

Internal Identifier: EITRM106886:  
AMICOS Training Material set 1:  
Simultaneous Localization and  
Mapping





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# Importance of location

*Why do we need to know where we are?*

Without any information about our **location** and **spatial awareness**  
you wouldn't be able to:

- think about where you are now,
- remember where everything is.
- estimate a distance to something you see  
(eye-hand coordination wouldn't exist),
- navigate to any place (another room, a workplace etc.)
- and many more, otherwise trivial activities.
- These abilities are *essential* for humans... as well as for *autonomous robots*.



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# Localization in an open space

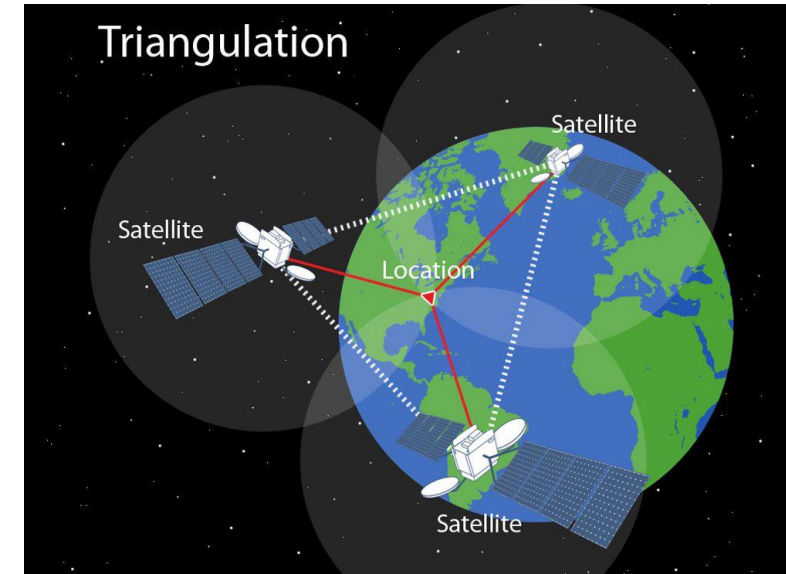
Plain solution:

## GNSS – Global Navigation Satellite System

Often incorrectly called GPS, because those systems include:

**GPS** (Global Positioning System; USA), **GLONASS** (Russia), **Beidou** (China), **Galileo** (EU).

They provide positioning services, using satellite constellations, which emit **radio time signals** along **line of sight** with high precision. Knowing satellites location at exact time, an electronic device (*GNSS receiver*) can determine its position with *triangulation*. Local correction services or differential measurements can further improve the reliability and accuracy.



Accuracy: up to a few metres for a plain solution, up to **~2 cm** in RTK mode.



Doesn't work properly indoors → demand for a suitable solution for an **indoor environment**.



# Problem introduction

To understand how does the robot can see and perceive the world,  
we should ask ourselves a question:

How do **we** see it?

How do we know where we are?

How can we identify and locate different objects around us?

How can we judge a distance to something?

Imagine your way from home to work/university. What did you imagine?

What information acquired in the past did you use to do it?





# How do we see the world?

## 5 core senses:

1. Sight
2. Hearing
3. Smell
4. Touch
5. Taste



...is that all?

Of course not!



# More senses!

Neurologists argue over the total number of human senses. Different classifications can include as many as **21** or even **53 senses**. Despite the dispute about most of them, there are **4** generally accepted additional senses:

**6. Thermoception** - the perception of heat,

**7. Nociception** - the perception of pain,

**8. Equilibrioception** - the perception of balance,

**9. Proprioception** (kinaesthesia) - the perception of body awareness (e. g. self-movement, body position).

For the most part, we use:

a) *sight* to create a „representation of the surroundings” in our brain (a **map**),

b) *sight, touch, equilibrioception* and *proprioception* to locate ourselves in the environment and determine **our position**.





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# Spatial knowledge: A map

A **map** is a symbolic depiction emphasizing relationships between elements of some space, such as objects, regions, or themes<sup>1</sup>. In robotics, we can think of it as a 2D or 3D model of the robot's surroundings.

**Local map** precisely describes the space in the proximity of the robot. It's important for collision avoidance, object detection and interaction with them (equivalent of eye-hand coordination).

**Global map** can be much sparser. Information from it should allow the robot to find and plan a path (usually the shortest or the fastest) from its position to the destination.



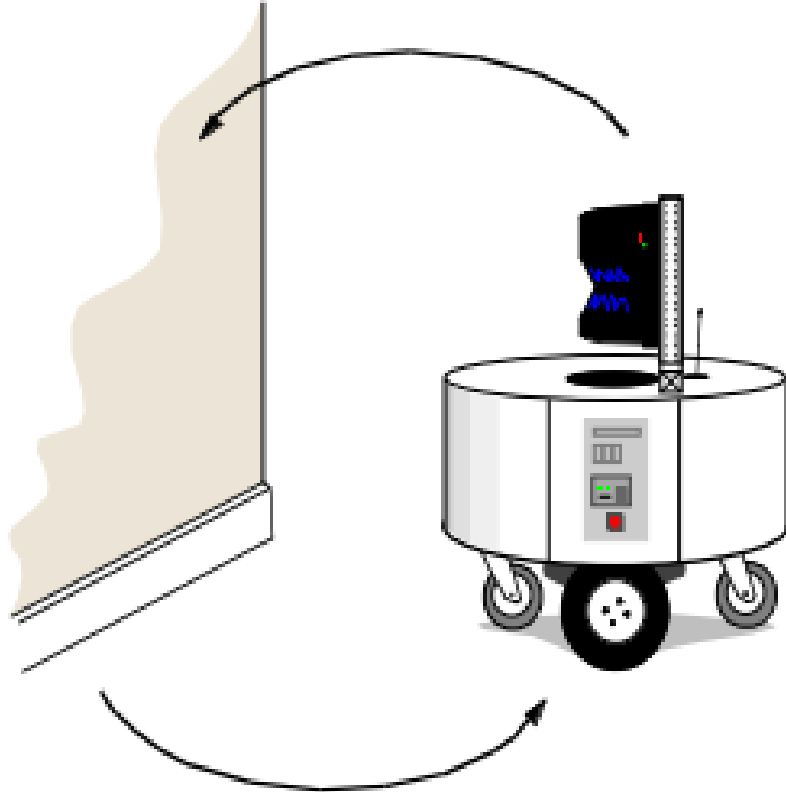
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<https://en.wikipedia.org/wiki/Map>

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# Creating a map from scratch



### *Chicken-or-egg problem:*

- to create a map, you need to know the robot (sensor) position,
- to localize the robot, you need both the sensor readings and the map of its surroundings.

### Potential solution must:

- be **autonomous**,
- allow **constant updates** of the **changing** environment,
- provide good **accuracy** for a given robot application (up to a few **cm**),
- be able to be calculated in **real-time**.







# What data can we use?

Can we simulate **human senses** with different **robot sensors**?

Human sense	Task	Robot sensor
Sight	object recognition, spatial vision (distance estimation), visual map creation	cameras, laser scanner
Equilibrioception	movement estimation (change of direction, speed, acceleration)	accelerometer, gyroscope, magnetometer (integrated - Inertial Measurement Unit)
Proprioception	body position estimation	joint state sensors, odometry

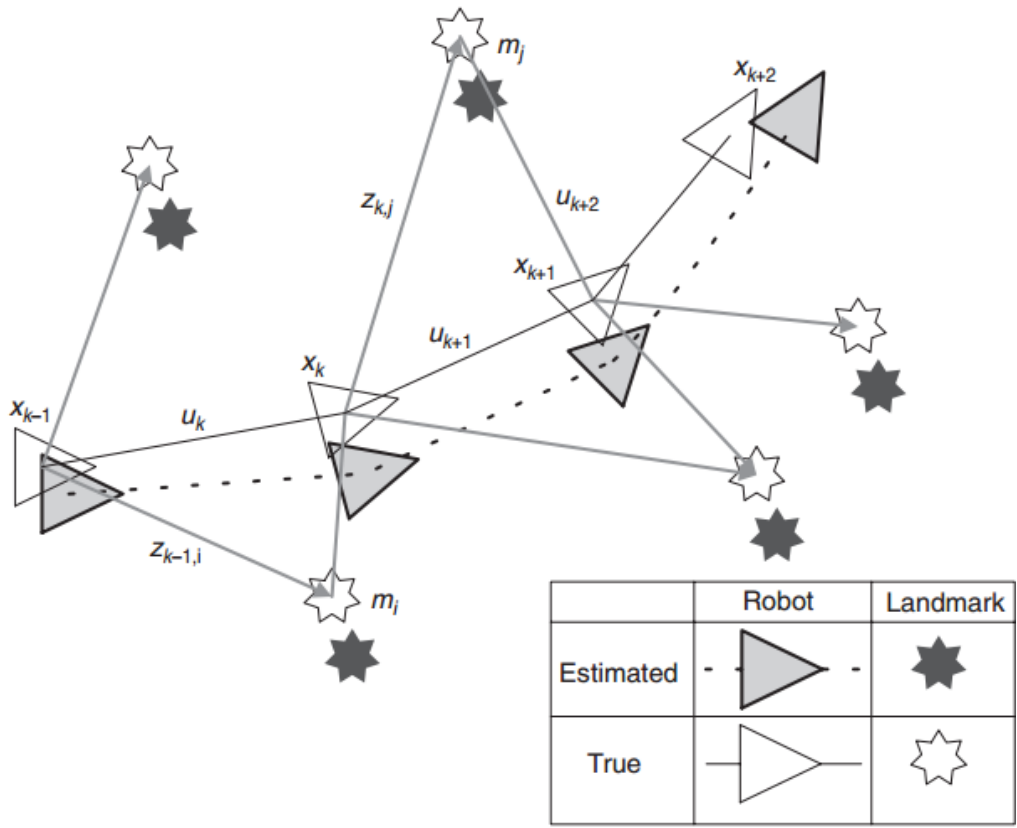
Apart from the **data acquisition**, the **data processing** is the real problem.

How do we get the **knowledge** from the raw data?



# Solution: SLAM

**SLAM**  
Simultaneous Localization and Mapping



Allows mapping and navigation in the unknown environment, without GNSS (buildings, mines, caves, mixed environment).

