# Visual SLAM

## An Overview

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# Outline


1. Introduction
   - What is SLAM
   - Motivations
2. Visual Odometry (VO)
   - Problem Formulation
   - VO Assumptions
   - VO Advantages
   - VO Pipeline
   - VO Drift
   - VO or SFM
3. Visual SLAM
   - VO vs Visual SLAM

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# SLAM

## Simultaneous Localization And Mapping

- **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

# Why using a camera?

Why using a camera?

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

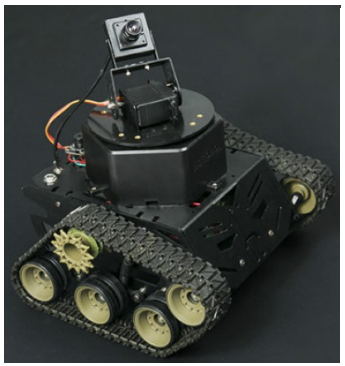
Challenge

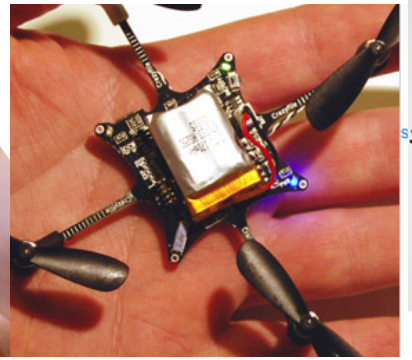
- We need power efficiency for truly capable always-on tiny devices; or to do much more with larger devices

Question

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

# Key Applications of Visual SLAM





- Low-cost robotics (e.g. a mobile robot with a cheap camera)
- Agile robotics (e.g. drones)
- Smartphones
- Wearables
- AR/VR: inside-out tracking, gaming

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# Why working on Visual SLAM?


Robotics and Computer Vision market is exponentially growing. Many robotic products, augmented reality and mixed reality apps/games, etc.

- **Google** (Project Tango, Google driverless car)
- **Apple** (acquisition of Metaio and Primesense, driverless car)
- **Dyson** (funded Dyson Robotics Lab, Research lab at Imperial College in London)
- **Microsoft** (Hololens and its app marketplace)
- **Magic Leap** (funded by Google with $542M)
- How many apps related to machine learning and pattern recognition?

# Why working on Visual SLAM?

From the article of **WIRED** magazine: *The Untold Story of Magic Leap, the Worlds Most Secretive Startup*

*But to really understand whats happening at Magic Leap, you need to also understand the tidal wave surging through the entire tech industry. All the major players* —**Facebook, Google, Apple, Amazon, Microsoft, Sony, Samsung** — *have whole groups dedicated to artificial reality, and theyre hiring more engineers daily. Facebook alone has over 400 people working on VR. Then there are some 230 other companies, such as* **Meta, the Void, Atheer, Lytro, and 8i**, *working furiously on hardware and content for this new platform.*

This technology will allow users to share and live active experiences by using Internet

# Videos

What research can do

- PTAM (with advanced AR)
- DTAM
- Elastic Fusion

What industry is actually doing

- Hololens
- Dyson360
- Project Tango
- Magic Leap

# Visual SLAM Modern Systems

- Positioning and reconstruction now rather mature... though many Researchers believe its still rather premature to call even that solved
- Quality open source systems: LSD-SLAM, ORB-SLAM, SVO, KinectFusion, ElasticFusion
- Commercial products and prototypes: Google Tango, Hololens, Dyson 360 Eye, Roomba 980
- But SLAM continues... and evolves into generic **real-time** 3D perception research

# Benefits

## Working on Visual SLAM

The skills learned by dealing the Visual SLAM will be very appreciated and highly valued in Industry

- Gain valuable skills in real-time C++ programming (code optimization, multi-threading, SIMD, complex data structures management)
- Work on a technology which is going to change the world
- Enrich your CV with a collaboration with the ALCOR Lab
- Have fun with Computer Graphics and Mixed Reality

