Robotics

Erwin M. Bakker| LIACS Media Lab

4-3 2024

Universiteit Leiden

Bij ons leer je de wereld kennen

Organization and Overview

Lecturer:
Dr Erwin M. Bakker (erwin@liacs.nl)
Room 126a and LIACS Media Lab (LML)

Teaching assistants:
Xia Tian
Aristidou Kyriakos
Dimitrios Kourntidis
Ruilin Ma

Period: February 5th - May 21st 2024
Time: Monday 15.15 - 17.00
Place (Rooms):
a) LMUY Havingazaal

2nd Session for ACS students and upon individual request:
Time: 17.15 – 19.00
Place: Room 4.02 Snellius Building

Schedule (tentative, visit regularly):

Date	Subject
5-2	Introduction and Overview
12-2	Locomotion and Inverse Kinematics
19-2	Robotics Sensors and Image Processing
26-2	No Class
4-3	SLAM + Workshop@Home
11-3	Robotics Vision + Intro Mobile Robot Challenge
18-3	Project Proposals I (by students)
25-3	Project Proposals II (by students) *
1-4	No Class (Eastern)
8-4	Robotics Reinforcement Learning + Workshop@Home
15-4	Project Progress Reports I
22-4	Project Progress Reports II
29-4	Mobile Robot Challenge I
6-5	Mobile Robot Challenge II
13-5	Project Demos I -
20-5	No Class (Whit Monday)
27-5	Project Demos II
7-6	Project Deliverables

Grading (6 ECTS):
- Presentations and Robotics Project (60% of grade).
- Class discussions, attendance, assignments (pass/no pass) 2 workshops (0-10) (20% of the grade).

Mobile Robot Challenge (0-10) (20% of the grade)
- ***It is necessary to be at every class and to complete every workshop and assignment.***

Next week INTRODUCTION MOBILE ROBOT CHALLENGE

Groups of 4 to 5 students

Website: http://liacs.leidenuniv.nl/~bakkerem2/robotics/

Universiteit Leiden. Bij ons leer je de wereld kennen

SLAM: Simultaneous Localization And Mapping

Mapping

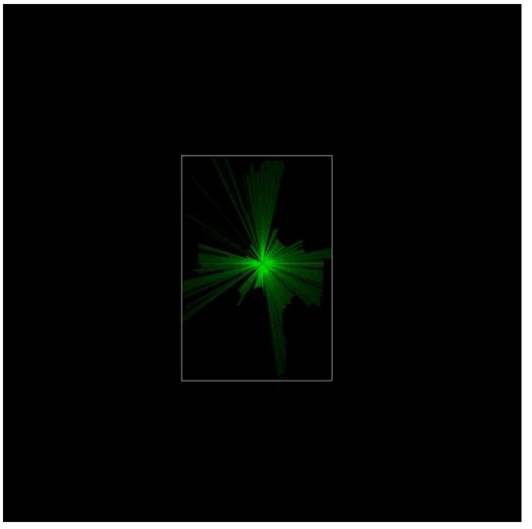
- Use sensor data: US, LIDAR, Camera, Structured Light, etc. to make a map of the environment of the robot.

Localization

- Determine the pose of the robot relative to the map.
- Initial pose can be given: **pose tracking problem**
- No initial pose given: **global localization problem**

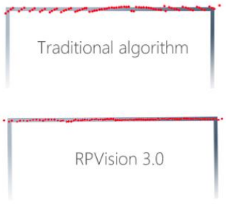
SLAM: do both Mapping and Localization at the same time.

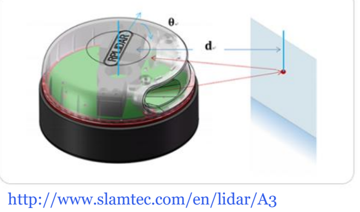
VSLAM: use camera (mono, stereo, multi-, depth, etc.) to solve SLAM



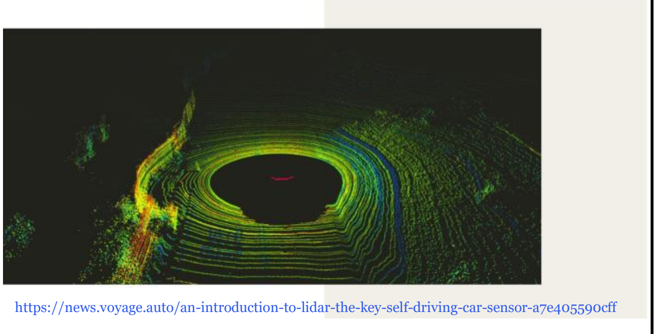
MonsterBorg SLAM by E. van der Zande

LIDAR

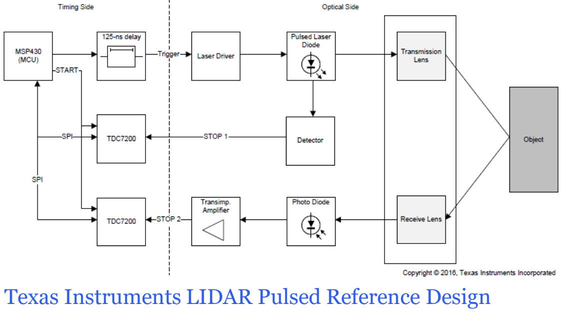




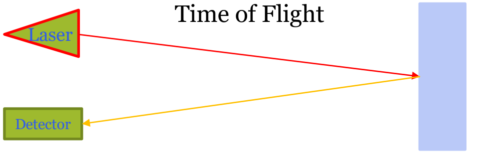
http://www.slamtec.com/en/lidar/A3



https://news.voyage.auto/an-introduction-to-lidar-the-key-self-driving-car-sensor-a7e405590cff



