

# Robotic 3D Vision

## Lecture 1: Introduction

WS 2017/18

Prof. Dr. Jörg Stückler

Computer Vision Group, TU Munich

<http://vision.in.tum.de>

# Organization

Lecturer:

- Prof. Dr. Jörg Stückler ([stueckle@in.tum.de](mailto:stueckle@in.tum.de))

Teaching Assistant:

- Rui Wang ([rui.wang@in.tum.de](mailto:rui.wang@in.tum.de))



Course Webpage:

- <https://vision.in.tum.de/teaching/ws2017/r3dv>
- Slides will be made available on the webpage

# Organization

- Structure: 3L (lecture) + 1E (exercises)
  - 6 ECTS credits
- Study programme: **M.Sc. Informatics**
- Place & Time
  - Lecture: Tue 14:15 – 15:45 00.09.038
  - Lecture/Exercises: Thu 14:15 – 16:00 00.11.038
- Exam
  - Planned as written exam
  - Date tba

# Course Organization

Computer Vision Group  
Faculty of Informatics  
Technical University of Munich

Home Teaching Winter Semester 2017/18 **Robotic 3D Vision (3h +1h, 6ECTS)**


**Robotic 3D Vision (3h +1h, 6ECTS)**  
WS 2017/18, TU München

**Lecture**

**Time and Date:**  
Tuesday, 14.15h - 15.45h in room 00.09.038 (**starting from Oct 24th**)  
Thursday (bi-weekly), 14.15h - 15.45h in room 00.11.038 (**starting from Oct 19th**)

Search

**TUM**

  
**Informatik IX  
Chair for Computer Vision  
& Artificial Intelligence**  
Boltzmannstrasse 3  
85748 Garching

Home  
Application Form  
Publications  
Research +  
Data +  
Members +  
Teaching -

- <https://vision.in.tum.de/teaching/ws2017/r3dv>
- A detailed course schedule will appear soon on the website

# Exercises and Demos

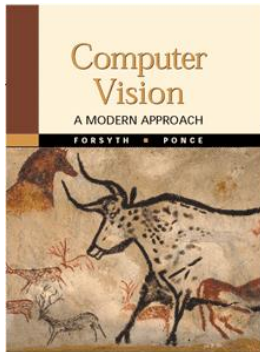
- Exercises
  - Typically 1 exercise sheet every 2 weeks (theoretical and Matlab-based assignments)
  - Hands-on experience with the algorithms from the lecture
  - Send in your solutions the night before the exercise class
  - Handing in the exercises is not mandatory to take the exam
  - First exercise class: Thursday Nov. 2<sup>nd</sup> 2017, 14.15-16.00
- Teams are encouraged!
  - You can form teams of up to 3 people for the exercises
  - Each team should only turn in one solution
  - List the names and matriculation numbers of all team members in the submission
  - Each exercise will be demo'ed by a team during the exercise class

# Course Requirements

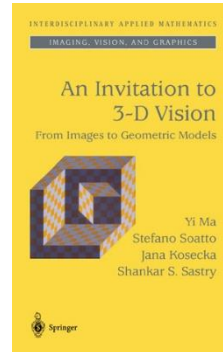
- We will build on basics from previous lectures
  - Computer Vision II: Multiple View Geometry  
<https://vision.in.tum.de/teaching/ss2017/mvg2017>
- Solid background in linear algebra and analysis

# Textbooks

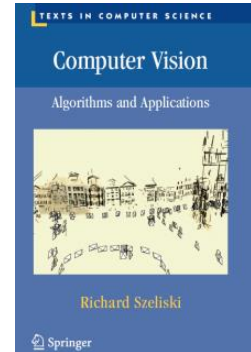
- No single textbook for the class, some basics can be found in



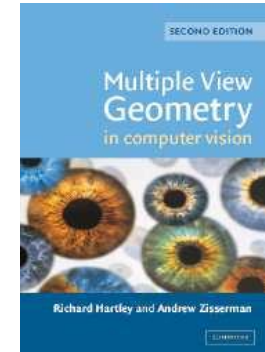
Computer Vision – A Modern Approach, D. Forsyth, J. Ponce, Prentice Hall, 2002



An Invitation to 3D Vision, Y. Ma, S. Soatto, J. Kosecka, and S. S. Sastry, Springer, 2004



Computer Vision – Algorithms and Applications, R. Szeliski, Springer, 2006



Multiple View Geometry – Geometry in Computer Vision, R. Hartley and A. Zisserman, Cambridge University Press, 2004

- We will also give out research papers
  - Tutorials for basic techniques
  - State-of-the-art research papers for current developments

# How to Find Us

- Office:
  - TUM Math&CS Building
  - Boltzmannstr. 3, Garching, 2<sup>nd</sup> floor
  - I9, rooms 02.09.044 (Rui Wang), 02.09.059 (me)
- Office hours
  - If you have questions about the lecture, come to Rui Wang or me.
  - Our regular office hours will be announced
  - Send us an email before to confirm a time slot.

*Questions are welcome!*



# Getting Involved

How can you get involved in scientific research during your study?

- Bachelor lab course (10 ECTS)
- Bachelor thesis (15 ECTS)
- Graduate lab course (10 ECTS)
- Interdisciplinary project (16 ECTS)
- Master thesis (30 ECTS)
- Student research assistant (10 EUR/hour, typically 10 hours/week)

# Vision-based Navigation

- We also offer a practical course on Vision-based Navigation in this semester
- Participants will work on a project related to vision-based navigation for multicopters
- We still have participant slots available. If you are interested, please contact us until Friday, Oct. 20<sup>th</sup> via [visnav\\_ws2017@vision.in.tum.de](mailto:visnav_ws2017@vision.in.tum.de)
- Further information on the course can be found at [https://vision.in.tum.de/teaching/ws2017/visnav\\_ws2017](https://vision.in.tum.de/teaching/ws2017/visnav_ws2017)