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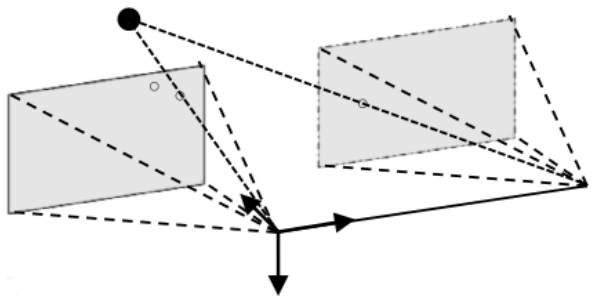
- An agent is moving through the environment and taking images with a rigidly-attached camera system at discrete times $k$
- In case of a **monocular system**, the set of images taken at times $k$ is denoted by

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

- 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

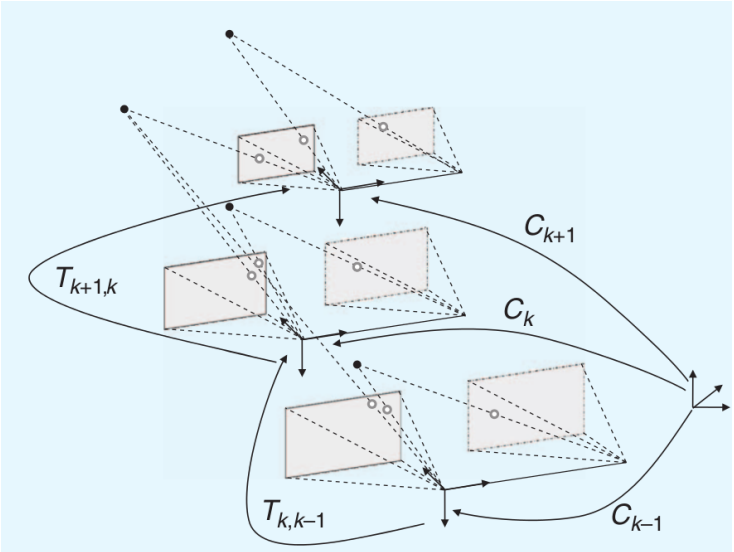


- In case of a **RGB-D camera**, the set of images taken at times $k$ is denoted by

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

- 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 motionsk

- 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 $k = 0$

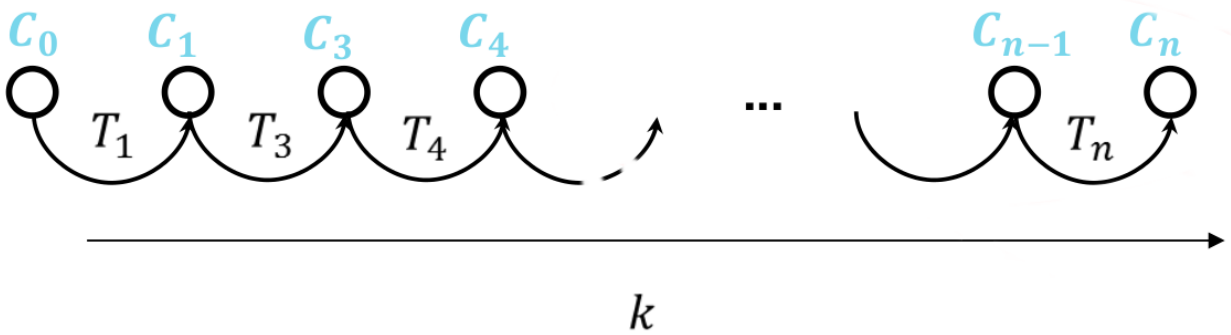



- The current camera pose $C_n$ can be computed by concatenating all the transformations $T_{1:k}$, therefore

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

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

- 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



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**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?