Texas Instruments LIDAR Pulsed Reference Design



- Speed of light ~ 3 x 10^8 m/s
- In 1 picosecond (= 10^{-12} sec) light travels ~ 3 x 10^{-4} m = 0.3 mm
- During 33 picoseconds light travels ~ 1cm

CES2019

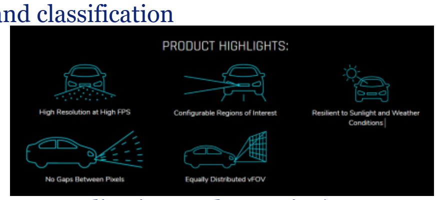
BMW Self Driving Car

InnovizOne Solid-state Lidar (goal: sub $1000 sensor)

- Angular resolution 0.1° x 0.1°
- FOV 120° x 25°
- 25 FPS
- Range 250m

Perception Capabilities

- Object detection and classification
- Lane detection
- Object Tracking
- SLAM

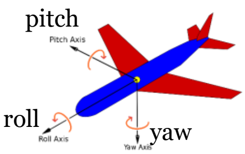


SLAM (Simultaneous Localization And Mapping)

IMU, or Inertial Measurement Unit

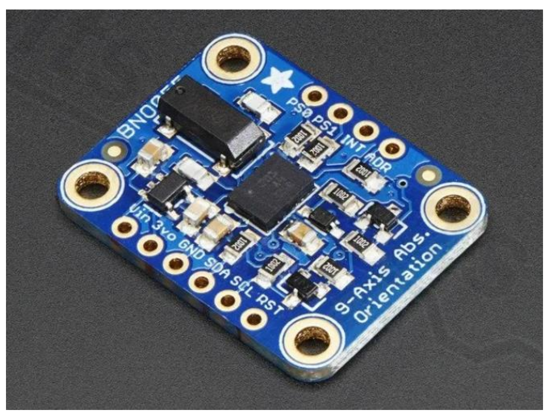
IMU consist of Sensors for

- orientation, by measuring the earths magnetic field and a gyroscope.
- acceleration,
- (angular) velocity.



In SLAM

- **Orientation** is very useful for scan matching: a good initial guess.
- **Acceleration** is calculated by subtracting the earth gravity vector from the raw accelerometer data.
- **Velocity** is calculated by time integration of the acceleration (tends to accumulate large errors)

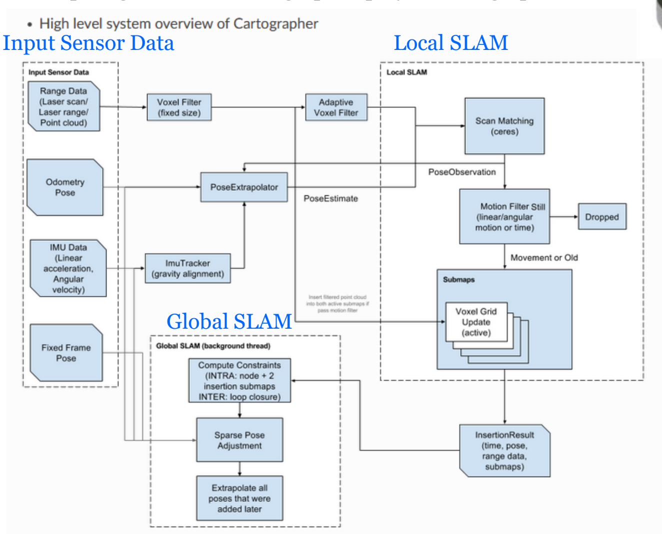


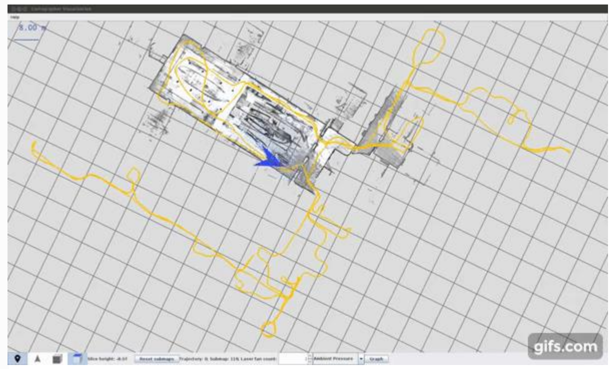
IMU Bosch BNO055 Sampling Frequencies:

- **Accelerometer** updates: 1 KHz
- **Gyroscope** updates: 523 Hz
- **Magnetometer** updates: 30Hz