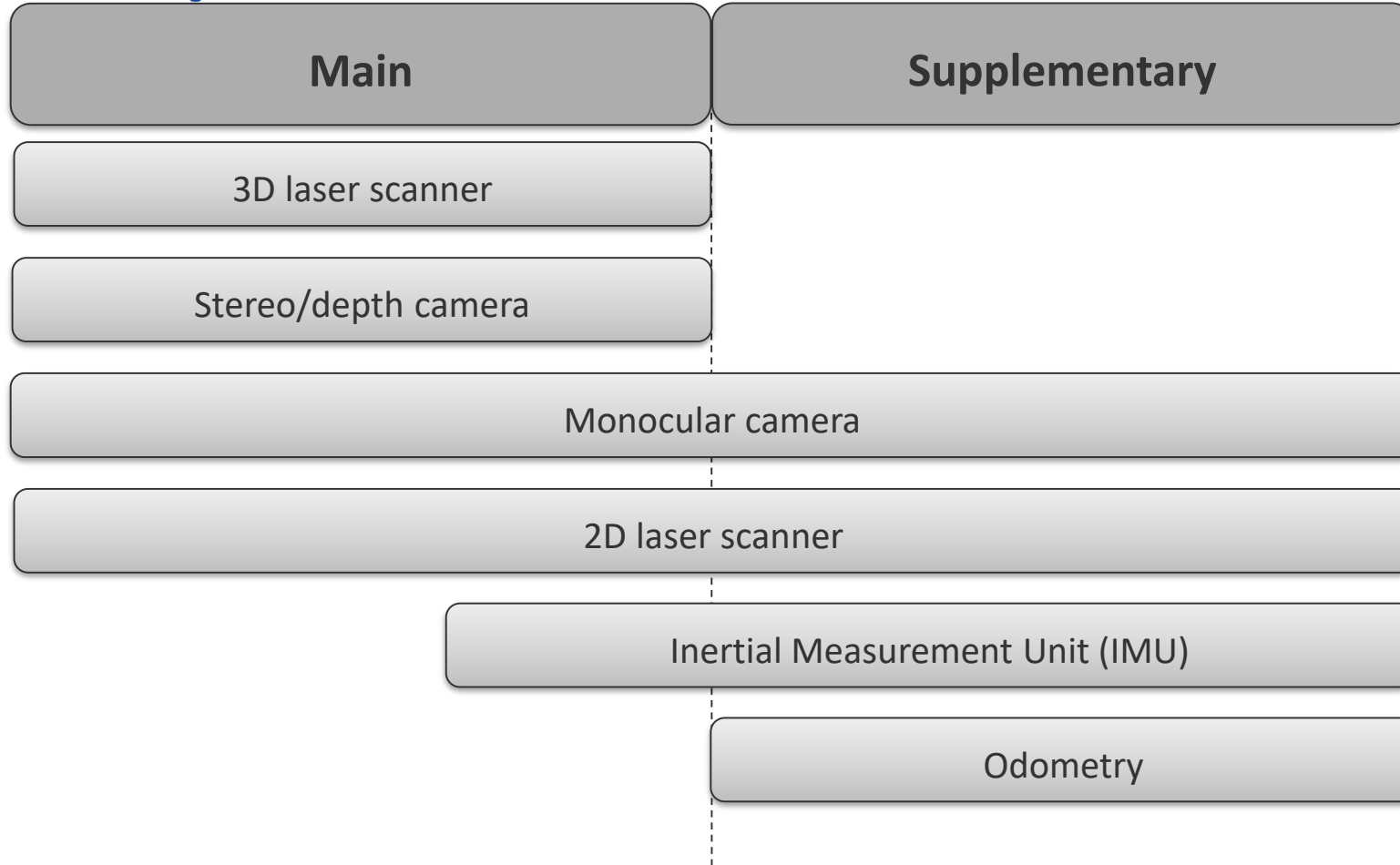
Ability to use data fusion from various sensors: laser scanner, gyroscopes, accelerometers, magnetometers, odometers, cameras, GNSS.

**Applications:**  
Autonomous: vacuum cleaners (*Roomba*), lawn movers, drones, vehicles, robots for exploring dangerous places (mines, caves), planetary rovers.



# SLAM: Sensors

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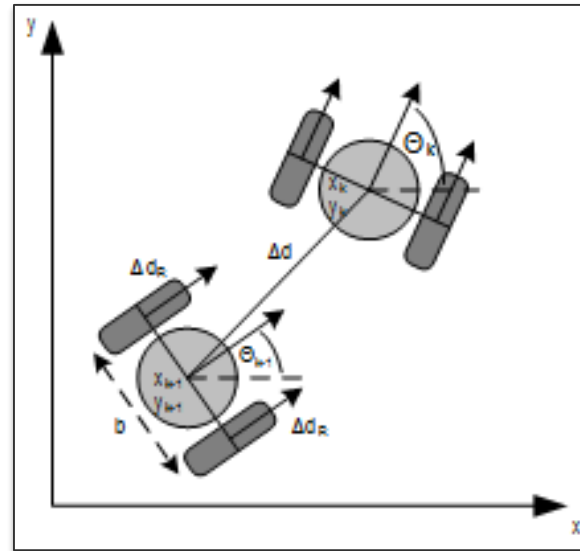
# SLAM: Sensors

## Odometry



- Simple implementation and calculations,
- Cheap

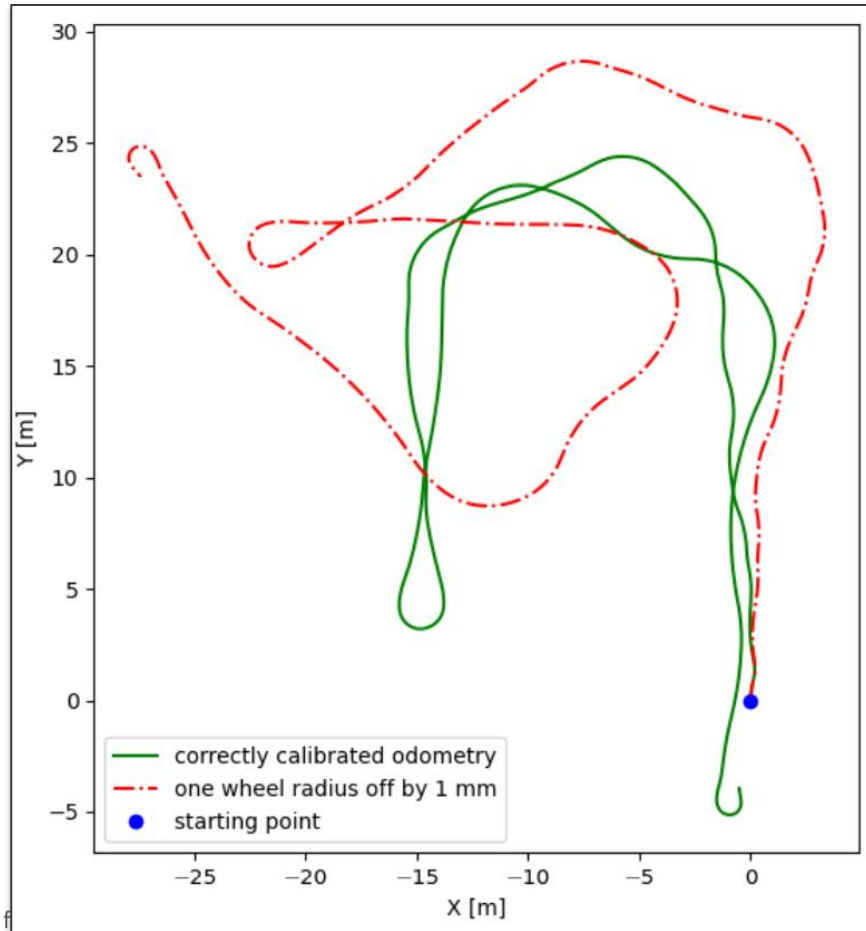
Robot localization based on travelled distance, measured with wheel encoders



- Differential method: positioning drift increasing with time,
- Only planar positioning,
- Many possible error sources (calibration, slippage, impact),
- Available only for wheeled devices

# SLAM: Sensors

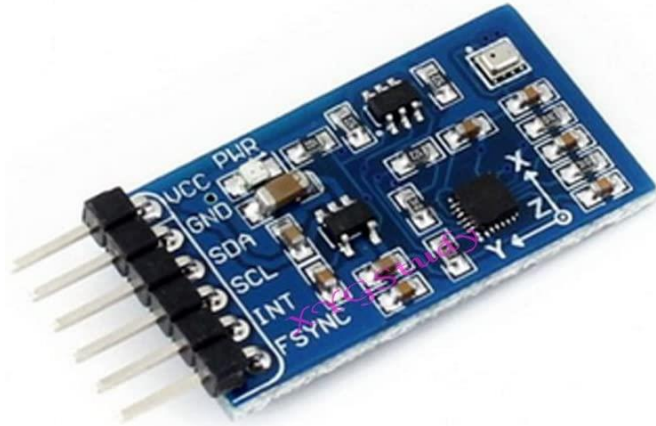
## Odometry



Influence of small calibration error on the odometry-derived robot path

# SLAM: Sensors

## Inertial Measurement Unit (IMU)



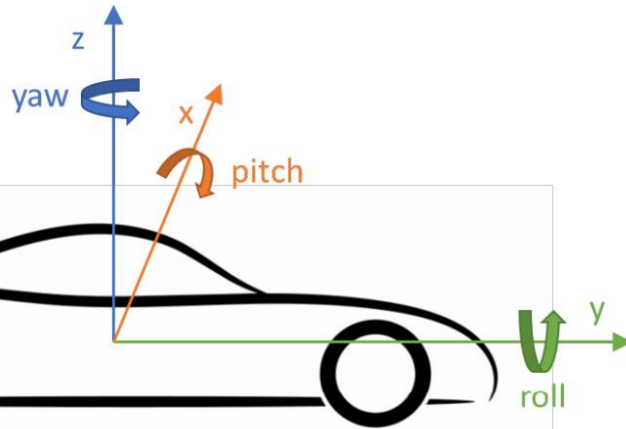
IMU consists of elements measuring:

- a) Gyroscope – angular velocity (yaw pitch roll),
- b) Accelerometer, - linear acceleration,
- c) Magnetometer (optional) – magnetic field.

3 DoF for each component = 9 DoF IMU

- Cost scalability: cheap entry-level sensors, costly precise units,
- 3D positioning and orientation information,
- Possible to use in UGVs, UAVs or UUVs

- Positioning drift with time,
- Prone to sudden motion changes (vibrations, impact),
- No information about robot's surroundings



# SLAM: Sensors

Inertial Measurement Unit (IMU)

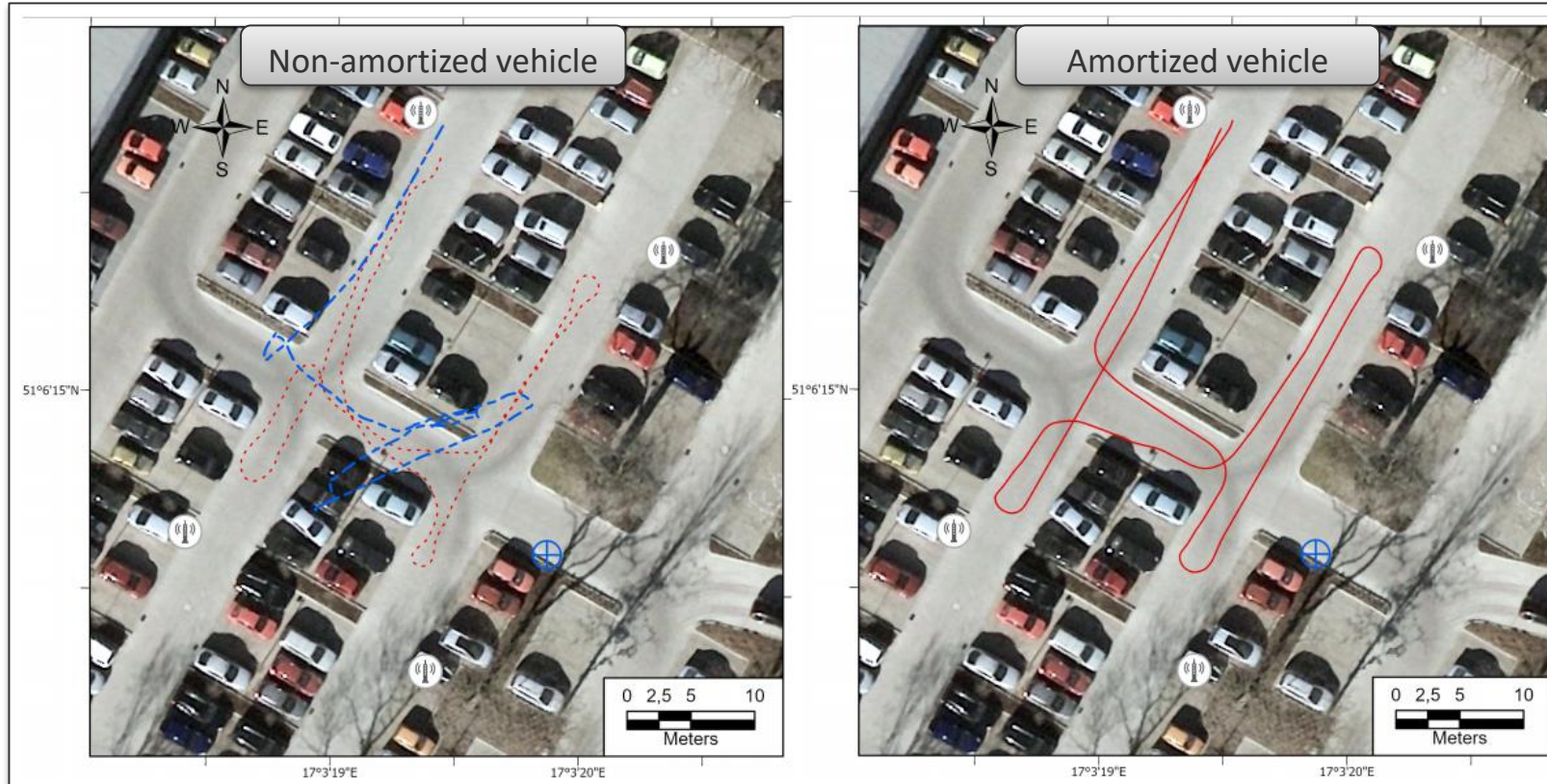
IMU + device with software calculating attitude and heading  
= Attitude Heading Reference System (AHRS)