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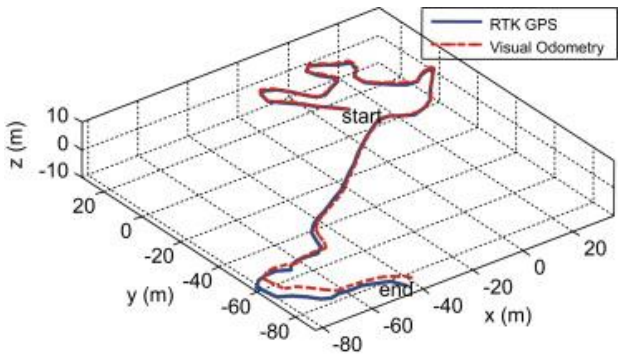
## Advantages of Visual odometry

- 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

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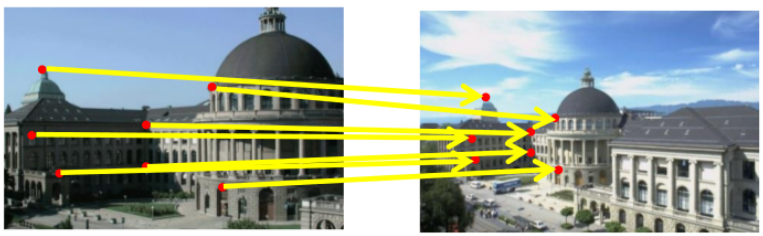
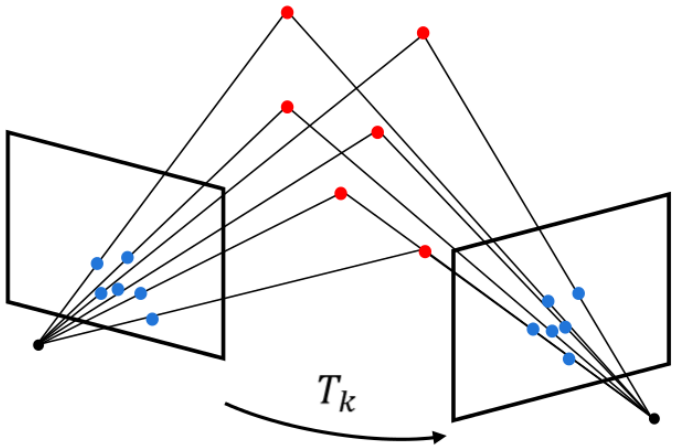
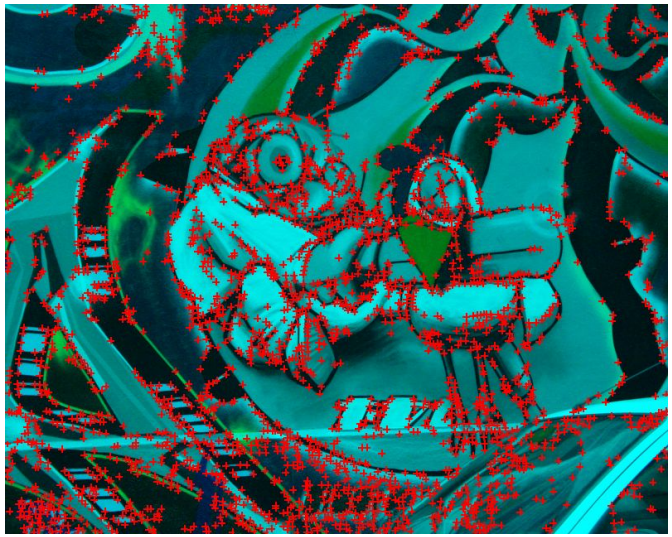
**Visual odometry (VO) feature-based**

