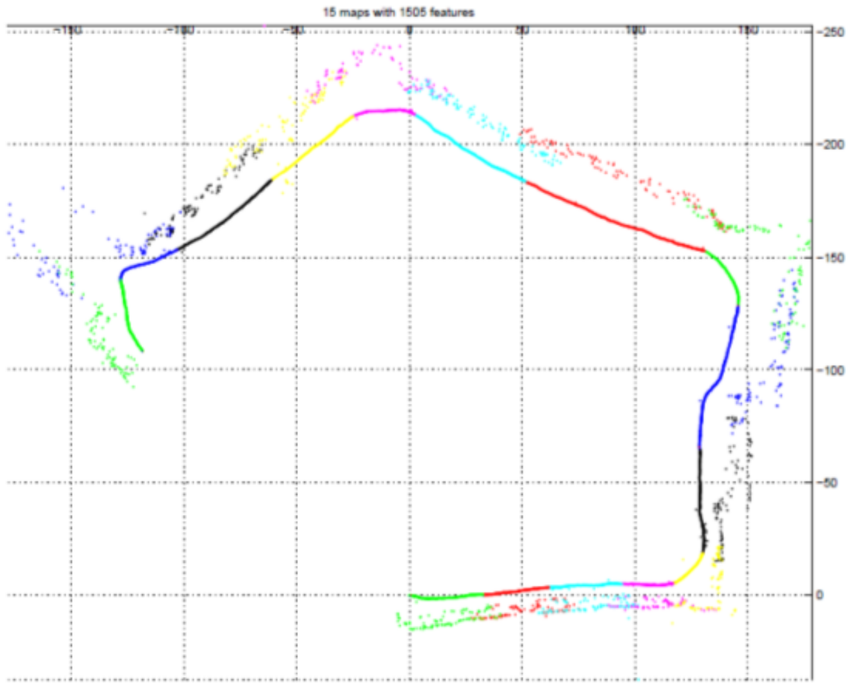
VO or SFM

- VO is a particular case of SFM
- VO focuses on estimating the 3D motion of the camera sequentially (as a new frame arrives) and in **real time**.
- Bundle adjustment can be used (but its optional) to refine the local estimate of the trajectory

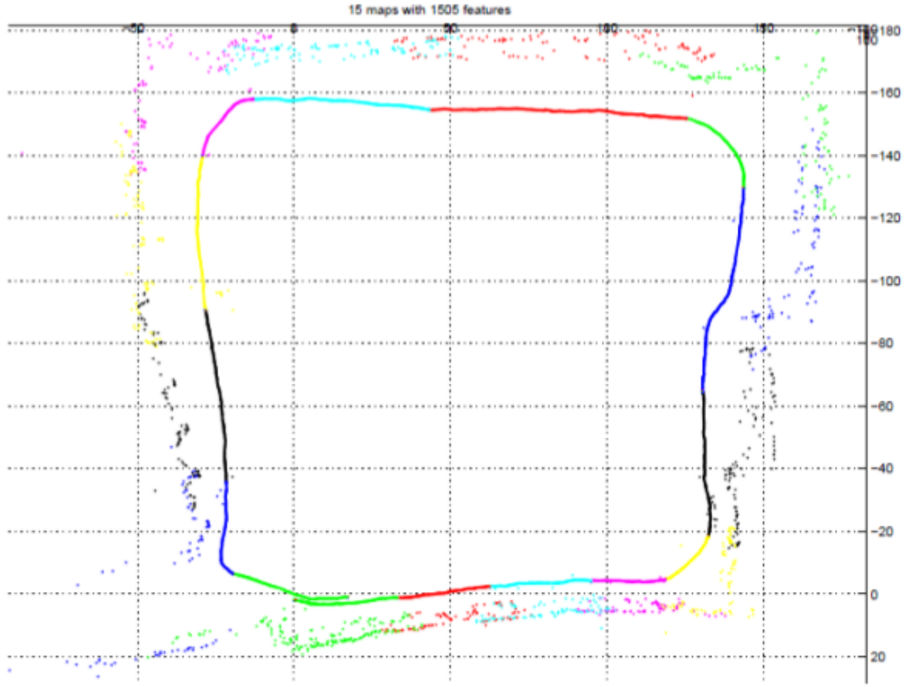
VO vs vSLAM

- The goal of **SLAM** in general is to obtain a **global** and **consistent** estimate of the robot **path** and the **map**. This is done by identifying **loop closures**. When a loop closure is detected, this information is used to reduce the drift in both the map and camera path (**global bundlel adjustment**)
- Conversely, **VO** aims at recovering a **path** incrementally, pose after pose, It can potentially use optimization only over the last m pose path (**windowed bundle adjustment**)