# Robots in Complex Environments



Image credit: Amazon



Image credit: DHL



Image credit: Waymo

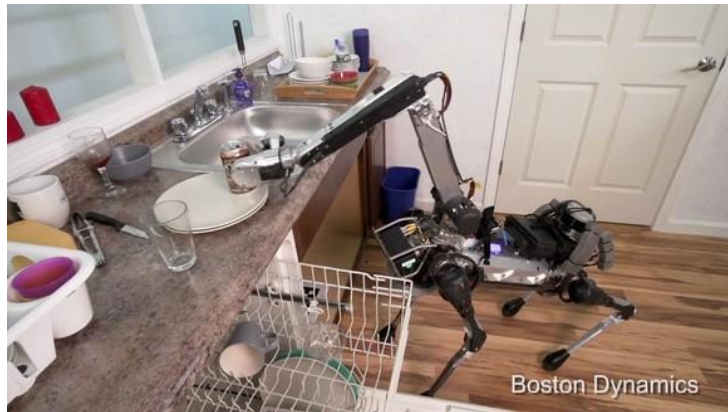


Image credit: Boston Dynamics



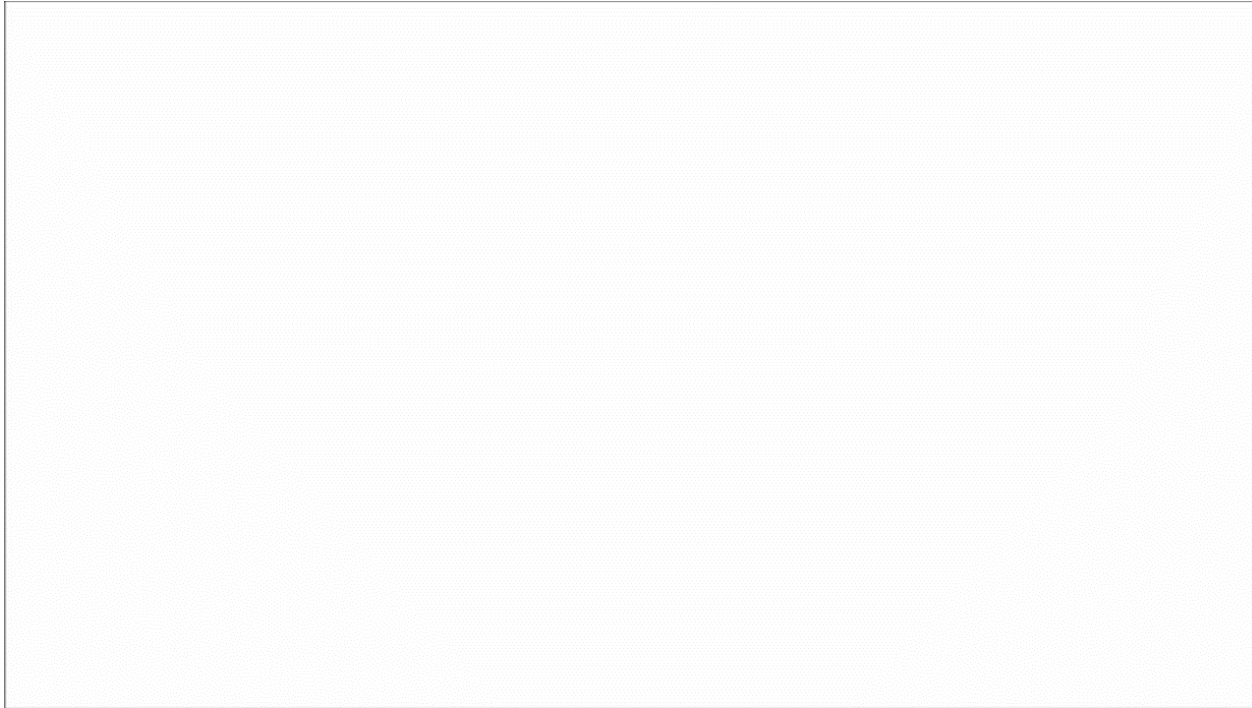
Image credit: IAS TUM / UBremen

# Robotic Perception

We propose a novel trajectory replanning method that follows a globally planned smooth trajectory and simultaneously avoids unmodelled obstacles using measurements from RGB-D camera

(Usenko, von Stumberg, Pangercic, Cremers, IROS 2017)

# Robotic Perception



(Stückler, Schwarz, Behnke, Frontiers 2016)

# Robotic Perception



(Kappler et al., arXiv 2017)

# What We Will Cover Today

- Why Vision for Robotic Perception?
- What is Robotic 3D Vision?
- Terminology of
  - Visual Odometry
  - Visual-Inertial Odometry
  - Visual Simultaneous Localization and Mapping
  - Map Representations
  - Dense vs. Sparse Reconstruction
  - Visual 3D Object Detection and Tracking
  - Indirect and Direct Methods

# Sensors for Robotic Perception



## Vision

- + low power consumption
- + **dense** 2D projection
- + **appearance**
- + **high frame-rate**
- indirect distance



## Laser

- + accurate distance
- power consumption
- sparse
- low frame-rate
- scan plane



## Inertial

- + linear acceleration
- + gravity
- + rotational velocity
- + high frame-rate
- noise & bias
- local



## Proprioceptive

- + forward kinematics (+ forward dynamics)
- only internal



## Tactile

- + contact with environment

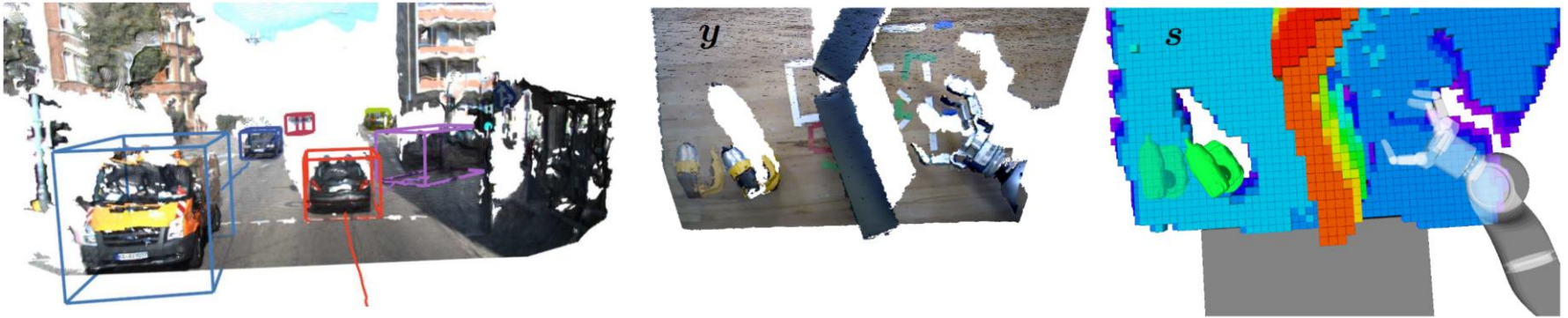
## RGB-D

- + **depth image**
- power consumption





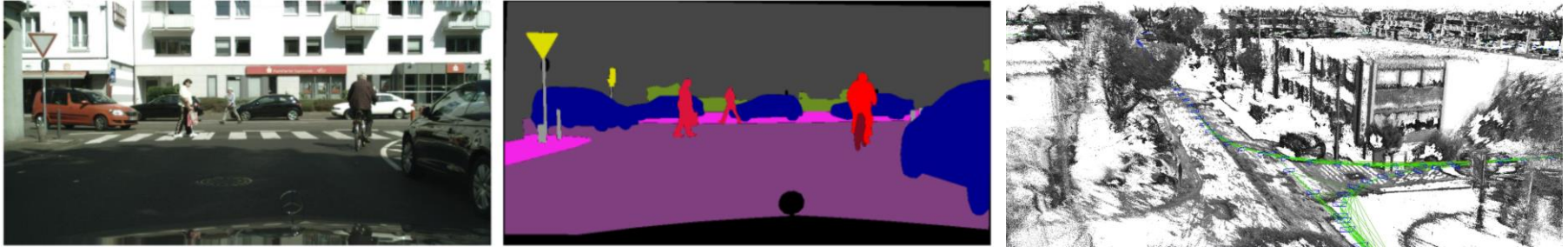
# Robotic 3D Vision



- Robots require 3D scene understanding
  - Where is the robot in the environment?
  - What is the shape (structure) of the environment?
  - Where are task-relevant objects?
- 3D Vision: 3D scene understanding from camera images

Images from: (Osep et al., ICRA 2016), (Kappler et al., arXiv 2017)