Overview

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



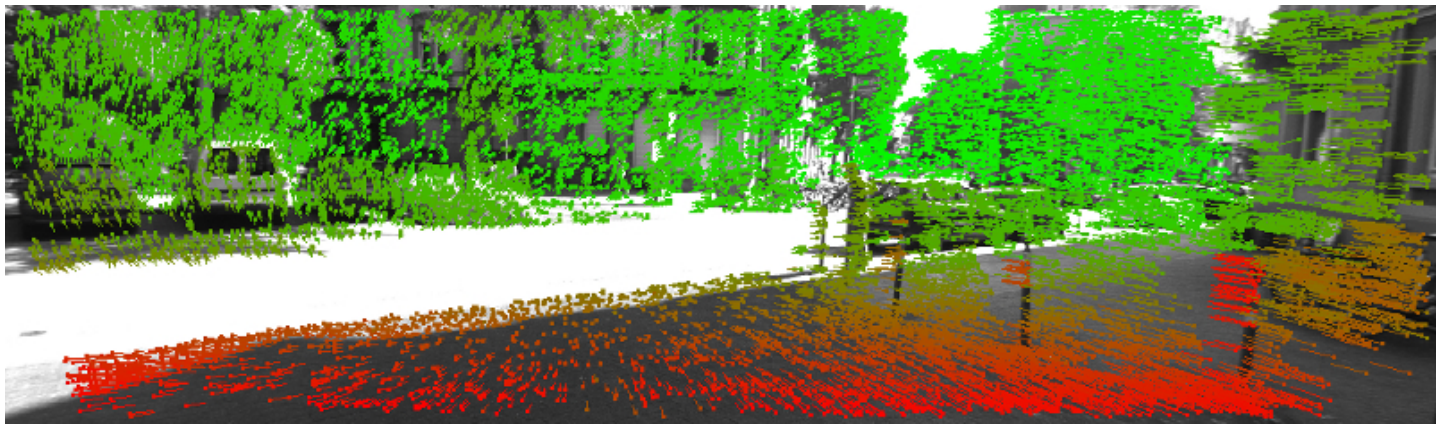





**Visual odometry (VO) feature-based**

*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)



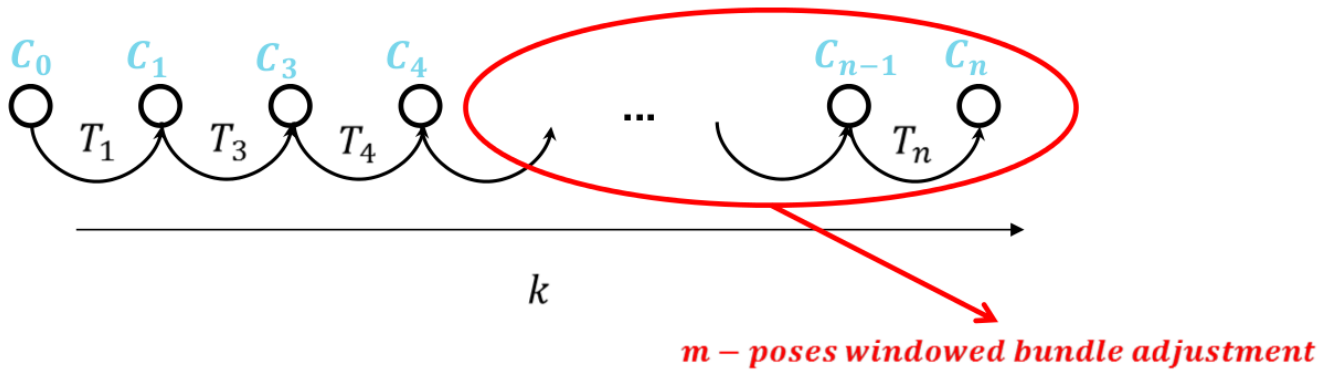
2. **Feature matching/Feature tracking**
   Find correspondences between set of features $f_{k-1}$ , $f_k$
   - tracking: locally search each feature (e.g. by prediction and correlation)
   - matching: independently detect features in each image and find correspondences on the basis of a similarity metric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

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 |

## Local optimization

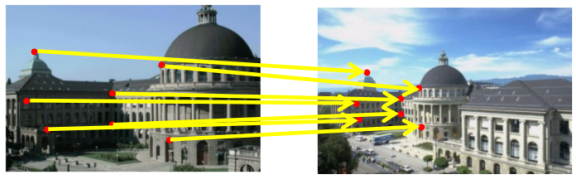
4. An iterative refinement over last $m$ poses can be **optionally** performed after motion estimation to obtain a more accurate estimate of the **local** trajectory