Cartographer

https://github.com/cartographer-project/cartographer





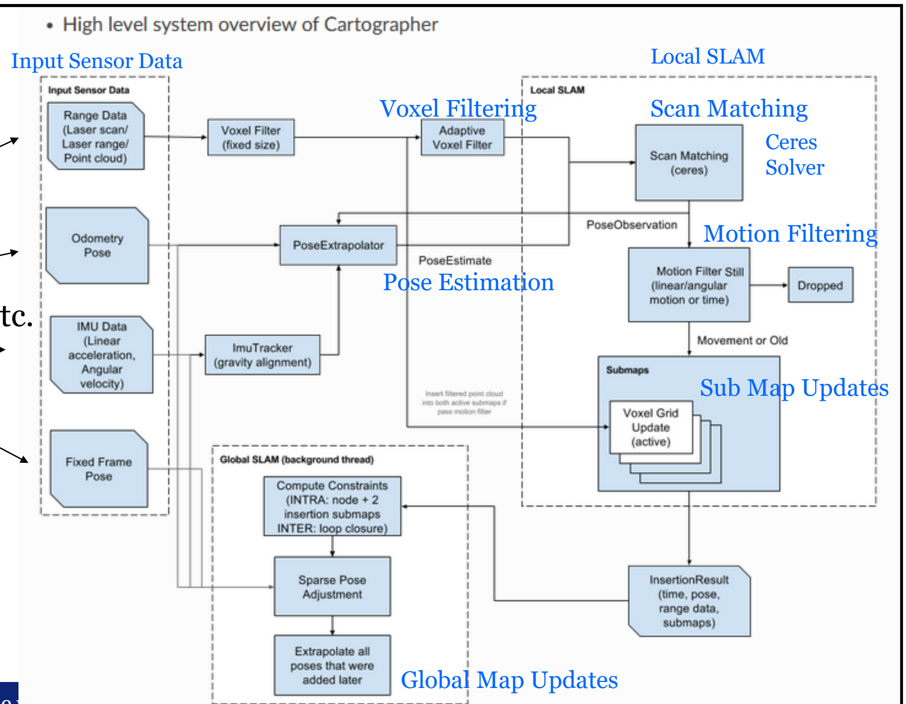
Cartographer gives real-time simultaneous localization and mapping (SLAM) in 2D and 3D.

Universiteit Leiden. Bij ons leer je de wereld kennen

Cartographer

https://github.com/cartographer-project/cartographer

- Lidar
- Odometry
  - wheel encoders, etc.
- IMU
- Fixed Frame

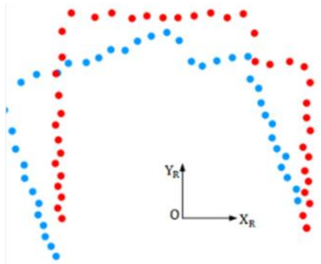


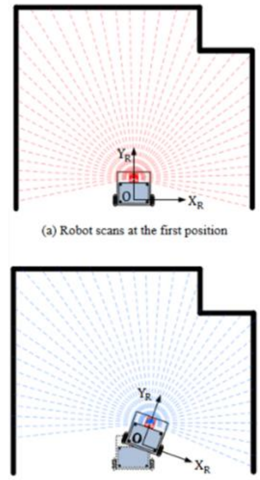
Universiteit Leiden. Bij ons leer je de

2D and 3D Lidar SLAM

Front-end:

- Matching new measurements against the current belief of the environment
- Measurements:
  - typically point clouds of lidar data
  - Movement and heading data: IMU, wheel-encoders, etc.
- Filtering of the data
  - Missing or invalid data (zero length rays)
  - Noisy data: measured too far away
  - Distorted data: e.g., as a result of robot acceleration
- Transform
  - Scan matching tries to find a rigid body transform: translation and rotation
  - IMU can give heading information: more reliable than deriving it from scan matching





Riadh Dhaoui, Ruhr-Universität Bochum

Universiteit Leiden. Bij ons leer je de wereld kennen

2D and 3D Lidar SLAM: Scan Matching

Point to Point Matching

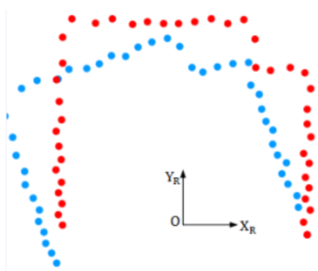
- Between the 2 scans point associations are found
- The translation from points to associated points determines a rigid body transform
- E.g found by Singular Value Decomposition (**Ceres Solver**)
- Fails in case of degenerate clouds (coplanar)
- Point association is difficult to obtain

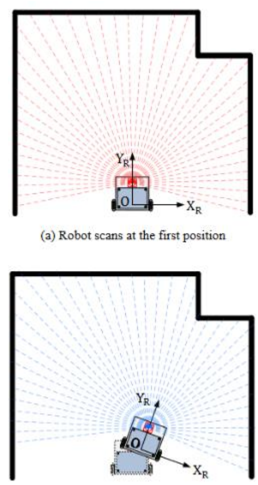
Iterative closest point (ICP) determination

Tangent Matching

Point to Grid Map

- Etc.