IMU + device with software calculating position, velocity and heading  
= Inertial Navigation System (INS)



# SLAM: Sensors

Inertial Measurement Unit (IMU)



Vibration impact on  
IMU positioning

IMU-derived path (blue) and  
ground truth (red)

IMU-derived path (blue) and  
ground truth (red)





# SLAM: Sensors

## Monocular camera



Localization and mapping based on  
Structure-from-Motion (SfM) methods

- 3D positioning and map reconstruction,
- Additional data – RGB colors,
  - High frequency,
- Efficient image processing algorithms available,
  - High resolution

- Limited FOV,
- No scale of the resulting model,
  - Camera calibration needed,
- Affected by changing or weak lightning conditions,
  - Medium range



# SLAM: Sensors

## Stereo/depth camera



Localization and mapping based on  
Structure-from-Motion (SfM) methods

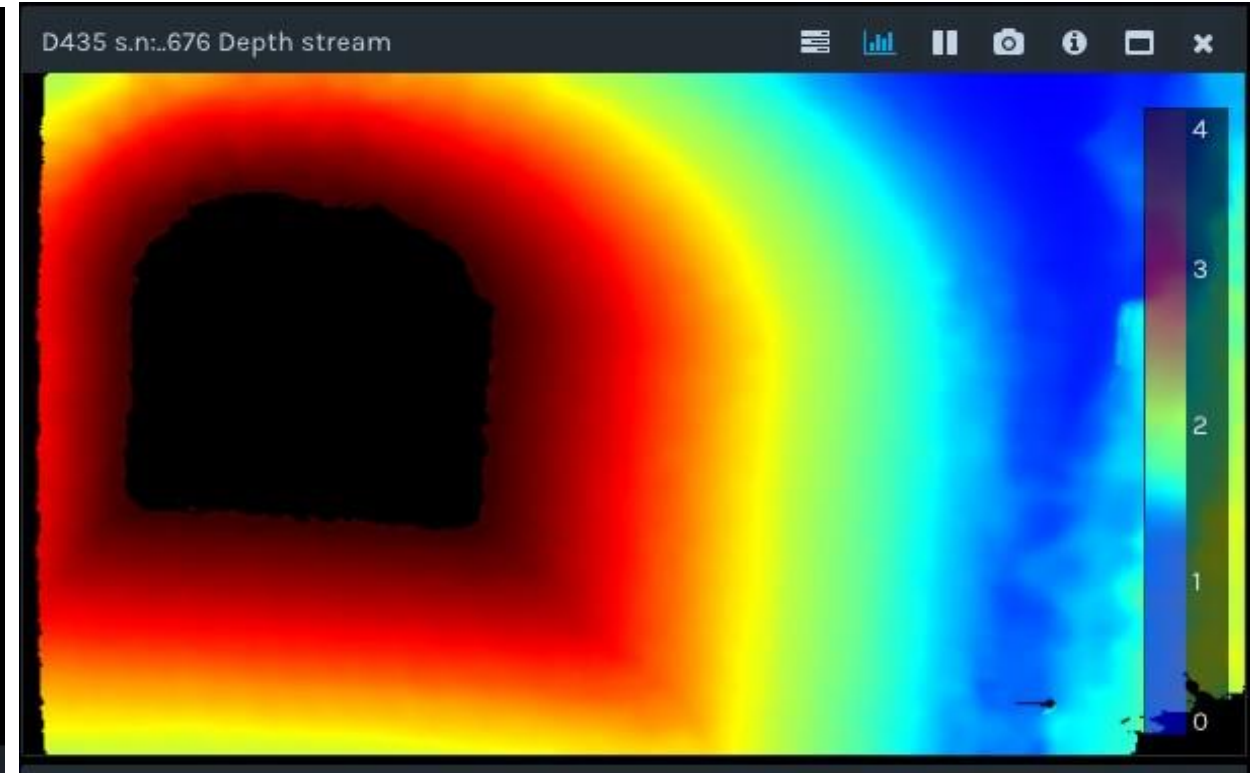
- 3D positioning and map reconstruction,
- Additional data – depth maps, RGB colors (and sometimes infrared),
- Sometimes active sensors,
- High resolution

- Limited FOV,
- Camera calibration needed,
- Affected by changing, weak lightning conditions or materials of low reflectivity,
- Medium range

# SLAM: Sensors

Stereo/depth camera

Sample data from a depth camera



# SLAM: Sensors

## 2D laser scanner



### Laser rangefinder rotating in one plane

- 2D positioning and map reconstruction,
- Metric data with good accuracy,
- High (often 360°) FOV,
  - Unaffected by illumination,
  - High range

- Only planar map and path estimation,
- No vertical motion data may influence planar map errors (e.g. robot pitch changes)



# SLAM: Sensors

## 3D laser scanner



Set of laser rangefinders acquiring data  
in more than one plane

- 3D positioning and map reconstruction,
- Metric data with good accuracy,
- High (often 360° in base plane) FOV,
- Unaffected by illumination,
- High range

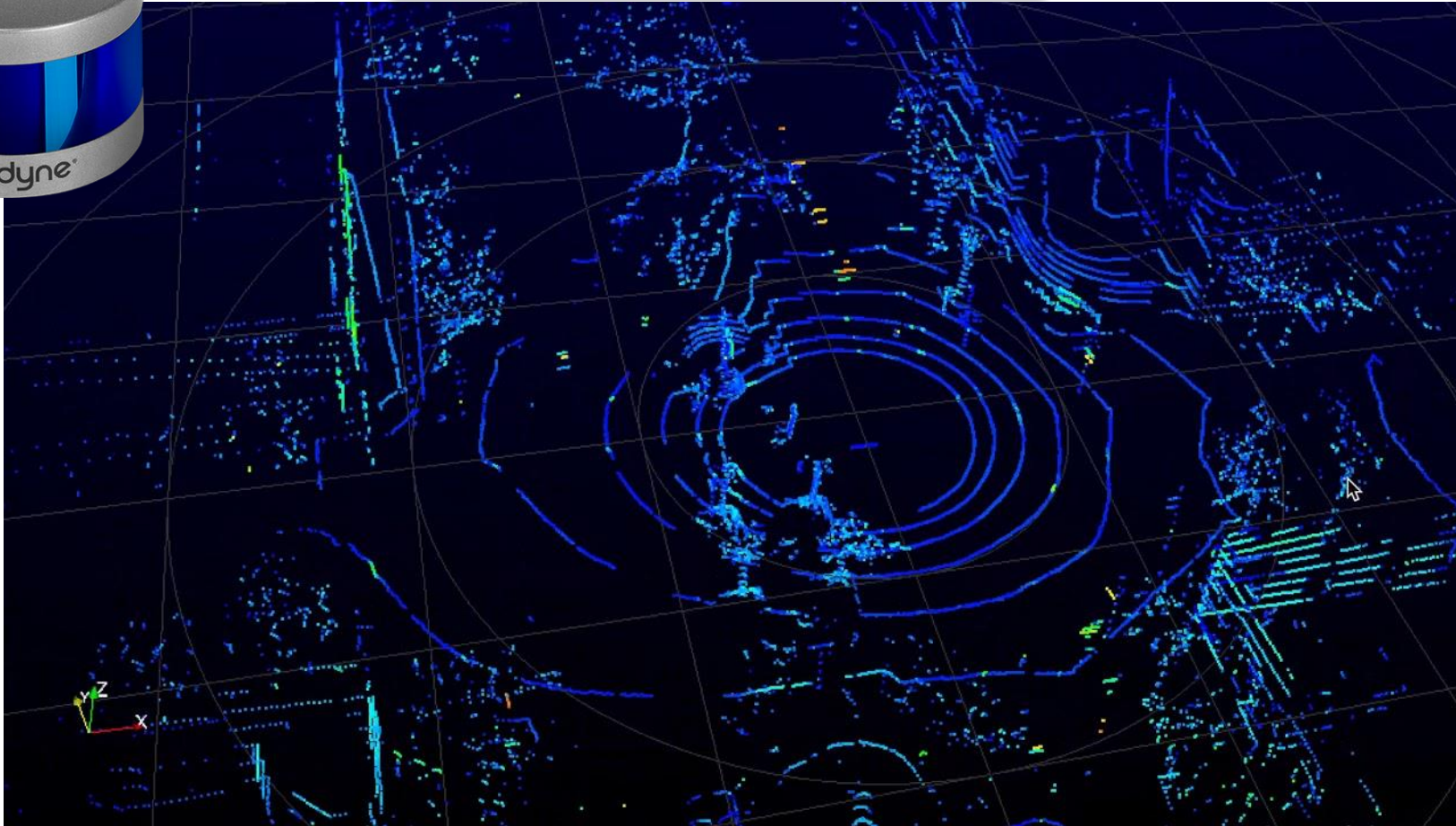
- Vertical motion can still cause robot pitch drift (no gravity vector estimation)





# SLAM: Sensors

3D laser scanner



360° FOV, limited vertical  
resolution (ring pattern)