# Why Vision?



Vision provides robots with rich information about the world

- Dense 2D measurements of the 3D world, in contrast to, for example, laser scanners or ultrasonic range scanners
- RGB/grayscale measurements of the appearance of objects available to detect and recognize objects
- Range (third dimension) assessable by stereo
- Lightweight and low power consumption (passive cameras)

Images from: (Pohlen et al., CVPR 2017), (Engel, Stückler, Cremers, IROS 2015)

# Types of Cameras



## Monocular camera

- Structure from motion (chicken-and-egg problem)
- Scale ambiguity



## Stereo camera

- Depth from stereo in fixed configuration
- Scale observable
- Fixed baseline



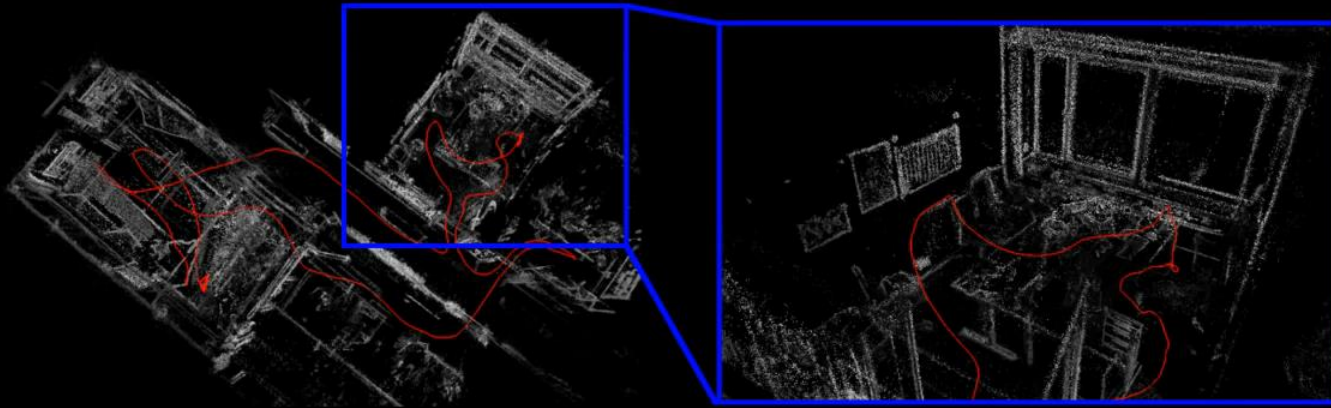
## RGB-D camera

- Directly measures per-pixel depth
- Active sensing

# Visual Odometry

## Direct Sparse Odometry

Jakob Engel<sup>1,2</sup>, Vladlen Koltun<sup>2</sup>, Daniel Cremers<sup>1</sup>  
July 2016



<sup>1</sup>Computer Vision Group  
Technical University Munich

<sup>2</sup>Intel Labs 

*How does the robot move?*

# What is Visual Odometry?

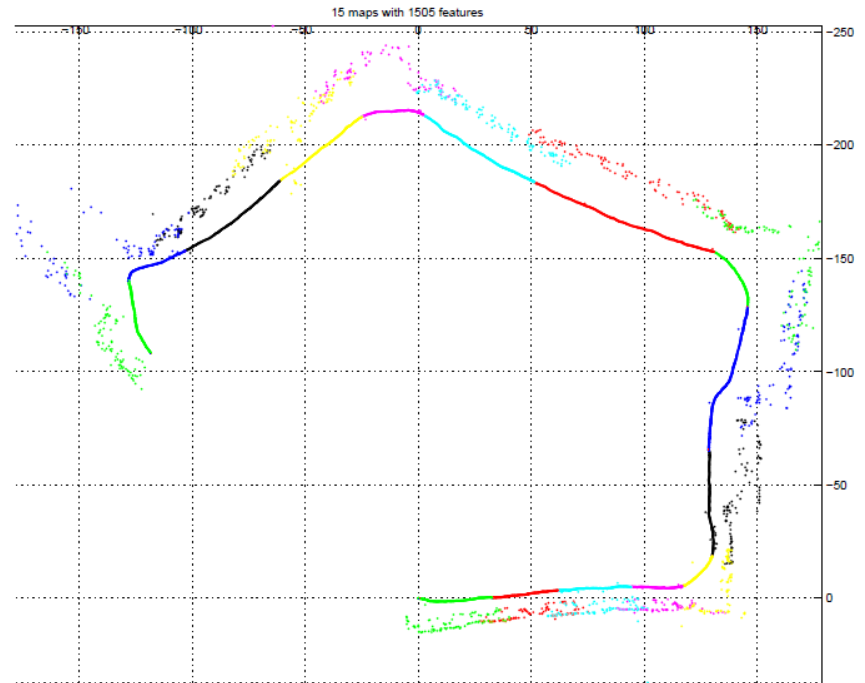
Visual odometry (VO)...

- ... is a variant of **tracking**
  - Track the current pose, i.e. position and orientation, of the camera with respect to the environment from its images
  - Only considers a limited set of recent images for real-time constraints
- ... involves a **data association** problem
  - Motion is estimated from corresponding interest points or pixels in images, or by correspondences towards a local 3D reconstruction

# What is Visual Odometry?

Visual odometry (VO)...

- ... is prone to **drift** due to its local view
- ... is primarily concerned with estimating camera motion
  - 3D reconstruction often a “side product”. If estimated, it is **only locally consistent**



# Visual-Inertial Odometry



Sensor includes

- Stereo camera
- 3-axis accelerometer
- 3-axis gyroscope
- Time-synchronization



(Usenko, Engel, Stückler, Cremers, ICRA 2016)