Riadh Dhaoui, Ruhr-Universität Bochum

Universiteit Leiden. Bij ons leer je de wereld kennen

2D and 3D Lidar SLAM: Scan Matching

Point to Point Matching

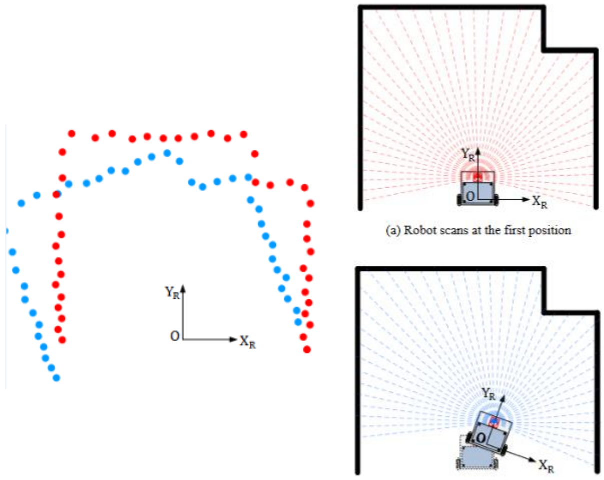
Iterative closest point (ICP) determination

- Compute closest points
- Compute and apply the transformation
- Check if it is good enough, otherwise repeat for the new situation after the transformation
- Converges to local optimum

Tangent Matching

Point to Grid Map

- Etc.



Riadh Dhaoui, Ruhr-Universität Bochum

Universiteit Leiden. Bij ons leer je de wereld kennen

2D and 3D Lidar SLAM: Scan Matching

Point to Point Matching

Iterative closest point (ICP) determination

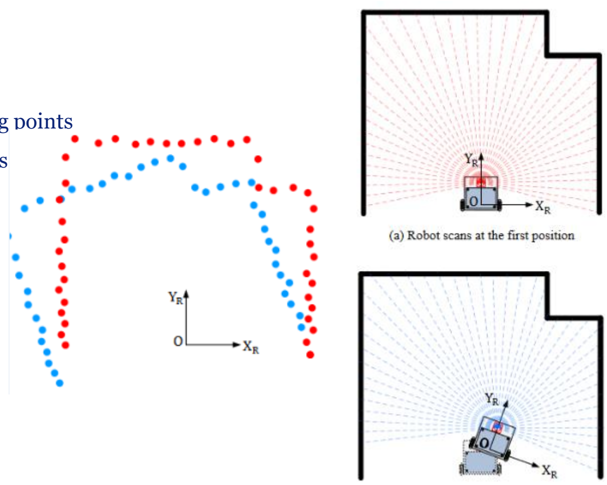
Tangent Matching

- In each of the 2 scans find Tangent lines between neighboring points
- Instead of point matching now line matching between 2 scans
- Movement and heading data from IMU, wheelencoders, etc. can help

Point to Grid Map

- Map the scan points to a coarser grid map and do matching on the grid.

Etc.



Riadh Dhaoui, Ruhr-Universität Bochum

Universiteit Leiden. Bij ons leer je de wereld kennen

SLAM: loop closing using OverlapNet

X. Chen et al. OverlapNet: a siamese network for computing LiDAR scan similarity with applications to loop closing and localization. Autonomous Robots, 2022.

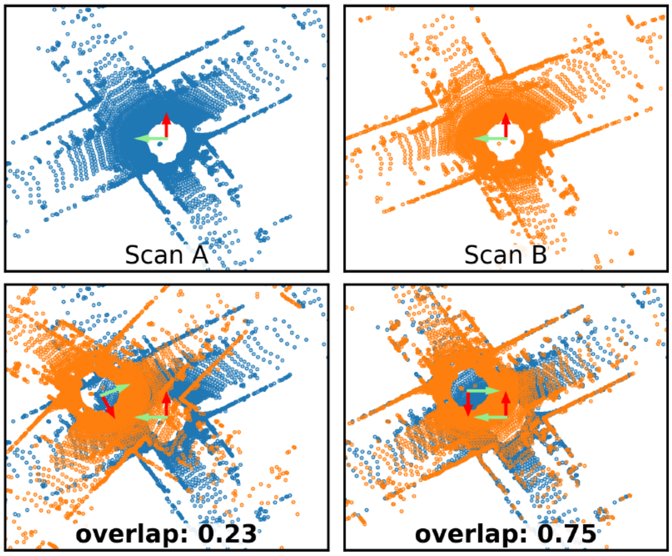
1) Pose estimation relative to recent poses: e.g. using incremental scan matching, IMU data odometry
2) Loop closing: correcting accumulated drift, maintaining consistency between measurements

Loop closure detection:

- Estimate lidar point clouds overlap (note: also used in photogrammetry):
  - Yaw transformation estimate
  - Score, e.g., using Iterative Closest Point
- Can also be used for global scan matching.

OverlapNet a DNN (2021) method that does an estimate without transformation guessing, uses spherical projection of 3D Lidar data.

Performance on Kitty-odometry dataset.

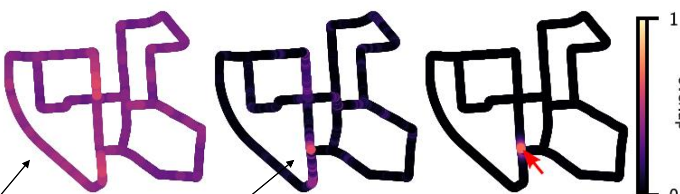


Example: Scan A and B overlap detection: scored after transformation.