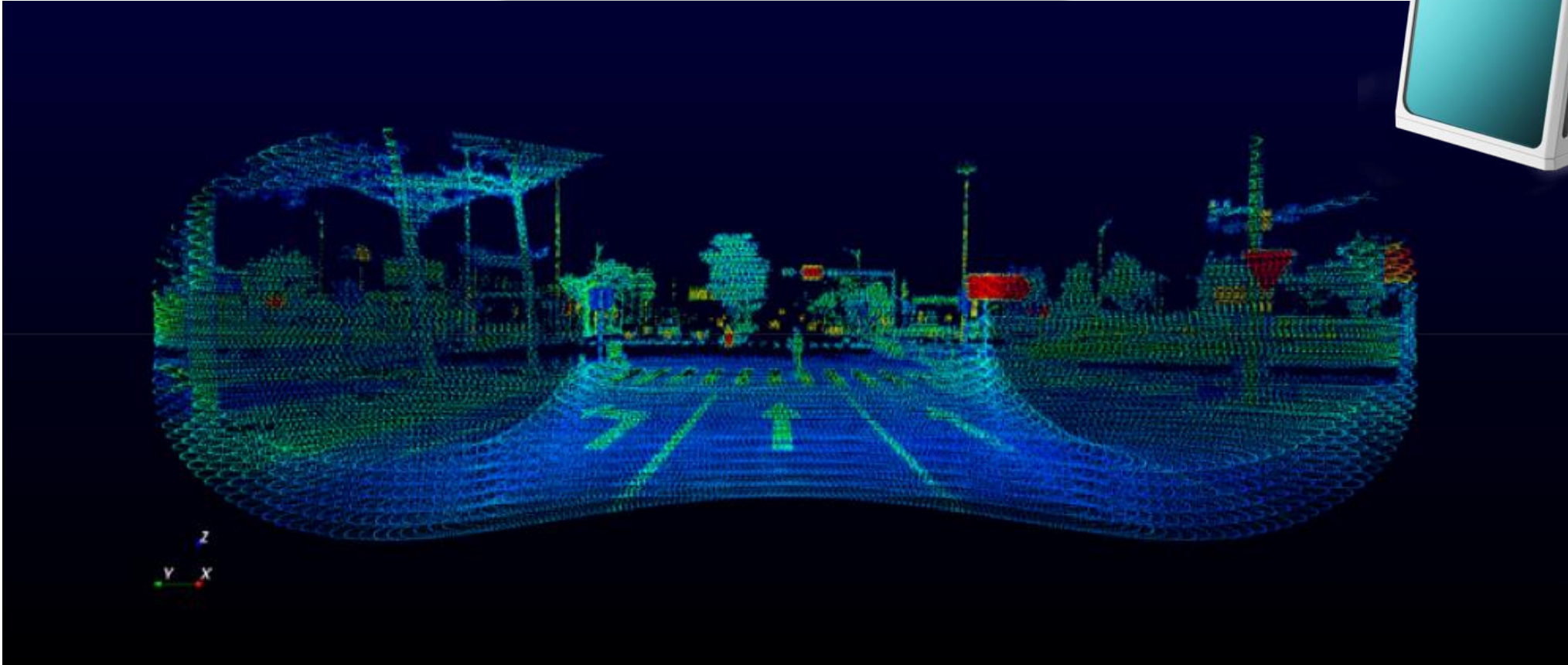


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# SLAM: Sensors

3D laser scanner



Lower FOV, better vertical resolution  
(more regular pattern)



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# SLAM: Approaches

There are 2 main subtypes of SLAM algorithms:

- a) **Grid-based:** using the division of space into small squares or cubes (*pixels/voxels*) of chosen size; we then check if sensors detect anything in a a pixel/voxel or not and create a **grid** or **volumetric map**,
  
- b) **Feature-based:** extracting distinctive features from images/scans and using them to create a **landmark map**.

Choice of the algorithm depends mostly on the sensors used (laser scanners often utilized in *a*), cameras in *b*)) and the specific application requirements.

Accuracy – depending on method, sensor accuracy, site scale and numer of revisits (loop closures); up to a few cm.

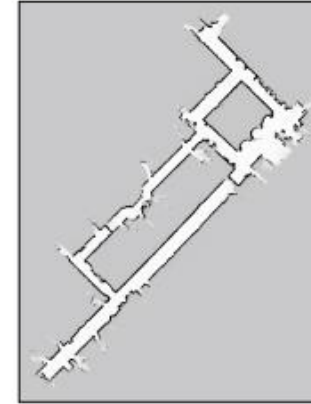
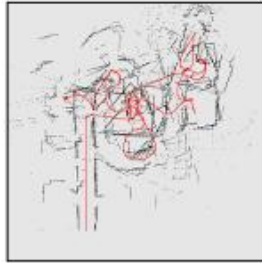


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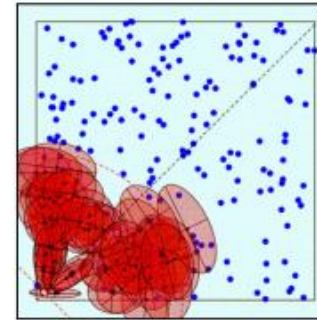
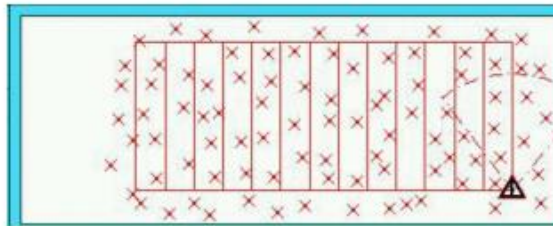


## Grid maps or scans, 2d, 3d



[Lu & Milios, 97; Gutmann, 98; Thrun 98; Burgard, 99; Konolige & Gutmann, 00; Thrun, 00; Arras, 99; Haehnel, 01; Grisetti et al., 05; ...]

## Landmark-based



[Leonard et al., 98; Castelanos et al., 99; Dissanayake et al., 2001; Montemerlo et al., 2002; ...]



# SLAM: Approaches

## a) Grid-based SLAM

Chosen methods used in matching data from subsequent poses:

- Kalman Filters,
- Particle filters,
- Iterative Closest Points (ICP),
- Normal Distribution Transform (NDT),
  - Plane fitting,
  - Edge detection,
- RANdom Sample Consensus (RANSAC).



# SLAM: Approaches

## b) Feature-based SLAM

Chosen methods used in visual, feature based SLAM:

- Feature detectors:
  - SIFT, SURF, BRISK, ORB, FAST, GFTT, STAR,
  - Feature descriptors:
    - SIFT, SURF, BRISK, ORB, BRIEF, FREAK,
    - Bag of Words,
    - Kalman Filters,
    - Particle filters,
- RANdom Sample Consensus (RANSAC).

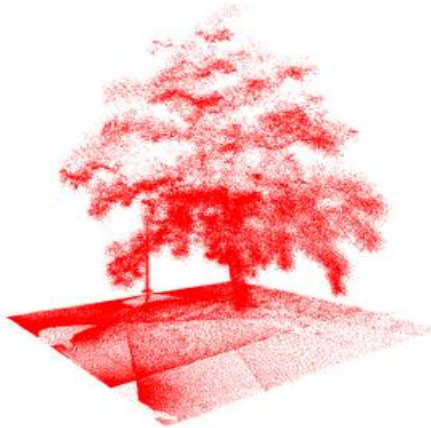




# SLAM: Data types of results

## Point cloud

Each point displayed



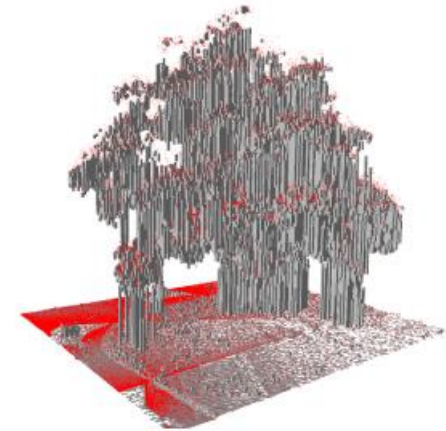
## 3D voxels

Cubes where *anything* was detected



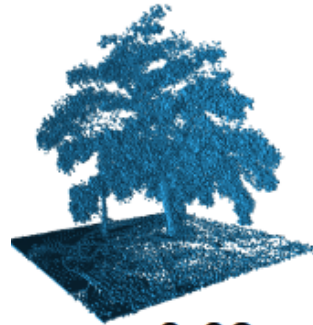
## 2.5D map

Only the highest cube is kept (less disk space needed)

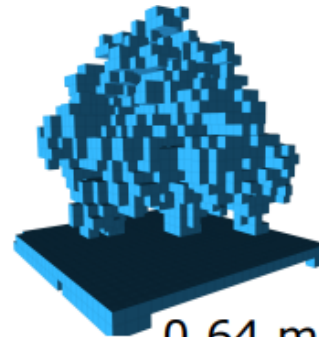


## Octree

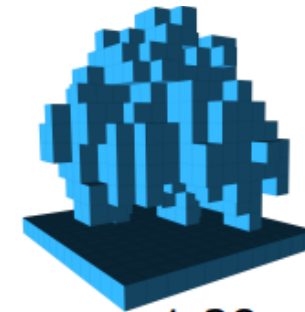
Multiple 3D voxel models  
for different resolutions  
(adaptable to different  
requirements)



0.08 m



0.64 m



1.28 m

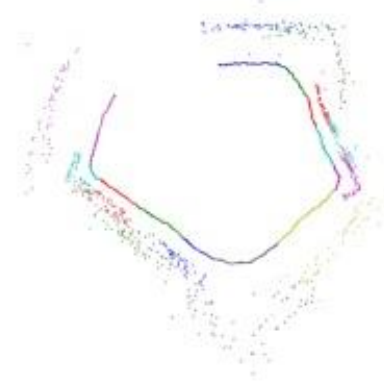


# SLAM: Loop closures

## Loop closure detection

- Recognizing a previously visited place

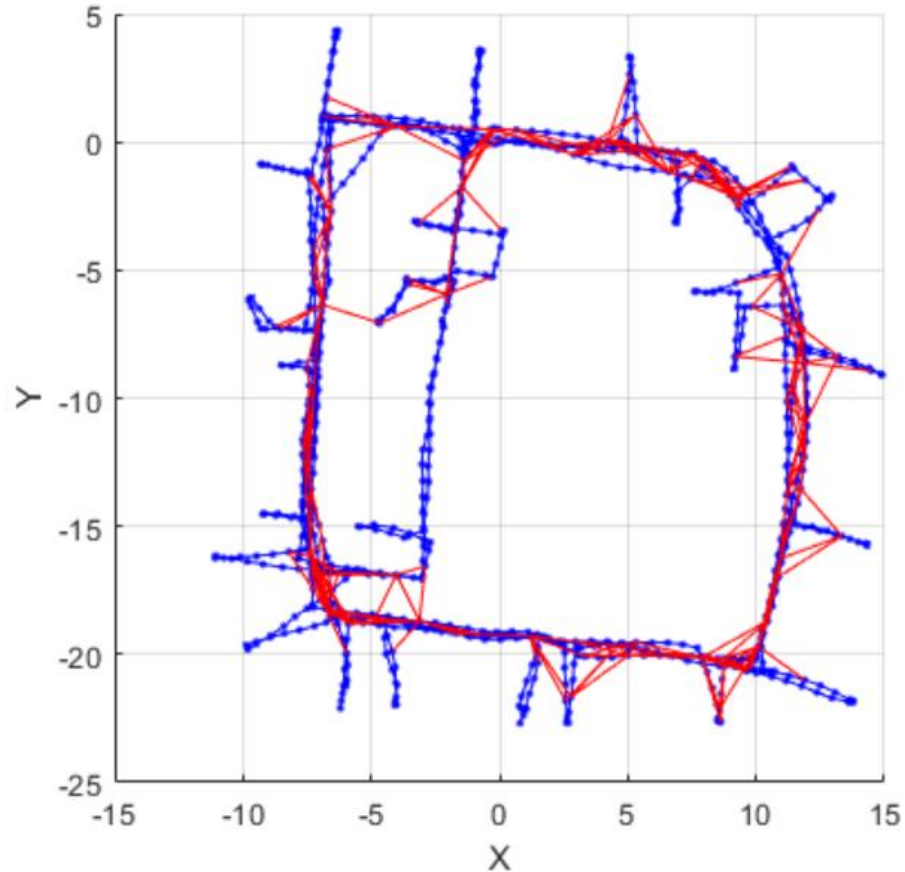
- Subsequent scan/image matching: **1-to-1** problem
  - Checking for a possible loop closure: **1-to-all** problem
- ↓
- Computation complexity very quickly growing over time