VO vs vSLAM



Before loop closing



After loop closing

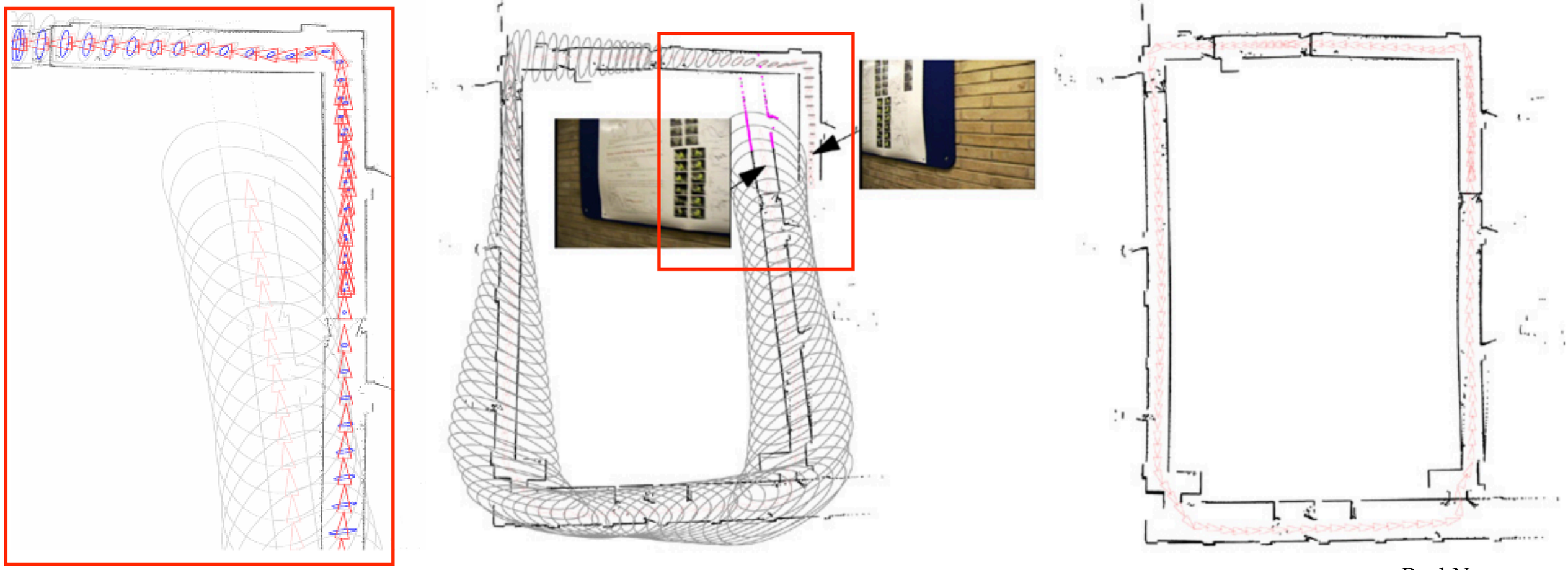
Image courtesy of Clemente et al. RSS'07

VO vs vSLAM

- VO only aims at the **local consistency** of the **trajectory**
- SLAM aims to the **global consistency** of the **trajectory** and of the **map**
- VO can be used as building block of SLAM
- VO is SLAM before closing the loop
- The choice between VO and V-SLAM depends on the tradeoff between *performance*, *consistency* and *simplicity of implementation*
- VO trades off consistency for real-time performance, without the need to keep track of all the previous history of the camera