Universiteit Leiden. Bij ons leer je de wereld kennen

SLAM: Loop Closing OverlapNet

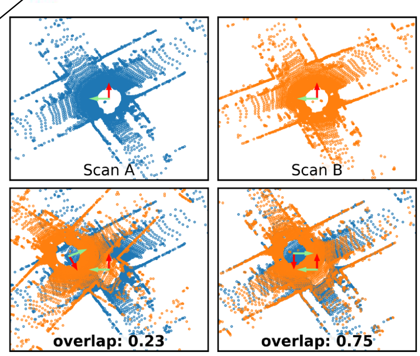
1) Pose estimation relative to recent poses: incremental scan matching, odometry
2) Loop closing: correcting accumulated drift



(a) Exhaustive evaluation of Eq. (3) (b) OverlapNet estimates (c) Ground truth

Loop closure detection:

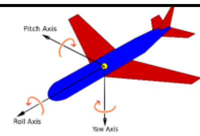
- In general overlap scores based on point-cloud differences (*use Eq. 3 of X Chen et al., OverlapNet ..., Autonomous Robots, 2022*) will be high at many locations of the map.
- OverlapNet a DNN method that does an estimate without transformation guessing, uses spherical projection of 3D Lidar data.

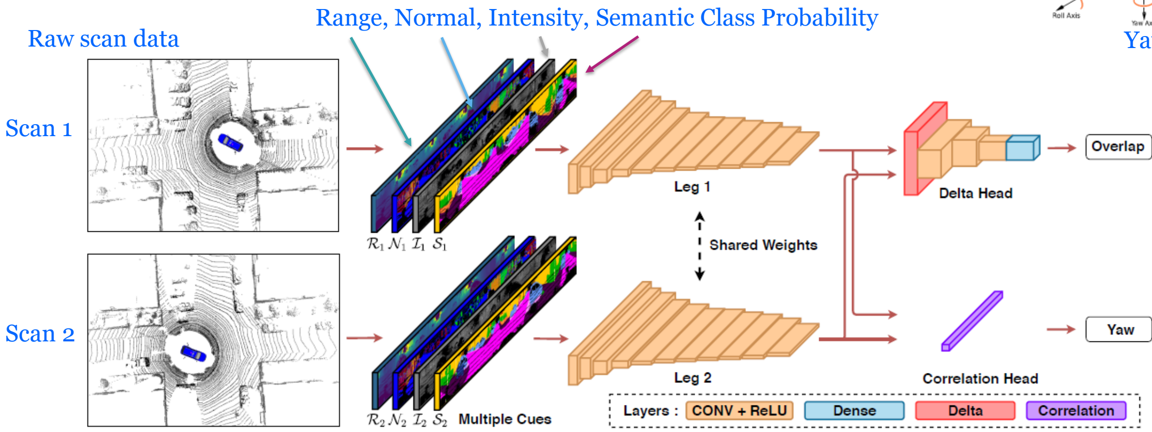


Example: Scan A and B overlap detection: scored after transformation.

Universiteit Leiden. Bij ons leer je de wereld kennen

OverlapNet



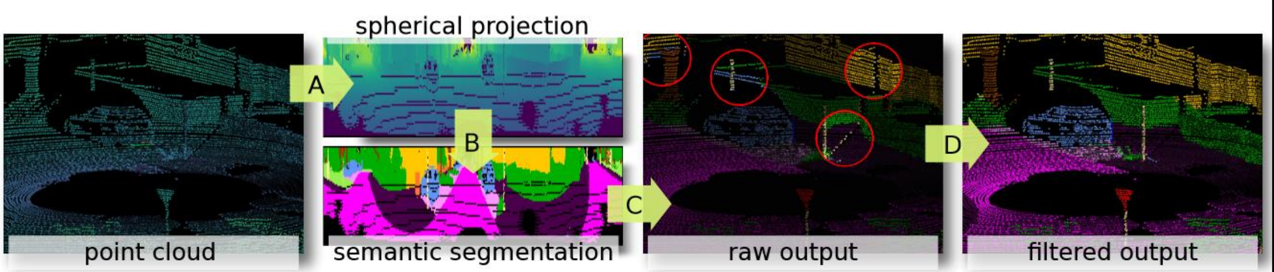


" Pipeline overview of our proposed approach. The left-hand side shows the preprocessing of the input data which exploits multiple cues generated from a single LiDAR scan, including range $\mathcal{R}$, normal $\mathcal{N}$, intensity $\mathcal{I}$, and semantic class probability $\mathcal{S}$ information. The right-hand side shows the proposed OverlapNet which consists of two legs sharing weights and the two heads use the same pair of feature volumes generated by the two legs. The outputs are the overlap and relative yaw angle between two LiDAR scans."

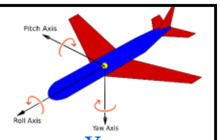
Milioto et al. **RangeNet++: Fast and Accurate Lidar Semantic Segmentation.** IEEE IROS, 2019.