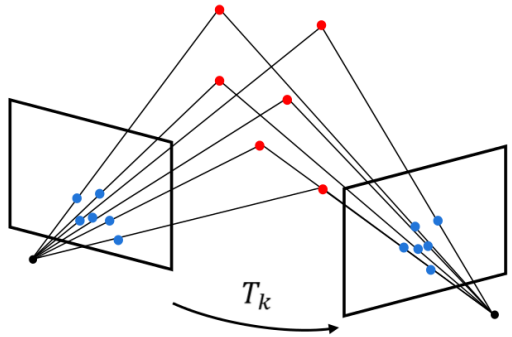



One has to minimize the following image reprojection error

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

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 $C_k$

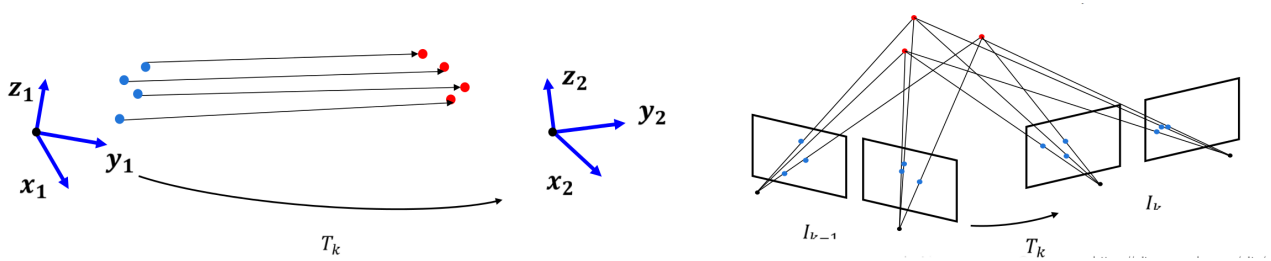



**VO from 2-D to 2-D** (feature-based)

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).

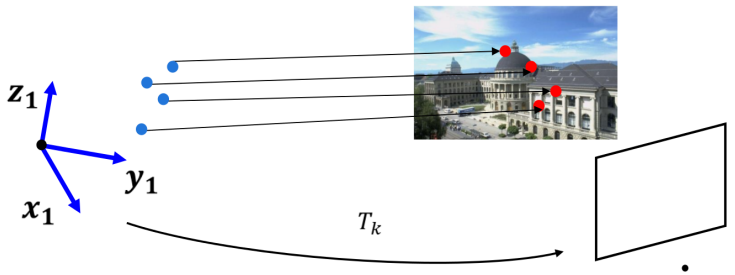
NOTE: The minimal-case solution involves 5-point correspondences




**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).

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




**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

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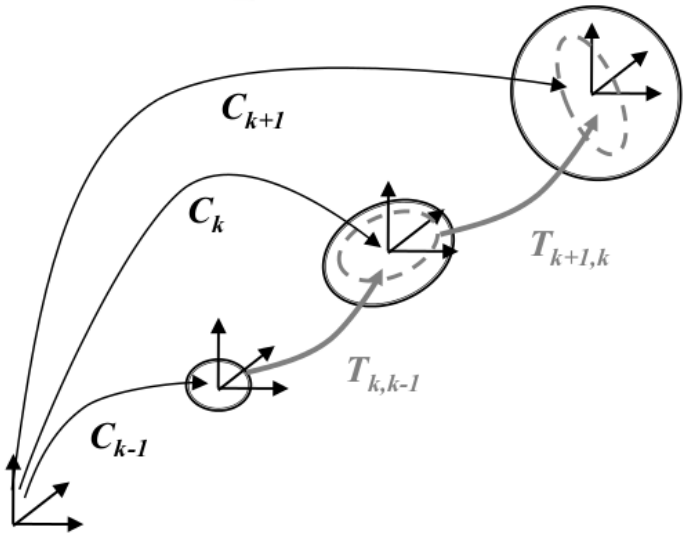
## VO drift

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)

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## VO or SFM

1. SFM is more general than VO and tackles the problem of 3D reconstruction of both the structure and camera poses from unordered image sets
2. The final structure and camera poses are typically refined with an offline optimization (i.e., bundle adjustment), whose computation time grows with the number of images