# SLAM: Loop closures

Pose graph optimization

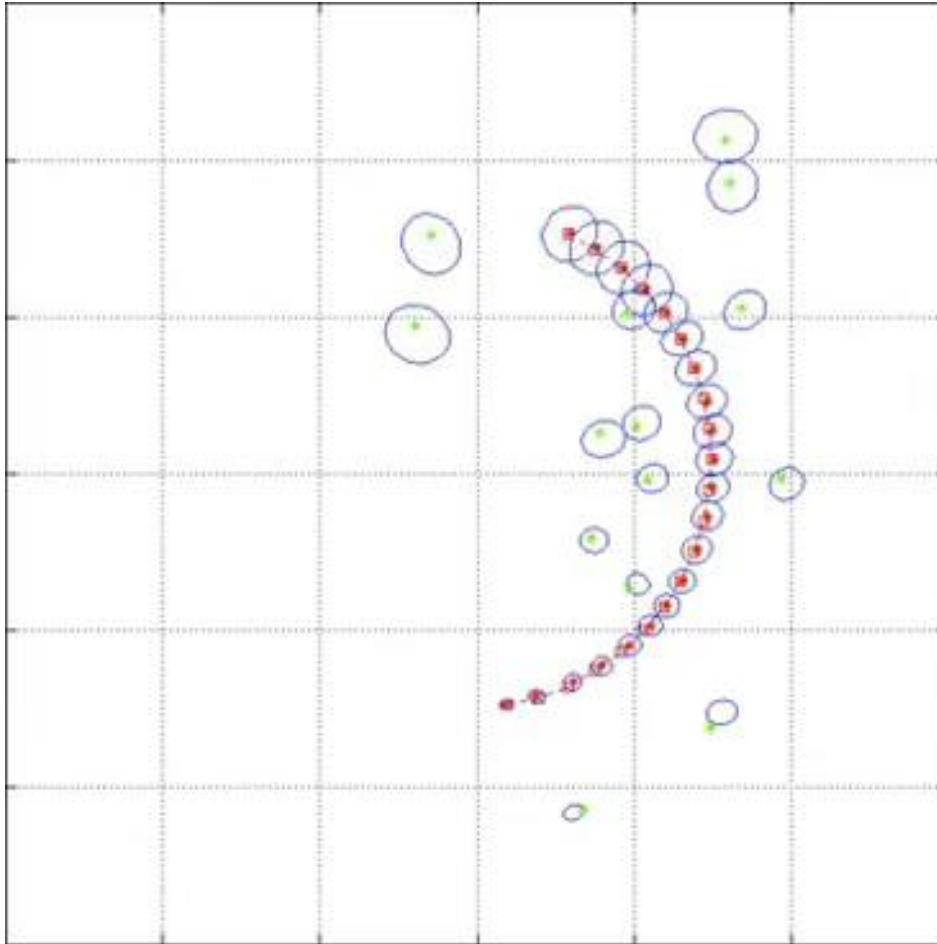


Example 2D pose graph.  
Edges connecting subsequent poses in blue,  
loop closure edges in red





# SLAM 2D: Examples



## FastSLAM 2D algorithm

Feature based.

Ellipses symbolize standard deviation of the robot's and landmarks' positions.

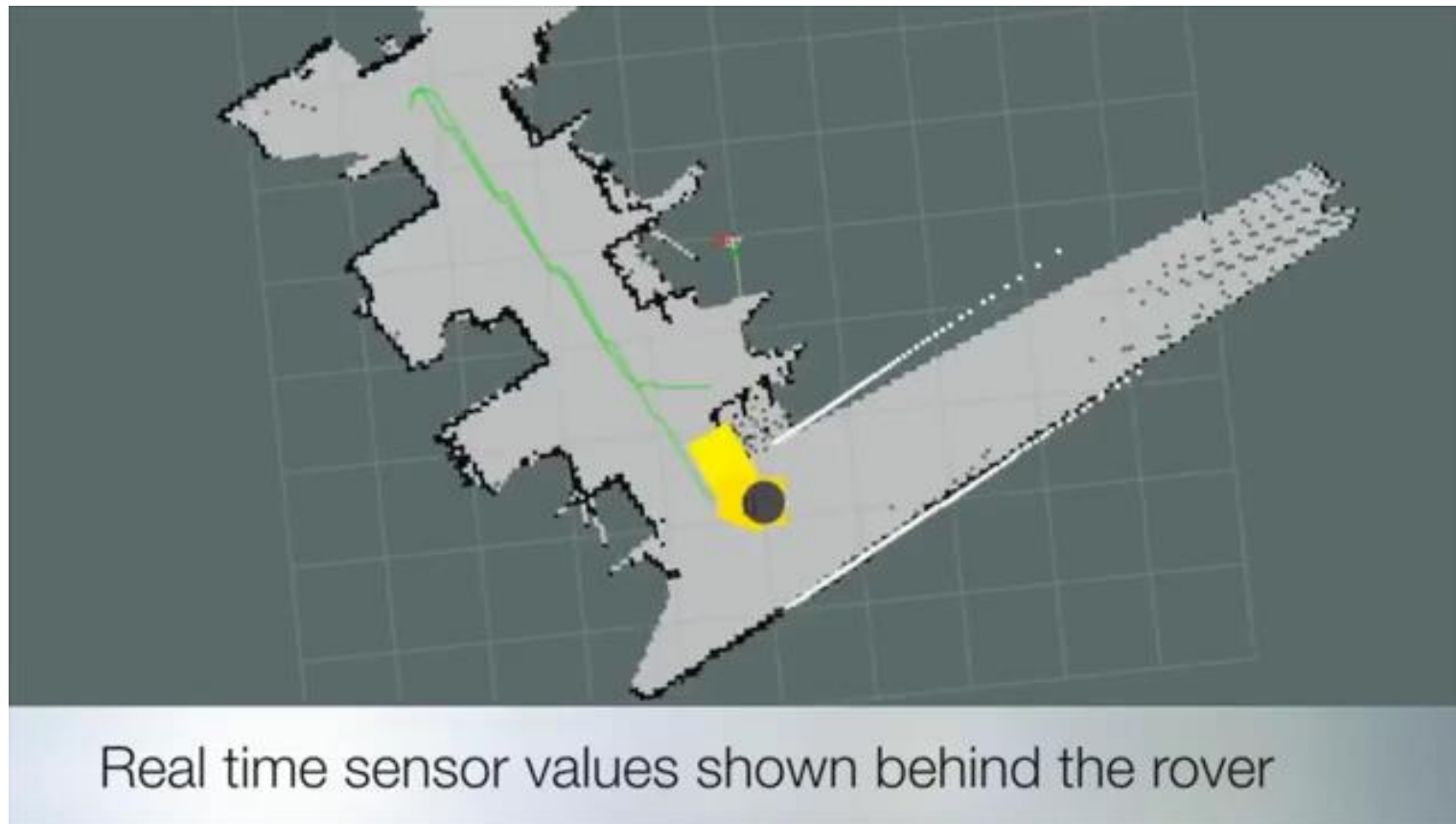
Loop closure at the end greatly improves precision!