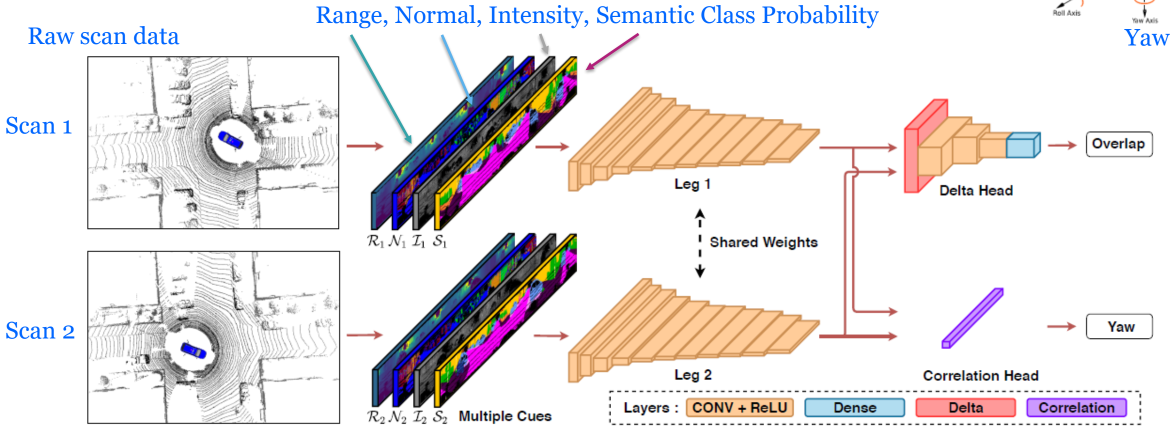
TABLE I: IoU [%] on test set (sequences 11 to 21). RangeNet21 and RangeNet53 represent the new baselines with augmented Darknet backbones (21 and 53 respectively), and the versions with (++) are treated with our fast point cloud post-processing based on range.

Approach	Size	car	bicycle	motorcycle	truck	other-vehicle	person	bicyclist	motorcyclist	road	parking	sidewalk	other-ground	building	fence	vegetation	trunk	terrain	pole	traffic-sign	mean IoU	Scans/sec
Pointnet [14]	50000pts	46.3	1.3	0.3	0.1	0.8	0.2	0.2	0.0	61.6	15.8	35.7	1.4	41.4	12.9	31.0	4.6	17.6	2.4	3.7	14.6	2
Pointnet++ [15]		53.7	1.9	0.2	0.9	0.2	0.9	1.0	0.0	72.0	18.7	41.8	5.6	62.3	16.9	46.5	13.8	30.0	6.0	8.9	20.1	0.1
SPGraph [10]		68.3	0.9	4.5	0.9	0.8	1.0	6.0	0.0	49.5	1.7	24.2	0.3	68.2	22.5	59.2	27.2	17.0	18.3	10.5	20.0	0.2
SPLATNet [19]		66.6	0.0	0.0	0.0	0.0	0.0	0.0	0.0	70.4	0.8	41.5	0.0	68.7	27.8	72.3	35.9	35.8	13.8	0.0	22.8	1
TangentConv [20]		86.8	1.3	12.7	11.6	10.2	17.1	20.2	0.5	82.9	15.2	61.7	9.0	82.8	44.2	75.5	42.5	55.5	30.2	22.2	35.9	0.3
SqueezeSeg [21]	64 × 2048 px	68.8	16.0	4.1	3.3	3.6	12.9	13.1	0.9	85.4	26.9	54.3	4.5	57.4	29.0	60.0	24.3	53.7	17.5	24.5	29.5	**66**
SqueezeSeg-CRF [21]		68.3	18.1	5.1	4.1	4.8	16.5	17.3	1.2	84.9	28.4	54.7	04.6	61.5	29.2	59.6	25.5	54.7	11.2	36.3	30.8	55
SqueezeSegV2 [22]		81.8	18.5	17.9	13.4	14.0	20.1	25.1	3.9	88.6	45.8	67.6	17.7	73.7	41.1	71.8	35.8	60.2	20.2	36.3	39.7	50
SqueezeSegV2-CRF [22]		82.7	21.0	22.6	14.5	15.9	20.2	24.3	2.9	88.5	42.4	65.5	18.7	73.8	41.0	68.5	36.9	58.9	12.9	41.0	39.6	40
RangeNet21 [Ours]		85.4	26.2	26.5	18.6	15.6	31.8	33.6	4.0	91.4	57.0	74.0	26.4	81.9	52.3	77.6	48.4	63.6	36.0	50.0	47.4	20
RangeNet53 [Ours]	64 × 2048 px	86.4	24.5	32.7	25.5	22.6	36.2	33.6	4.7	**91.8**	64.8	74.6	**27.9**	84.1	55.0	78.3	50.1	64.0	38.9	52.2	49.9	13
	64 × 1024 px	84.6	20.0	25.3	24.8	17.3	27.5	27.7	7.1	90.4	51.8	72.1	22.8	80.4	50.0	75.1	46.0	62.7	33.4	43.4	45.4	25
	64 × 512 px	81.0	9.9	11.7	19.3	7.9	16.8	25.8	2.5	90.1	49.9	69.4	2.0	76.0	45.5	74.2	38.8	62.7	25.5	38.1	39.3	52
RangeNet53++ [Ours+kNN]	64 × 2048 px	**91.4**	**25.7**	**34.4**	**25.7**	**23.0**	**38.3**	**38.8**	**4.8**	**91.8**	**65.0**	**75.2**	27.8	**87.4**	**58.6**	**80.5**	**55.1**	**64.6**	**47.9**	**55.9**	**52.2**	12
	64 × 1024 px	90.3	20.6	27.1	25.2	17.6	29.6	34.2	7.1	90.4	52.3	72.7	22.8	83.9	53.3	77.7	52.5	63.7	43.8	47.2	48.0	21
	64 × 512 px	87.4	9.9	12.4	19.6	7.9	18.1	29.5	2.5	90.0	50.7	70.0	2.0	80.2	48.9	77.1	45.7	64.1	37.1	42.0	41.9	38