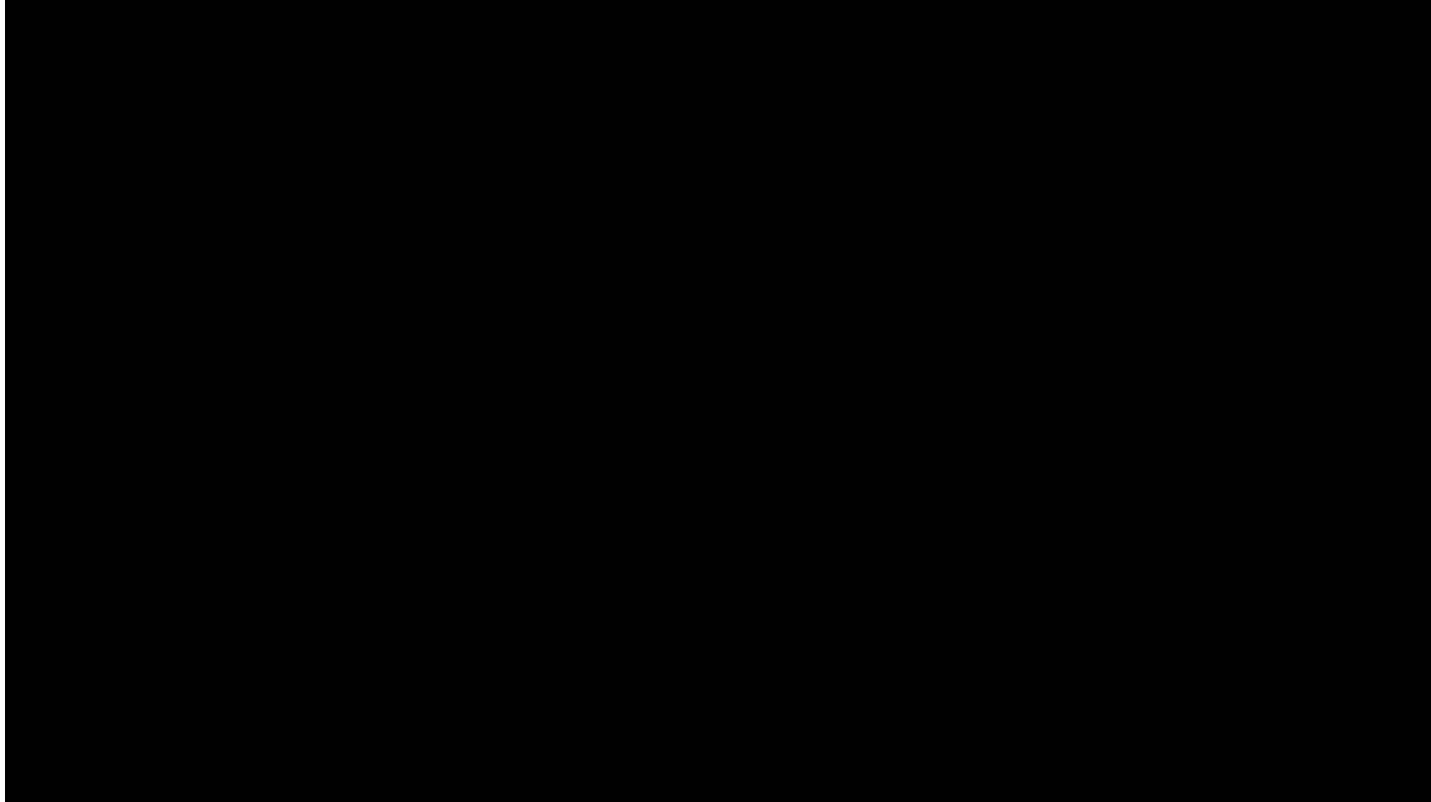
# What is Visual-Inertial Odometry?

Visual-inertial odometry (VIO)...

- ... complements visual odometry with inertial measurements
  - Visual measurements provide up to 6-DoF relative motion using the **environment as reference**
  - Inertial sensors measure **3D linear accelerations and angular velocities**, typically at much **higher frame-rate** than images
  - **Gravity** is also included in the acceleration measurements serving as an **absolute external reference**
  - Pure integration of gravity-compensated linear accelerations and angular velocities **drifts**
  - Vision helps to **reduce integration drift**, estimate sensor **biases**, discern gravity from motion-induced accelerations
  - Inertial measurements help to **compensate degenerate cases** of pure visual tracking (textureless areas, fast motion, etc.)



# Simultaneous Localization and Mapping



(Engel, Stückler, Cremers, IROS 2015)

*Where is the robot and what is the  
3D structure of the environment?*

# What is Visual SLAM?

- Visual simultaneous localization and mapping (VSLAM)...
  - Tracks the **pose of the camera** in a map, and **simultaneously**
  - Estimates the parameters of the **environment map** (f.e. reconstruct the 3D positions of interest points in a common coordinate frame)
- **Loop-closure**: Revisiting a place allows for drift compensation
  - How to detect a loop closure?

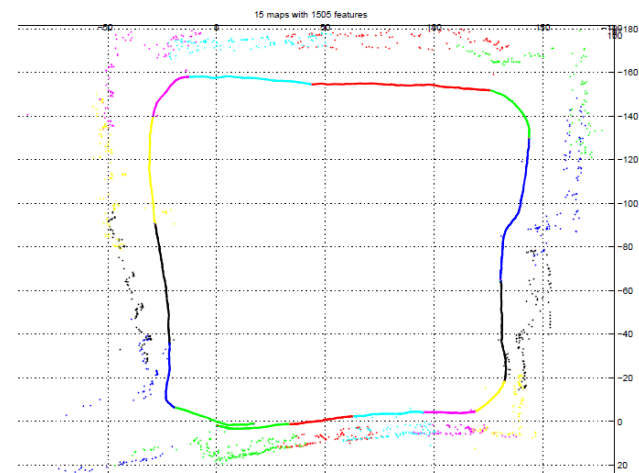
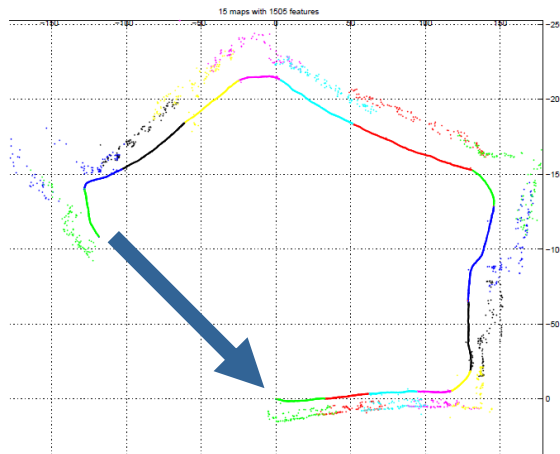


Image credit: Clemente et al., RSS 2007

# What is Visual SLAM?

- Visual simultaneous localization and mapping (VSLAM)...
  - Tracks the **pose of the camera in a map**, and **simultaneously**
  - Estimates the parameters of the **environment map** (f.e. reconstruct the 3D positions of interest points in a common coordinate frame)
- **Loop-closure**: Revisiting a place allows for drift compensation
  - How to detect a loop closure?
- **Global and local optimization** methods
  - Global: bundle adjustment, pose-graph optimization, etc.
  - Local: incremental tracking-and-mapping approaches, visual odometry with local maps. Often designed for real-time.
  - **Hybrids**: Real-time local SLAM + global optimization in a slower parallel process (f.e. LSD-SLAM)

# Visual SLAM with RGB-D Cameras

## Dense Visual SLAM for RGB-D Cameras

Christian Kerl, Jürgen Sturm,  
Daniel Cremers



Computer Vision and Pattern Recognition Group  
Department of Computer Science  
Technical University of Munich



# RGB-D SLAM by Map Deformation

## ElasticFusion: Dense SLAM Without A Pose Graph

Thomas Whelan, Stefan Leutenegger, Renato Salas-Moreno, Ben Glocker, Andrew Davison

Imperial College London

# Visual SLAM using Bundle Adjustment



**Universidad**  
Zaragoza



Instituto Universitario de Investigación  
en Ingeniería de Aragón  
**Universidad Zaragoza**