video 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

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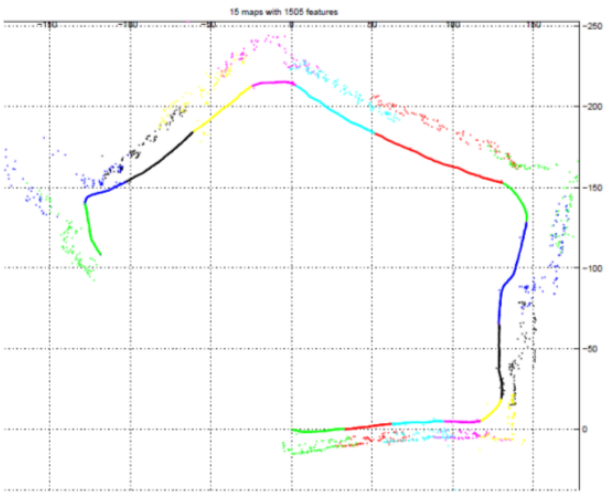
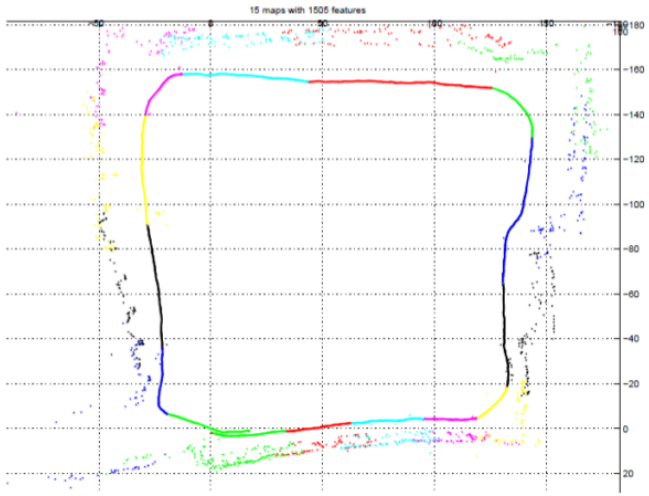
# Visual SLAM

## VO vs Visual SLAM 1/2

- 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**)




**Before loop closing**



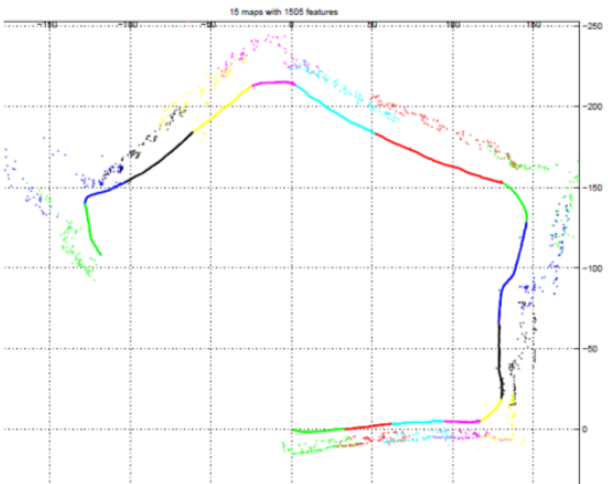

**After loop closing**

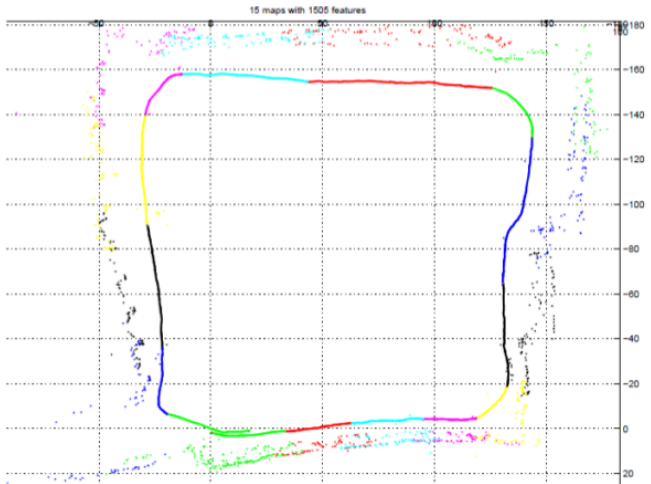
Image courtesy of Clemente et al. RSS'07

# Visual SLAM

## VO vs Visual SLAM 2/2

- 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



# Credits

- Davide Scaramuzza *"Tutorial on Visual Odometry"*