OverlapNet





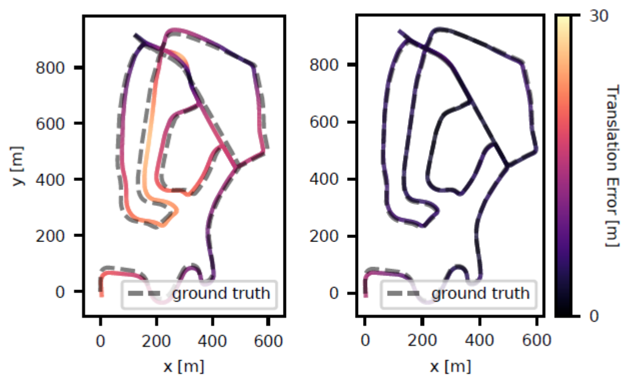
" Pipeline overview of our proposed approach. The left-hand side shows the preprocessing of the input data which exploits multiple cues generated from a single LiDAR scan, including range $\mathcal{R}$, normal $\mathcal{N}$, intensity $\mathcal{I}$, and semantic class probability $\mathcal{S}$ information. The right-hand side shows the proposed OverlapNet which consists of two legs sharing weights and the two heads use the same pair of feature volumes generated by the two legs. The outputs are the overlap and relative yaw angle between two LiDAR scans."

OverlapNet

X. Chen et al. OverlapNet: a siamese network for computing LiDAR scan similarity with applications to loop closing and localization. Autonomous Robots, 2022.

TABLE II: Comparison with state of the art.

Dataset	Approach	AUC	F1 score
KITTI	Histogram [26]	0.83	0.83
	M2DP [14]	0.83	0.87
	SuMa [2]	-	0.85
	Ours (AllChannel, TwoHeads)	**0.87**	**0.88**
Ford Campus	Histogram [26]	0.84	0.83
	M2DP [14]	0.84	**0.85**
	SuMa [2]	-	0.33
	Ours (GeoOnly)	**0.85**	0.84



(a) SuMa (b) Ours_CovNearestOfTop10

Fig. 6: Qualitative result on KITTI sequence 02.

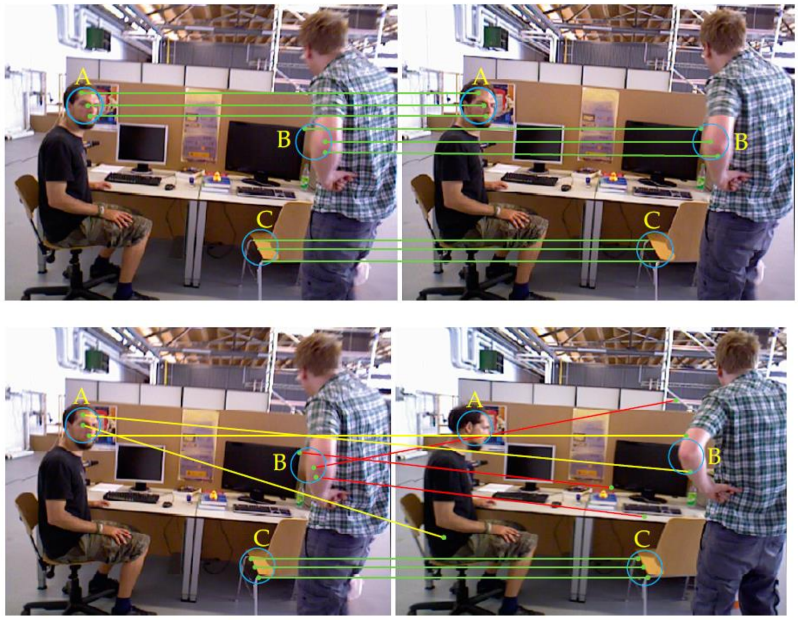
Visual SLAM

VSLAM: use camera (mono, stereo, multi-, depth, etc.) to solve SLAM

- Readily available on mobile platforms: drones, cars, mobile phones, AR/VR Glasses
- DMS-SLAM (2019), OpenVSLAM (2019)
- ORBSLAM (2015) (5979 citations in 2023, 7330 in 2024), feature based (ORB) monocular SLAM system

DMS-SLAM [2]: →

- pose tracking, closed-loop detection and re-localization based on static 3D map points of the local map
- supports monocular, stereo and RGB-D visual sensors in dynamic scenes.



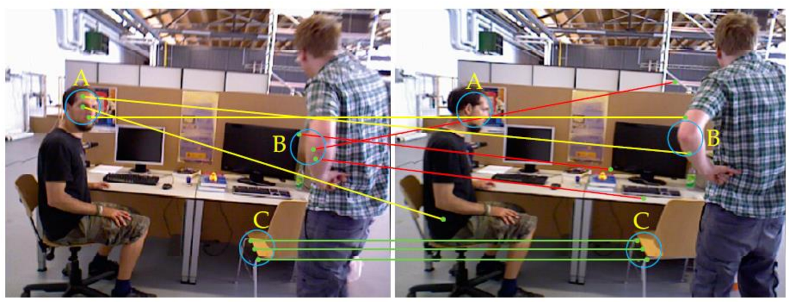
A and B partial Motion, C static => A and B matching errors, C still correct.