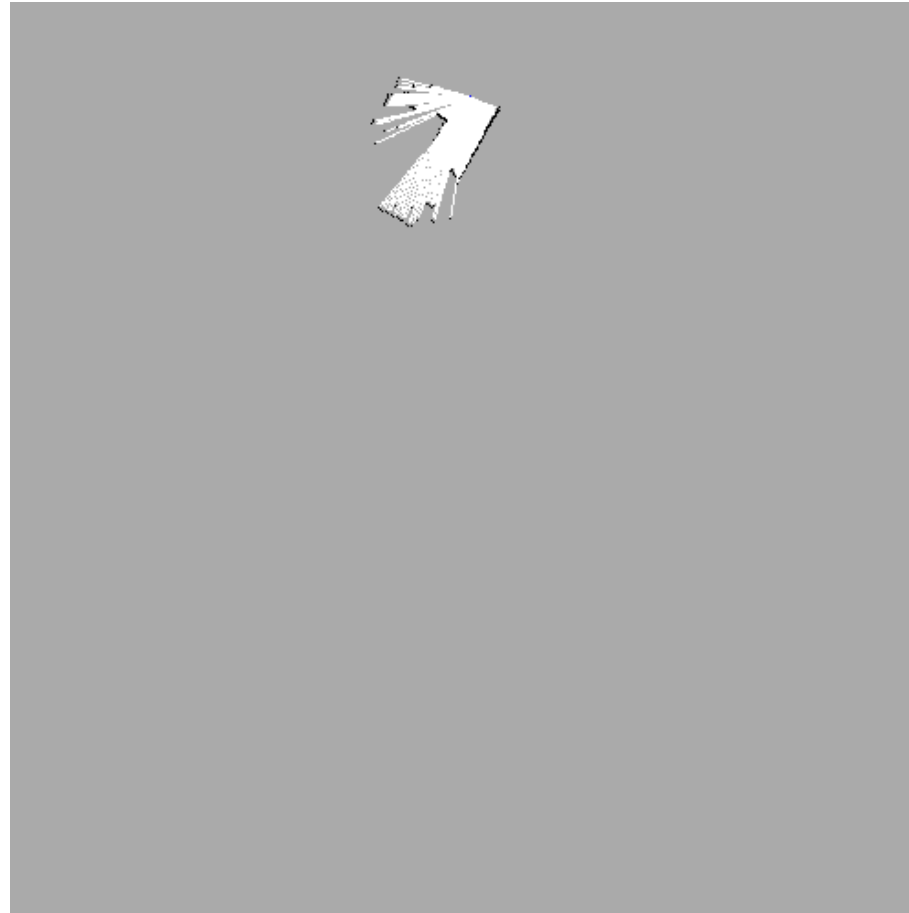
# SLAM 2D: Examples

**EKF SLAM 2D**  
Grid-based



# SLAM 2D: Examples

**EKF SLAM 2D**  
Grid-based

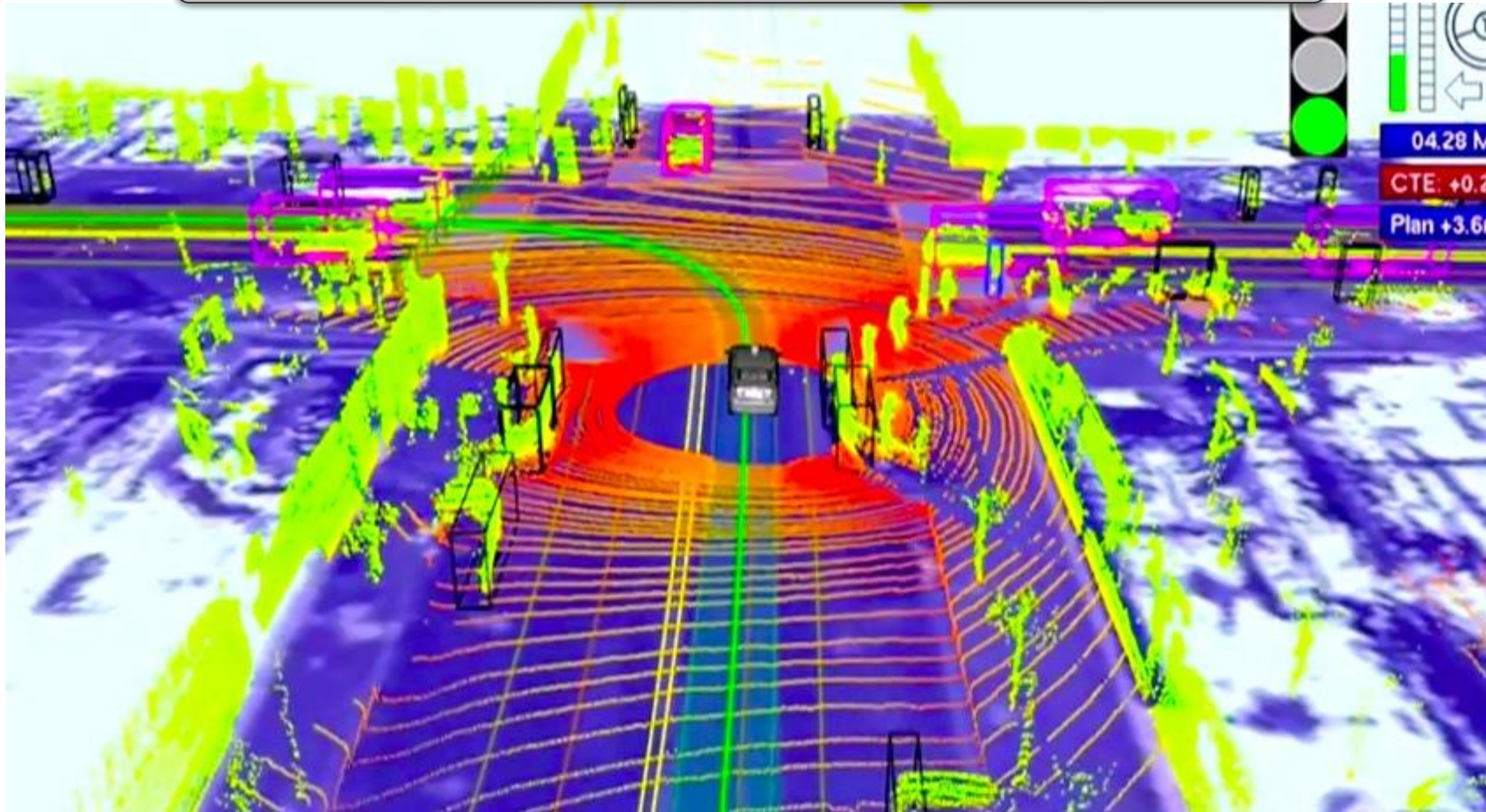




# RawMaterials LiDAR SLAM 3D: Examples

Conne

Google's Self-Driving Car's perception system based on SLAM



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Source: <http://spectrum.ieee.org/automaton/robotics/artificial-intelligence/how-google-self-driving-car-works>

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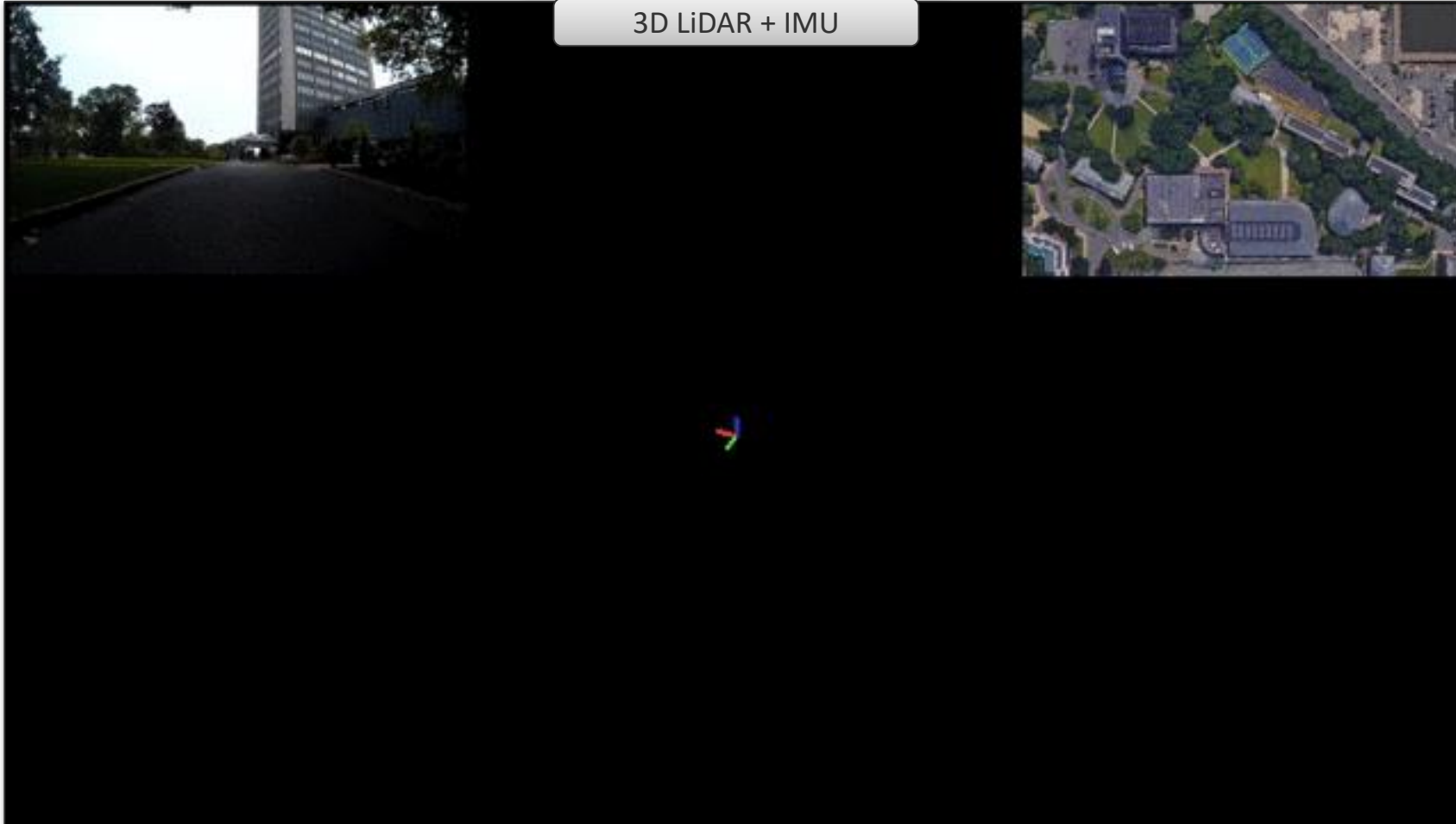


# RawMaterials LiDAR SLAM 3D: Examples

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LeGO-LOAM 3D SLAM

3D LiDAR + IMU



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# RawMaterials LiDAR SLAM 3D: Examples

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LeGO-LOAM 3D SLAM

3D LiDAR

Real-time Velodyne Lidar Odometry on Embedded System  
Using Nvidia Jetson TX 1



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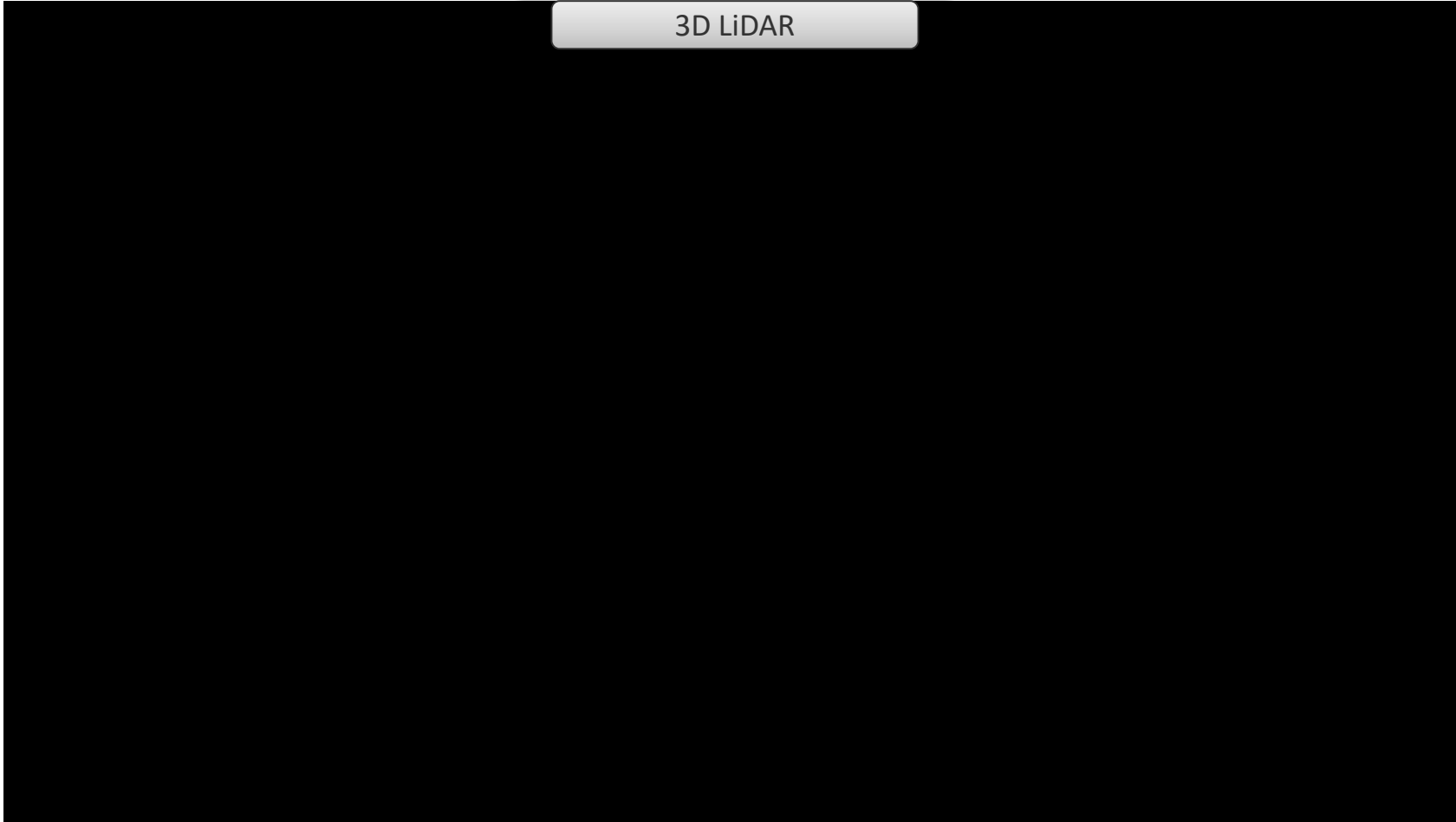


# RawMaterials LiDAR SLAM 3D: Examples

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BLAM SLAM

3D LiDAR



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# RawMaterials LiDAR SLAM 3D: Examples