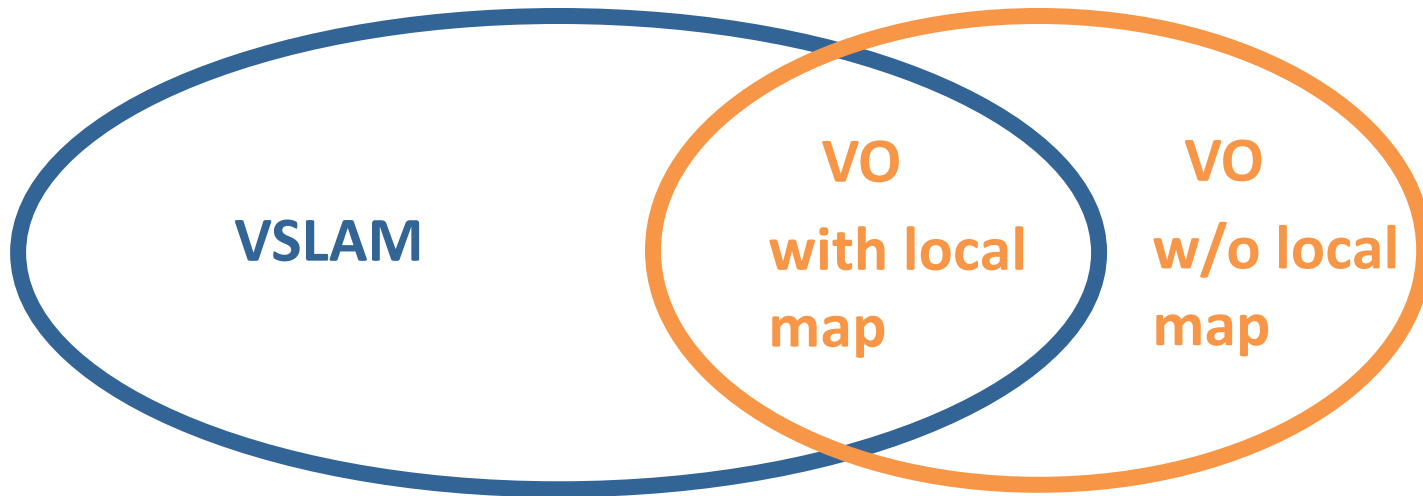
ORB-SLAM2: an Open-Source SLAM System  
for Monocular, Stereo and RGB-D Cameras

Raúl Mur-Artal and Juan D. Tardós

[raulmur@unizar.es](mailto:raulmur@unizar.es)

[tardos@unizar.es](mailto:tardos@unizar.es)

# VO vs. VSLAM



# Structure from Motion

- Structure from Motion (SfM) denotes the joint estimation of
  - Structure, i.e. 3D reconstruction, and
  - Motion, i.e. 6-DoF camera poses,from a collection (i.e. unordered set) of images
- Typical approach: keypoint matching and bundle adjustment

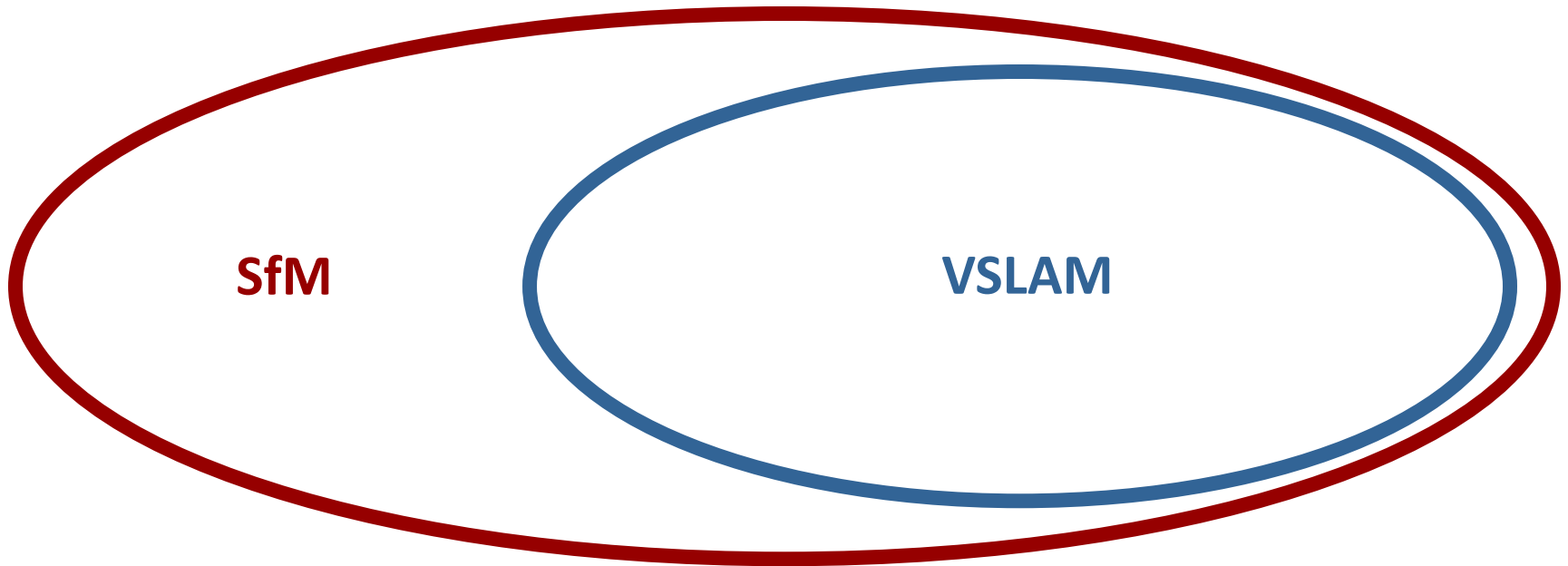


# Structure from Motion



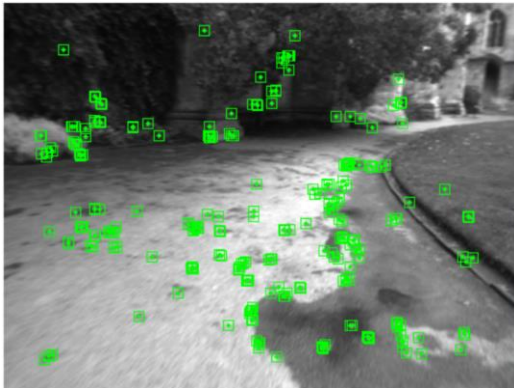
Agarwal et al., Building Rome in a Day, ICCV 2009, „Dubrovnik“ image set

# VSLAM vs. SfM



# Sparse vs. Dense Reconstruction

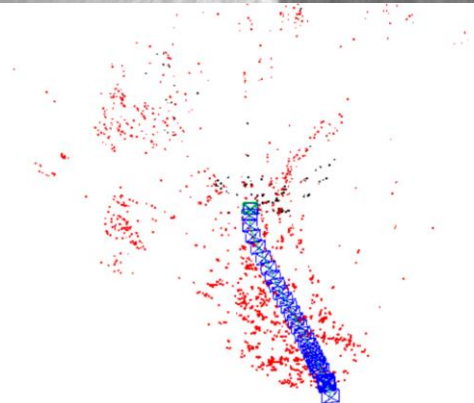
## Sparse (ORB-SLAM)



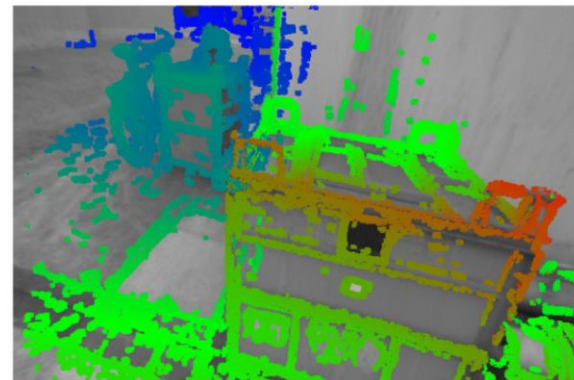
## Semi-Dense (LSD-SLAM)