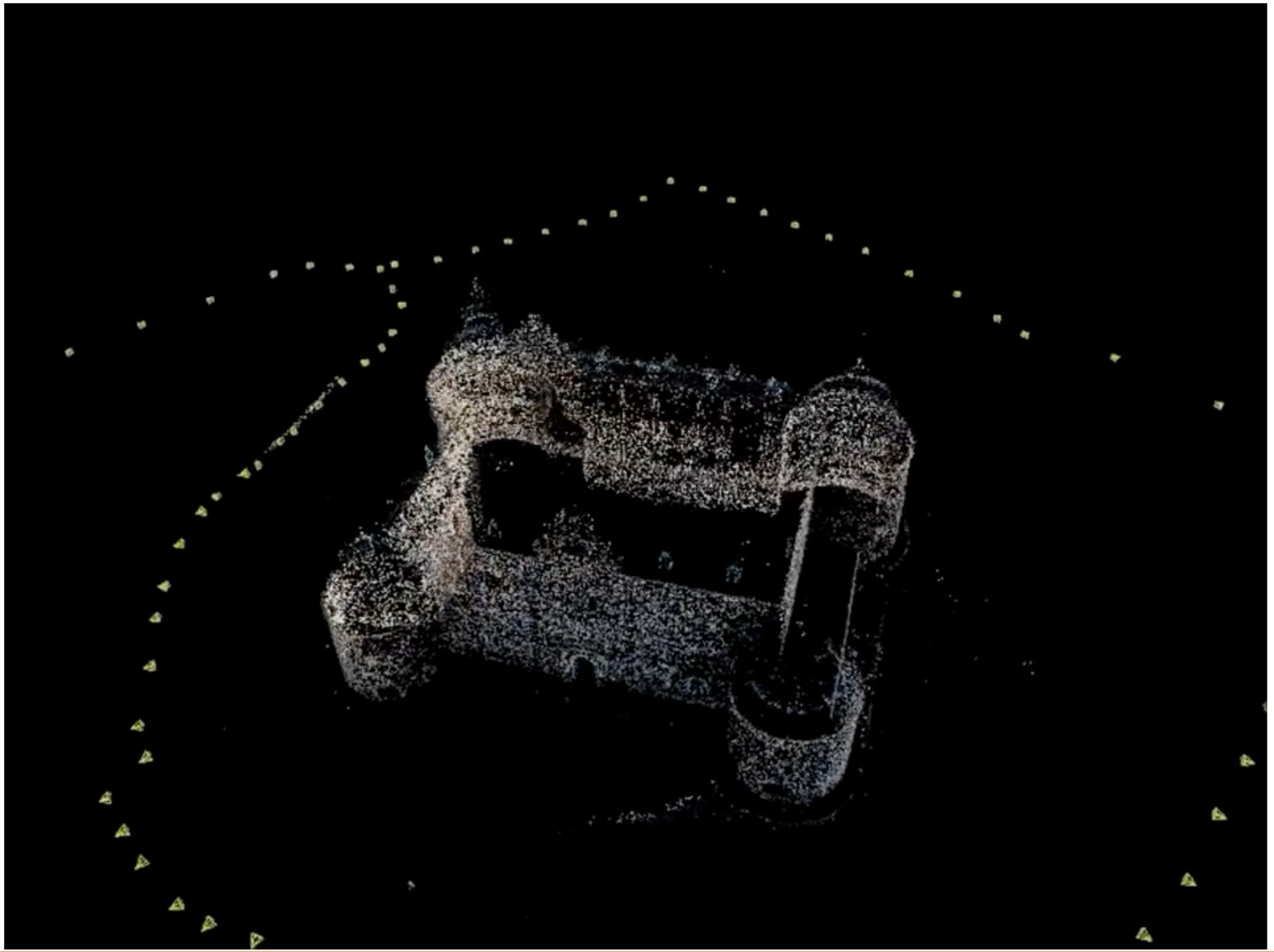
Loop Clousure

Recognizing an already mapped area, typically after a long exploration path.



Paul Newman

Structure from Motion (SfM)



ORB-vSLAM

Universidad Zaragoza

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Instituto Universitario de Investigación
en Ingeniería de Aragón
Universidad Zaragoza

ORB-SLAM2: an Open-Source SLAM System for Monocular, Stereo and RGB-D Cameras

Raúl Mur-Artal and Juan D. Tardós

raulmur@unizar.es tardos@unizar.es

Thank You !

Questions ?