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GICP-based Graph SLAM

3D LiDAR



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# Visual SLAM 3D: Examples

ORB-SLAM

Monocular and stereo camera examples



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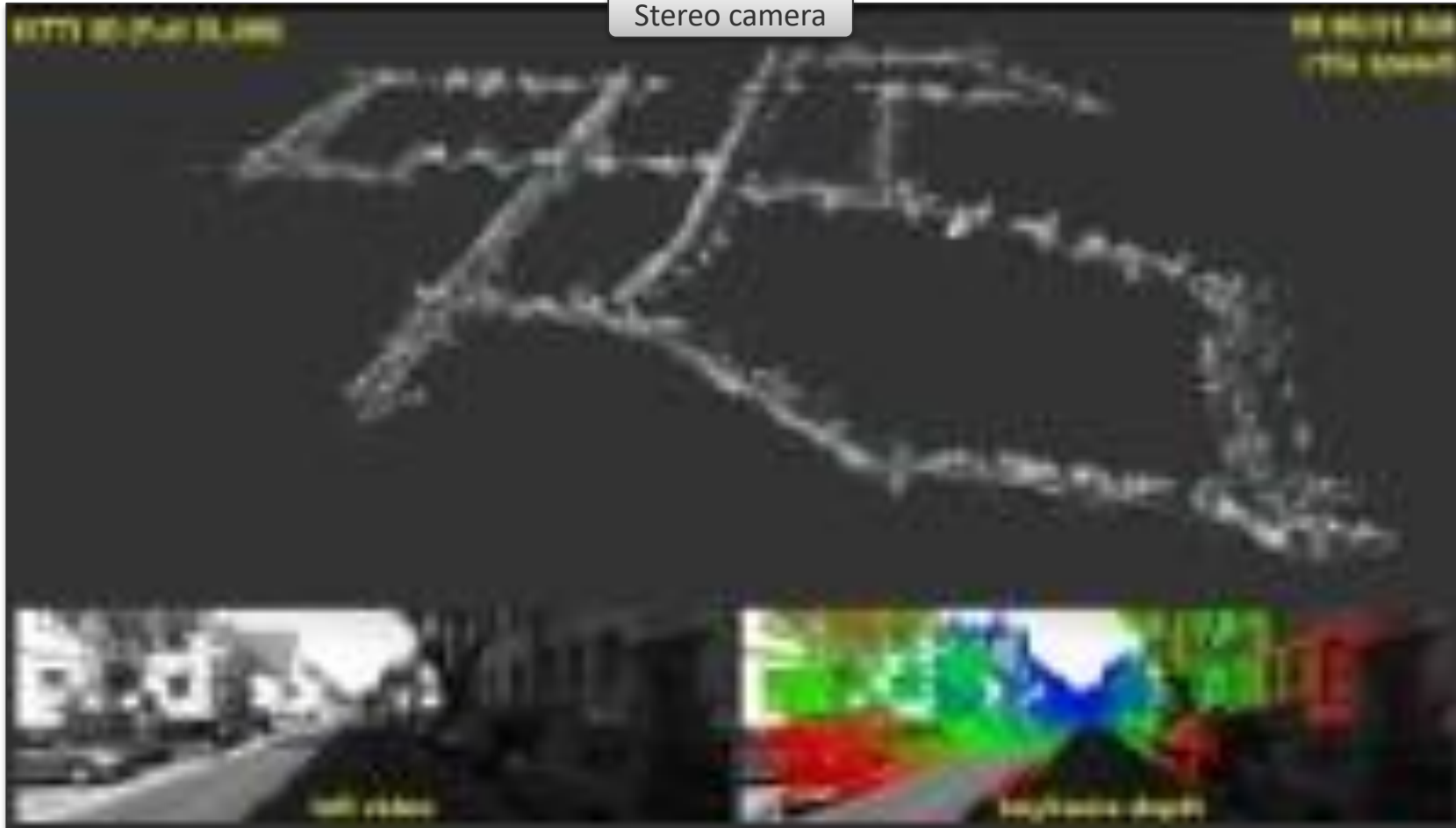


# RawMaterials Visual SLAM 3D: Examples

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LSD-SLAM

Stereo camera



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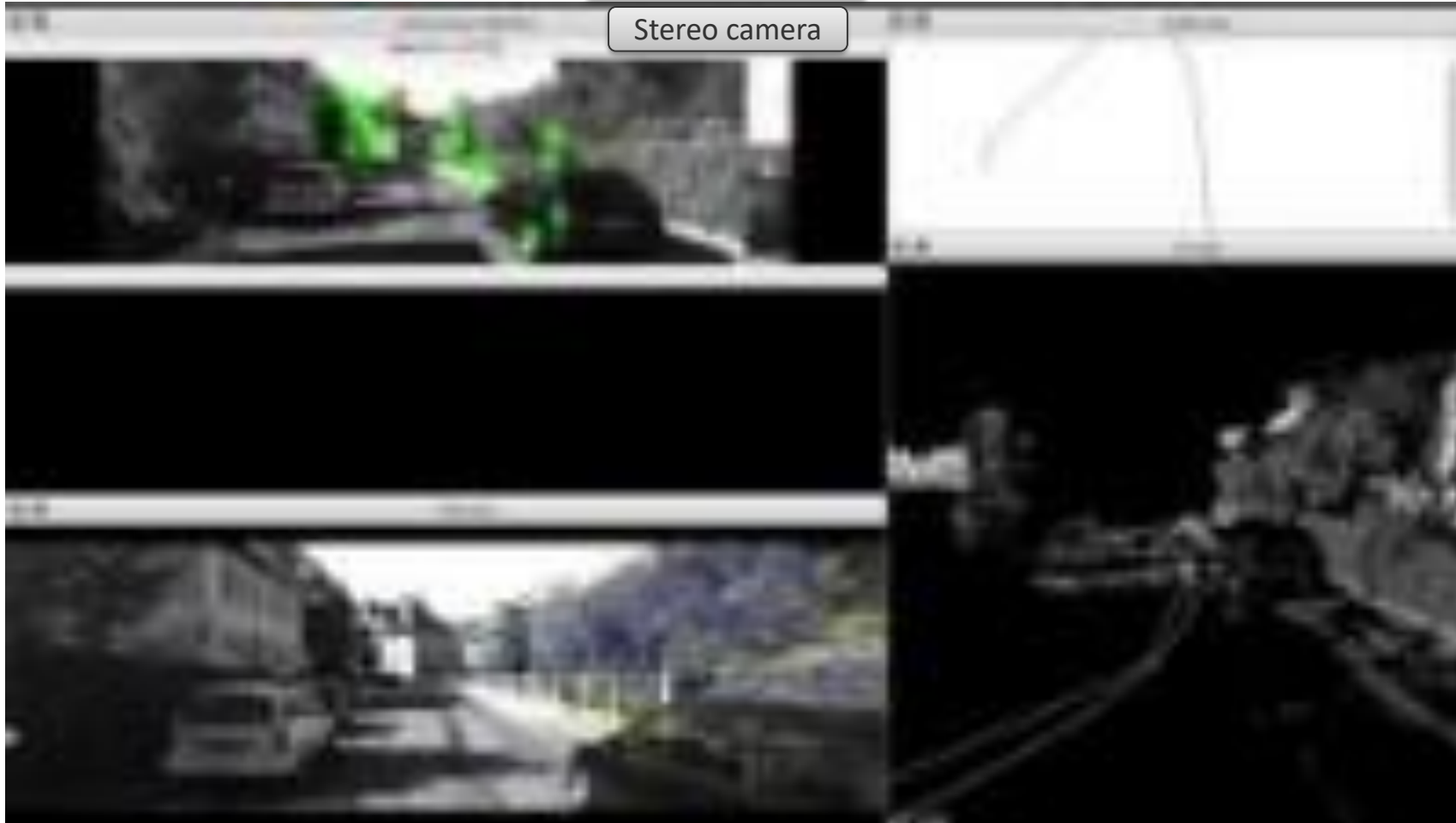


# RawMaterials Visual SLAM 3D: Examples

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RTAB-Map

Stereo camera



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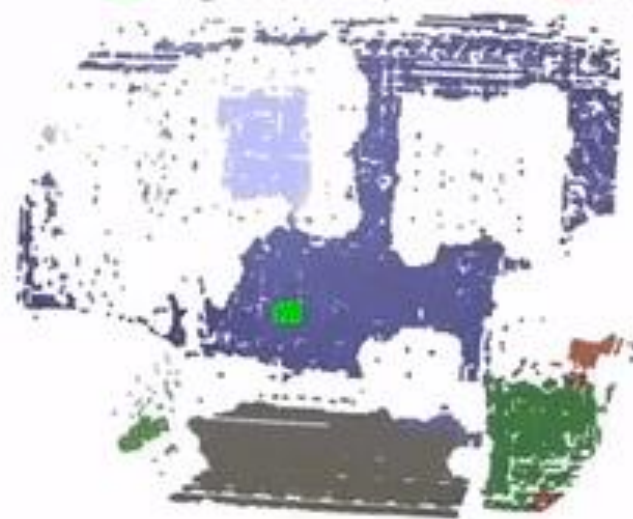
# RawMaterials SLAM: Further possibilities

Deep learning & SLAM → metric model with object detection



FPS: 29.644848

■:Floor ■:Vertical structure/Wall  
■:Large structure/furniture ■:Small structure



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Source: CNN-SLAM: Real-Time Dense Monocular SLAM With Learned Depth Prediction (thecvf.com)

## SLAM in a mine

### Challenges:

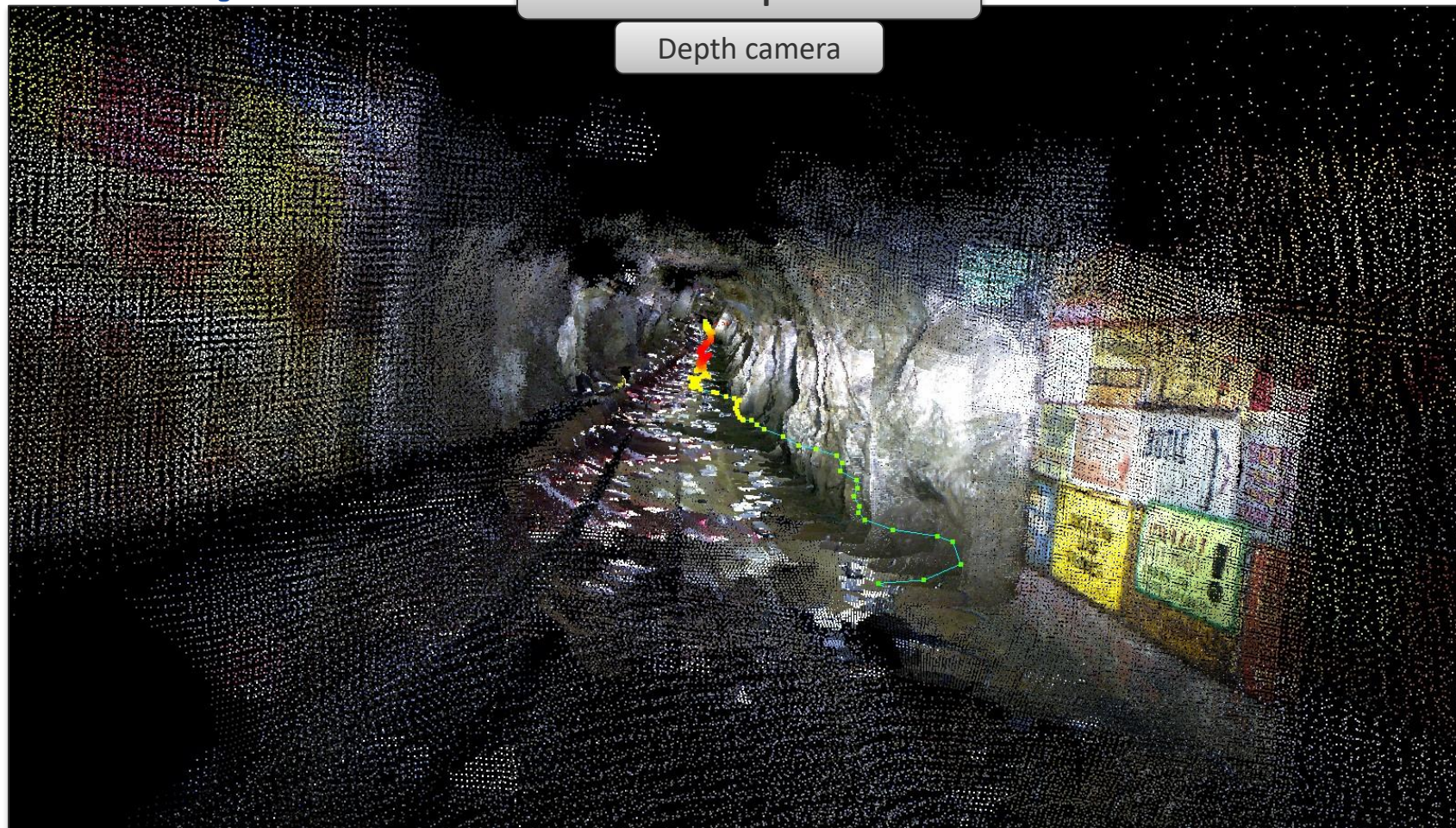
- Weak illumination,
- Dust,
- Rough, slippery terrain,
- Falling rocks,
- Irregular surroundings,
- Dark, obscure, narrow corridors,
- Moving people and vehicles,
- Magnetic field disturbances,
- Limited wireless network range.