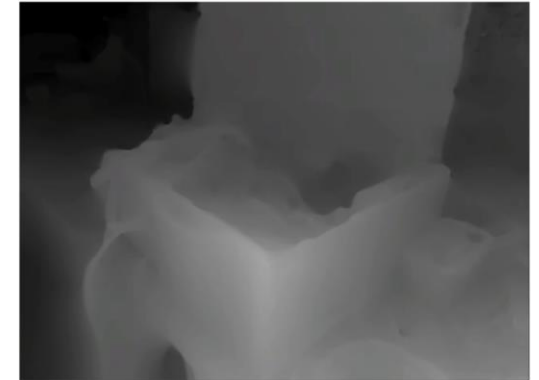
## Dense (DTAM)



(Mur-Artal and Tardós, TRO 2015)



(Engel et al., ECCV 2014)



(Newcombe et al., ICCV 2011)

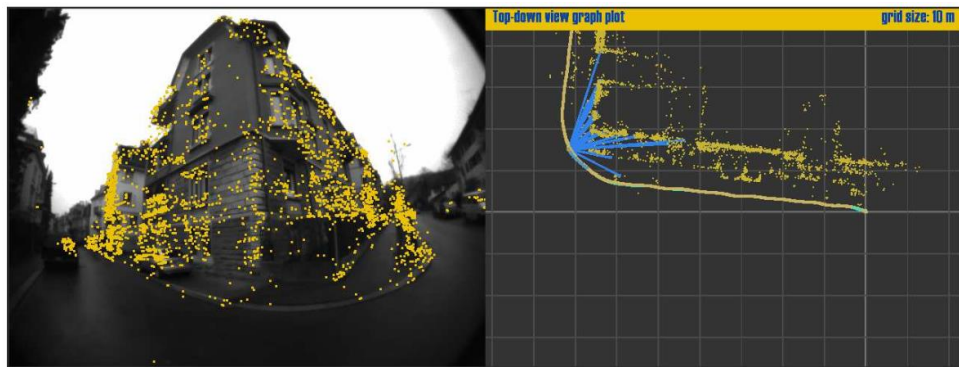
**Good for VO/VSLAM = Good for robotic perception?**

# Dense VSLAM with a Single Camera

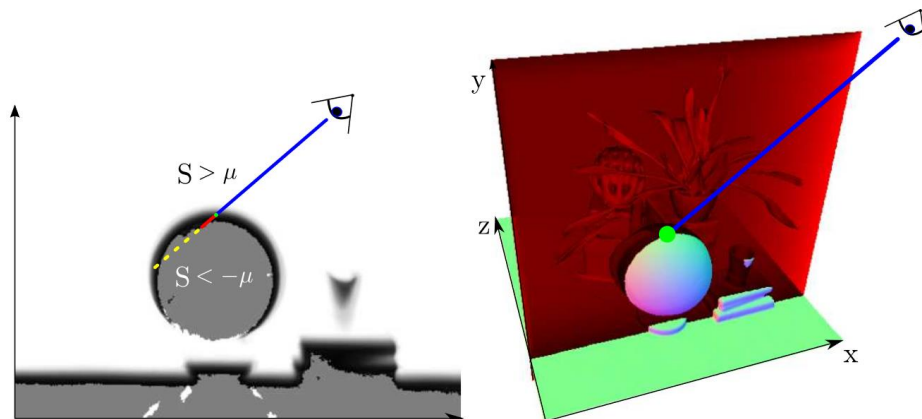
## DTAM: Dense Tracking and Mapping in Real-Time

(Newcombe et al., DTAM: Dense Tracking and Mapping in Real-time, ICCV 2011)

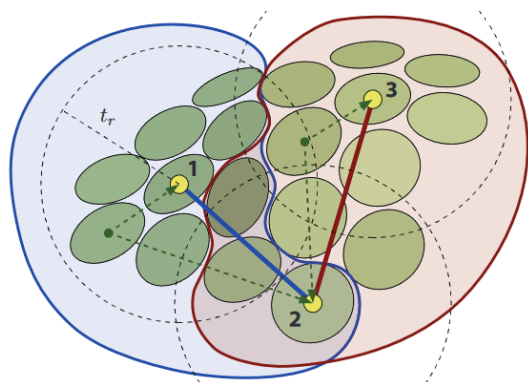
# How Should We Represent The Map?



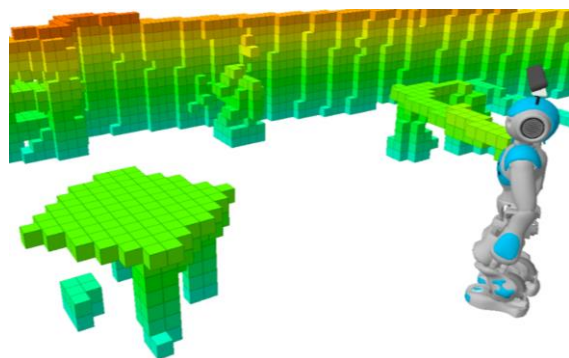
Sparse interest points



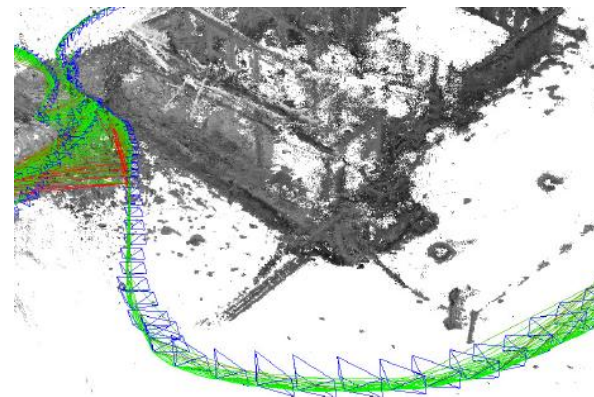
Volumetric, implicit surface



Explicit surface  
(surfels, mesh,...)



Volumetric, occupancy



Keyframe-based maps

**Good for VO/VSLAM = Good for robotic perception?**

(Lynen et al., RSS 2015), (Newcombe, 2015), (Weise et al., 2009), (Maier et al., 2012), (Engel et al., ECCV 2014)

# 3D Object Detection and Tracking

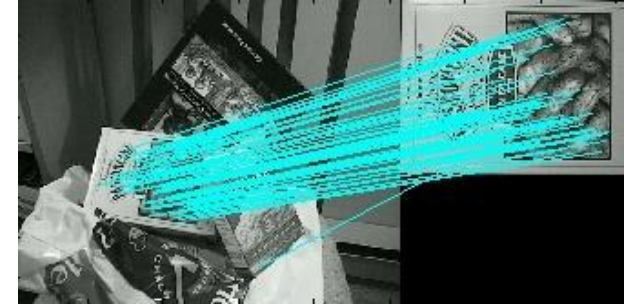


(Wüthrich et al., IROS 2013)

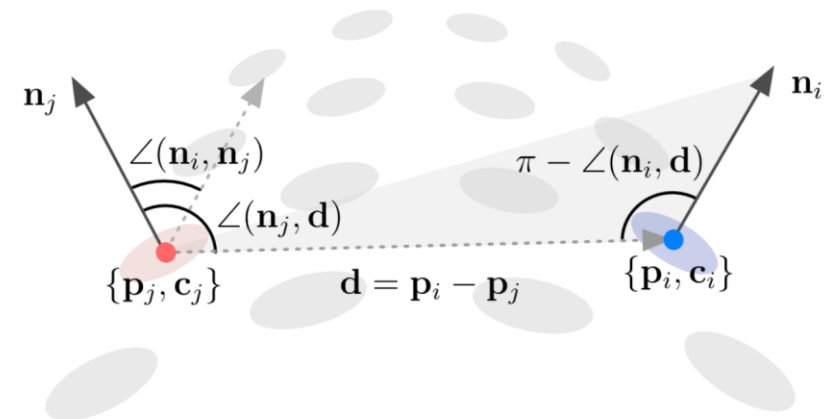
*Where are objects in the robot's surrounding?*

# What is Visual 3D Object Detection?

- Visual 3D object detection...
  - ...finds an object in an image and
  - ...estimates its 6-DoF pose from the image

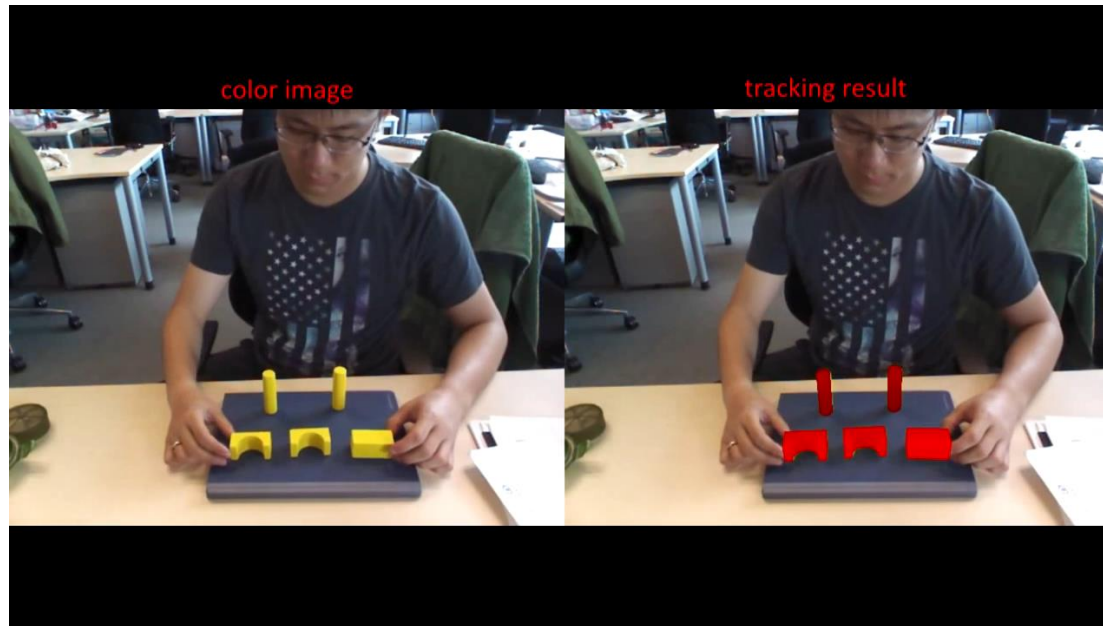


(Choi and Christensen, RAS 2016)



# What is Visual 3D Object Tracking?

- Visual 3D object tracking...
  - ...tracks the 6-DoF pose of an object in an image **sequence**
- Tracking-by-detection, incremental registration, ...
- Multi-object tracking involves **data association**

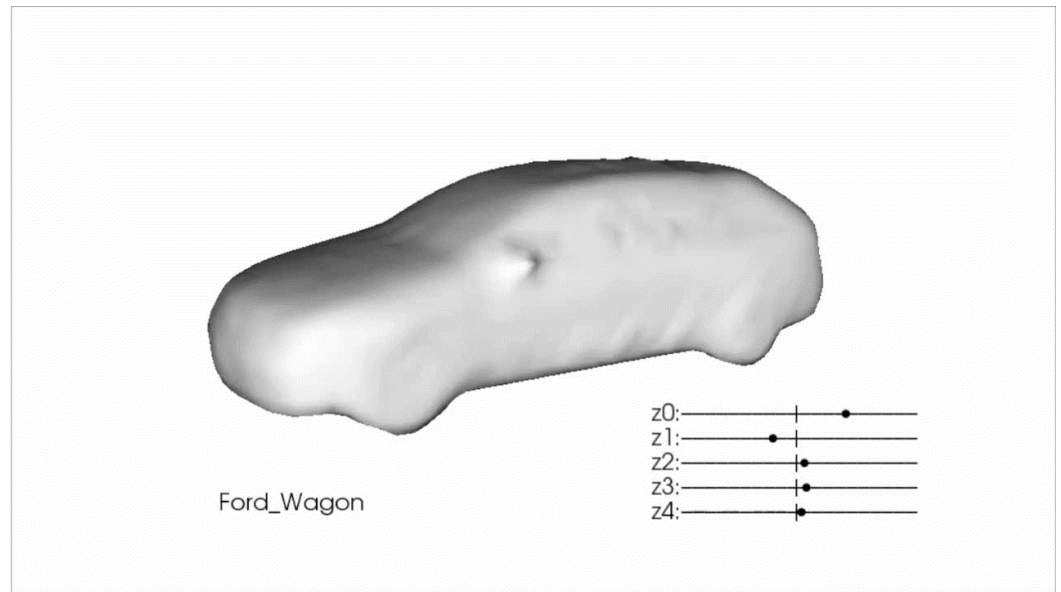
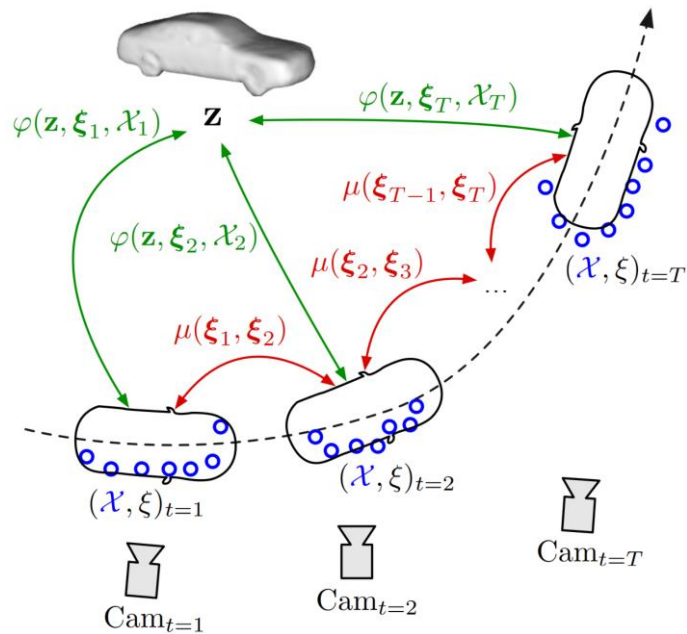


(Ren et al., Real-Time Tracking of Single and Multiple Objects from Depth-Colour Imagery Using 3D Signed Distance Functions, IJCV 2017)