# SLAM in a mine

RTAB-Map SLAM

Depth camera



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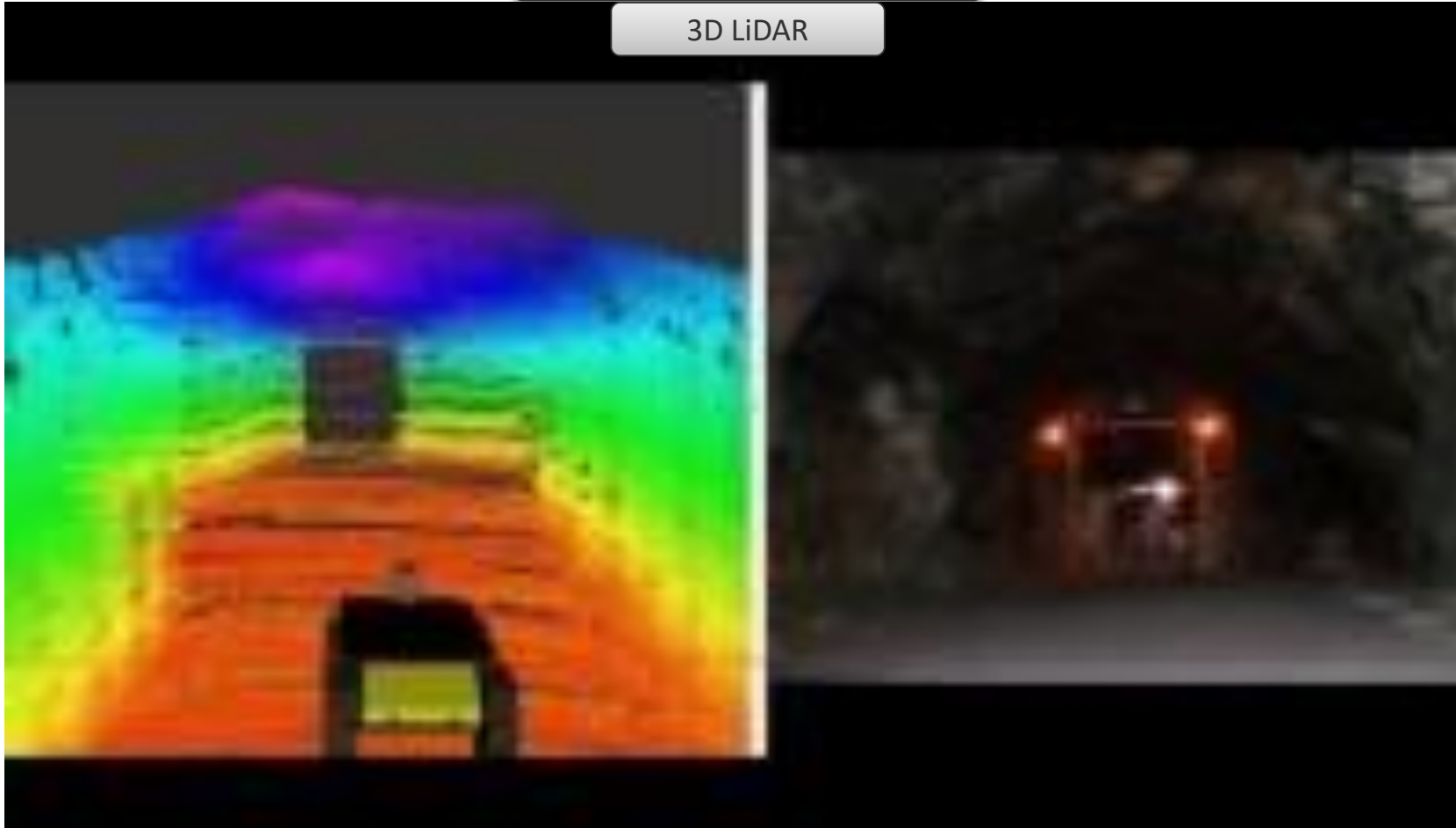
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# SLAM in a mine

GICP-based Graph SLAM

3D LiDAR



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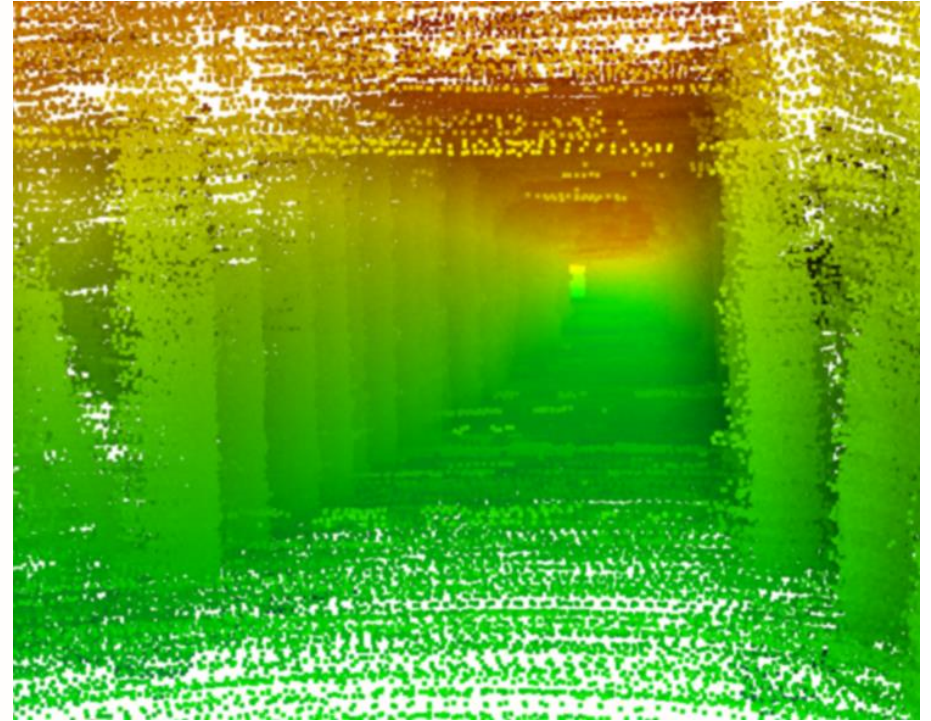
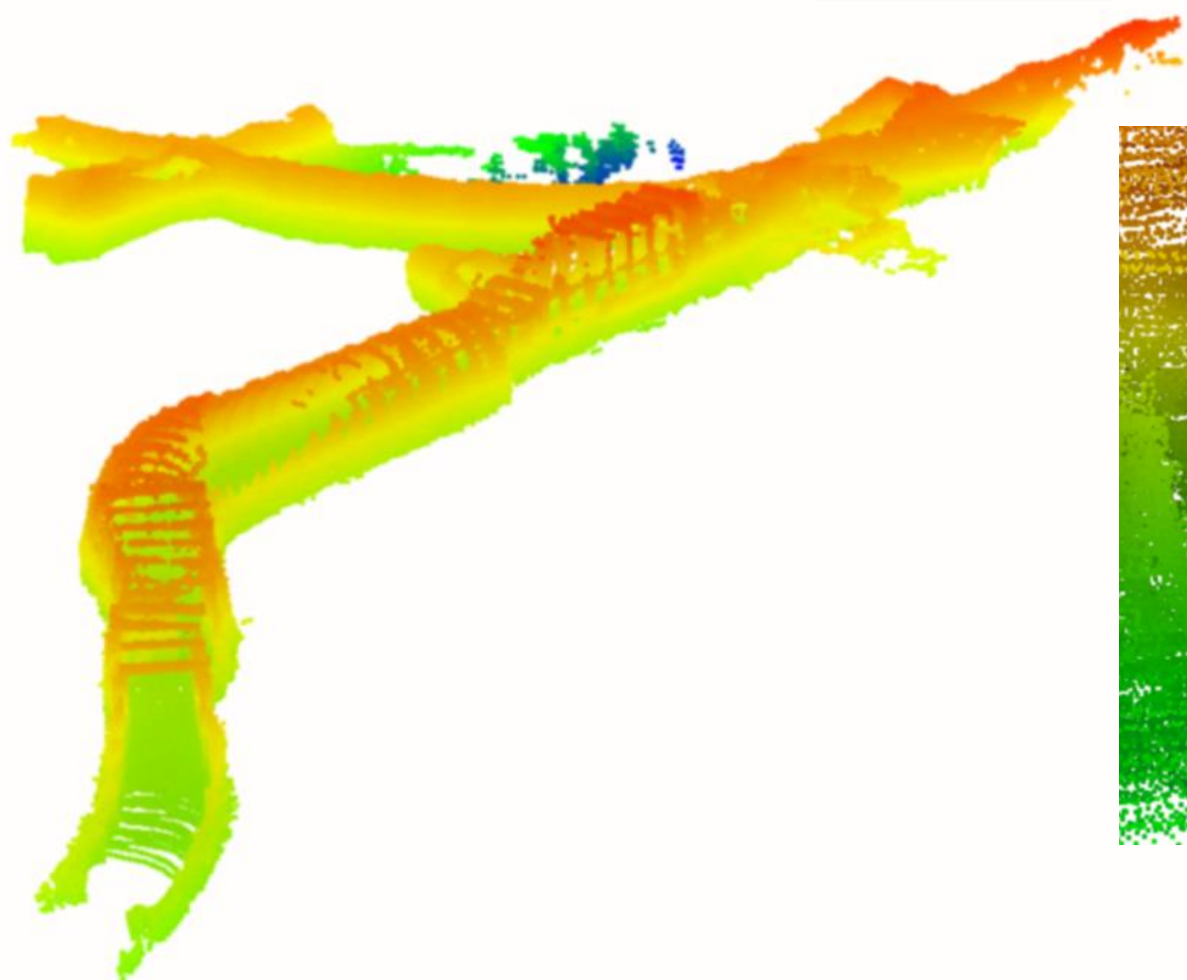
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# SLAM in a mine

GICP-based Graph SLAM

3D LiDAR



This active  
Technology  
Framework

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# Summary

- Robots can use variety of sensors to acquire spatial data.

Gigabytes of highly frequently updated data can be easily gathered, but gaining *knowledge* from *raw data* can be troublesome.

- SLAM algorithms are (for now) a suitable solution for autonomous vehicles.  
However, a lot of improvements and research is needed to achieve fully satisfying, reliable results, especially in demanding environments like underground mines.
- Algorithms based on fusing data from different sensors have the potential to leverage advantages of multiple methods and eliminate their weak sides. It will be necessary to achieve reliable SLAM solution in an underground mine.







# SLAM: Additional resources

- [OpenSLAM.org](#)
- [OpenVSLAM: A Versatile Visual SLAM Framework](#)
- [The list of vision-based SLAM / Visual Odometry open source, blogs, and papers](#)
- [Cartographer – opensource.google](#)



Thank you for your attention