# Joint Object Shape Estimation and Tracking

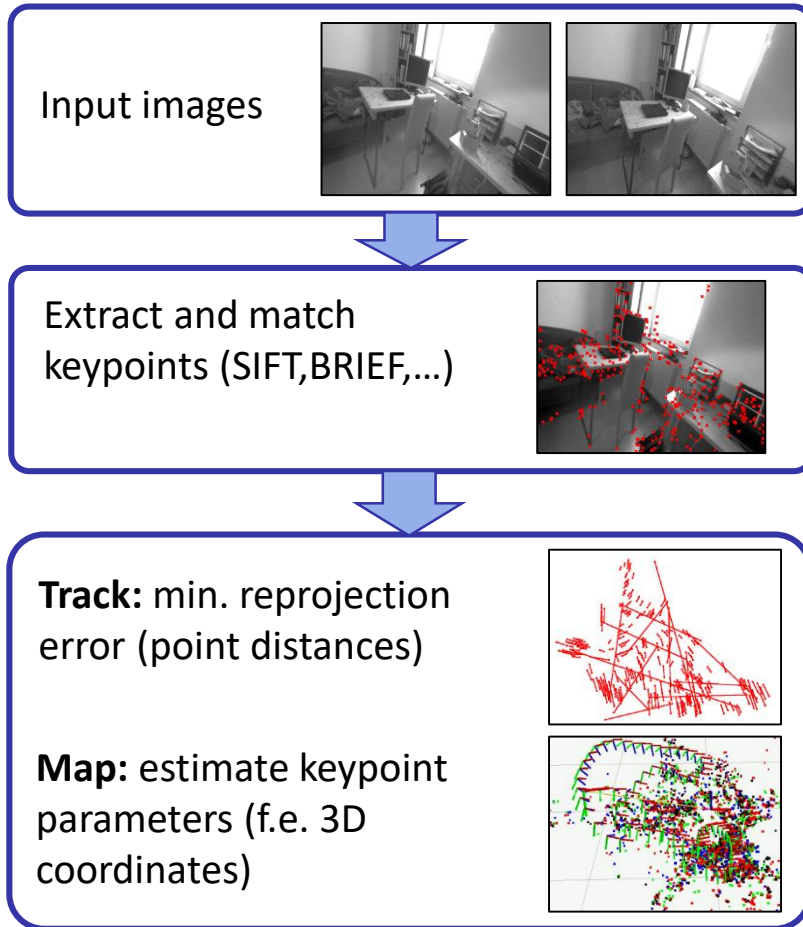
Impose shape and motion priors for spatio-temporal reconstruction of vehicles



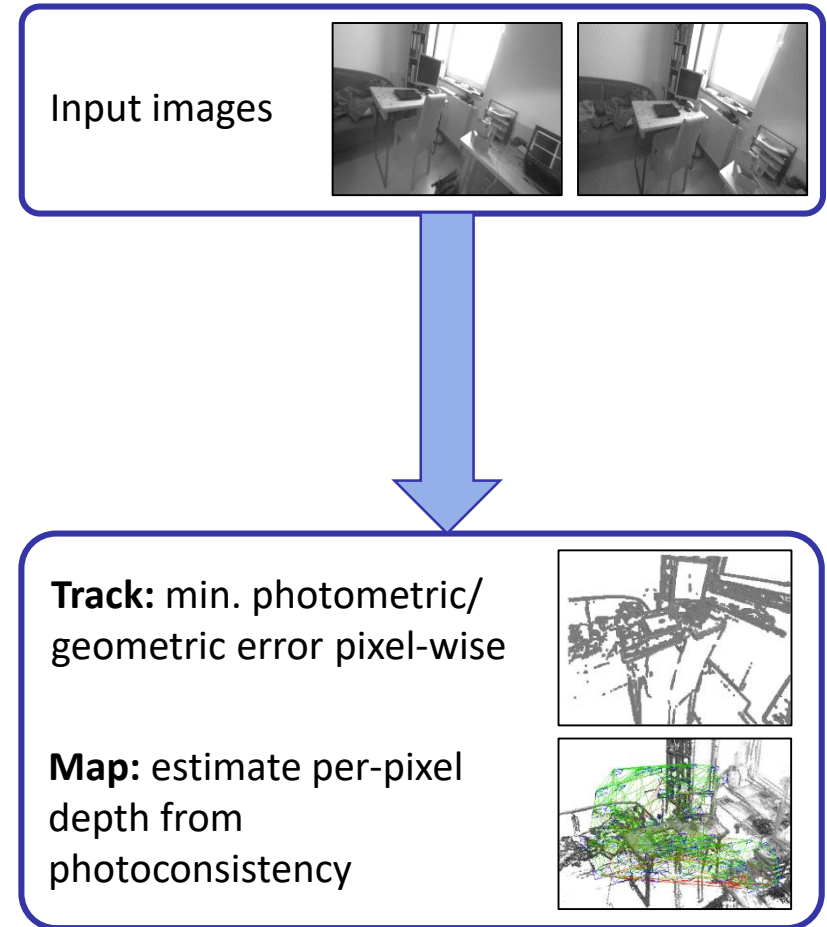
(Engelmann, Stückler, Leibe, WACV 2017)

# Indirect vs. Direct Methods

## Indirect



## Direct



# Indirect vs. Direct Methods

- **Direct** methods formulate image alignment objective in terms of **photometric error** (e.g. intensities)

$$E(\boldsymbol{\xi}) = \int_{\mathbf{u} \in \Omega} |\mathbf{I}_1(\mathbf{u}) - \mathbf{I}_2(\omega(\mathbf{u}, \boldsymbol{\xi}))| d\mathbf{u}$$

- **Indirect** methods formulate image alignment objective in terms of **reprojection error of geometric primitives** (e.g. points, lines)

$$E(\boldsymbol{\xi}) = \sum_i |\mathbf{y}_{1,i} - \omega(\mathbf{y}_{2,i}, \boldsymbol{\xi})|$$

# Indirect vs. Direct Methods

- Which of the approaches performs better is still in debate
- Indirect methods for VO and VSLAM have been investigated for a longer time by a broader research community
- Hence, indirect VO and VSLAM approaches are currently still more mature (f.e. ORB-SLAM2)
- However, recent methods such as direct sparse odometry (Engel et al., 2016) demonstrate better performance than several indirect visual odometry approaches
- Key to achieving high accuracy with direct methods is the proper treatment of camera properties such as vignetting, exposure times, rolling shutter etc.

# Visual SLAM in Dynamic Scenes

- So far VO or VSLAM assumed static environments
- How to handle moving or deforming objects in SLAM?
- Recently impressive results with RGB-D cameras

## *Dynamic*Fusion:

Reconstruction & Tracking of Non-rigid Scenes in *Real-Time*

Richard Newcombe, Dieter Fox, Steve Seitz

Computer Science and Engineering,  
University of Washington

# Course Contents

- Image formation, multi-view geometry, SE3 (recap)
- Probabilistic filtering, non-linear least squares
- Visual odometry
- Visual-inertial odometry
- Visual SLAM
- Dense reconstruction
- Map representations
- 3D object detection and tracking
- Outlook: Visual SLAM in dynamic scenes

Thanks for your attention!