Universiteit Leiden. Bij ons leer je de wereld kennen

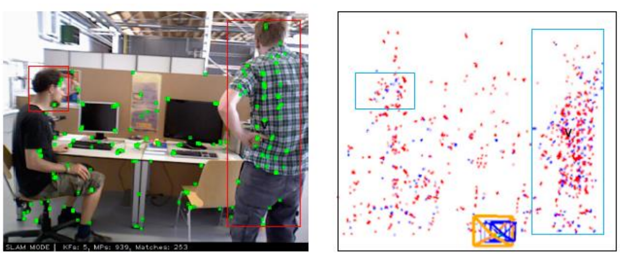
Visual SLAM

VSLAM

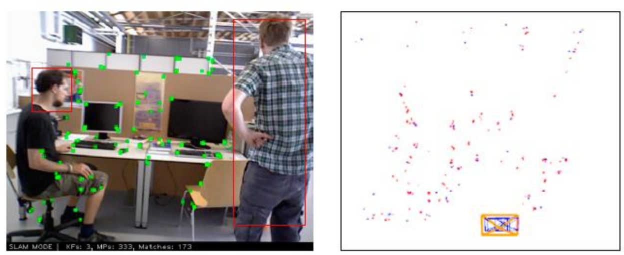
- use camera (mono, stereo, multi-cam, depth, etc.) to solve SLAM
- **DMS-SLAM [2]**, OpenVSLAM, ORBSLAM



A and B partial Motion, C static => A and B matching errors, C still correct.



ORB-SLAM2



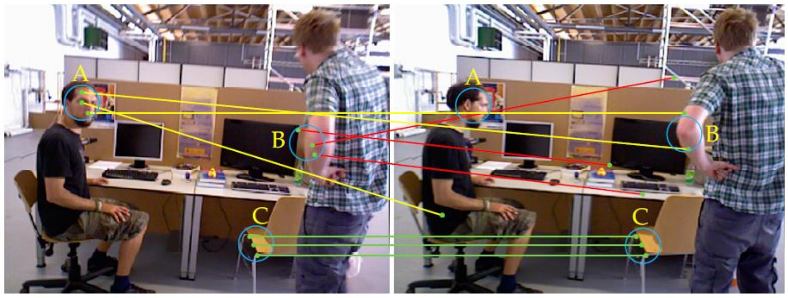
DMS-SLAM

RGB-D Initialization: DMS-SLAM produces a relatively static initial map

Visual SLAM

VSLAM: use camera (mono, stereo, multi-, depth, etc.) to solve SLAM

- **DMS-SLAM [2]**, OpenVSLAM, ORBSLAM



A and B partial Motion, C static => A and B matching errors, C still correct.

(**a**) ORB-SLAM2

Blue-boxes wrong feature matching point pairs.

(**b**) DMS-SLAM

Universiteit Leiden. Bij ons leer je de wereld kennen

(a) ORB-SLAM2 (b) DMS-SLAM

Sequence 01

(c) ORB-SLAM2 (d) DMS-SLAM

Sequence 03

(e) ORB-SLAM2 (f) DMS-SLAM

Sequence 09

Figure 15. The pose tracking experiments of ORB-SLAM2 and DMS-SLAM on the 01, 03, 09 sequences in the KITTI dataset. The rectangular box represents the moving object in the scene, and the others are static areas.

Note: DMS-SLAM does not track feature points on dynamic objects during camera pose estimation.

Universiteit Leiden. Bij ons leer je de wereld kennen

OpenVSLAM [3]

A Versatile Visual SLAM Framework. (S. Sumikura et al., 2019)

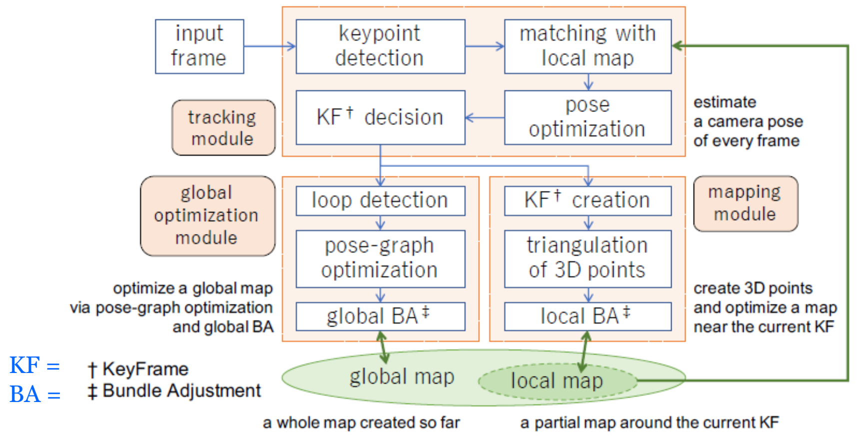


Figure 2: Main modules of OpenVSLAM: tracking, mapping, and global optimization modules.

ORB-SLAM [1]

R Mur-Artal et al. IEEE Trans. On Robotics, Nov. 2015.

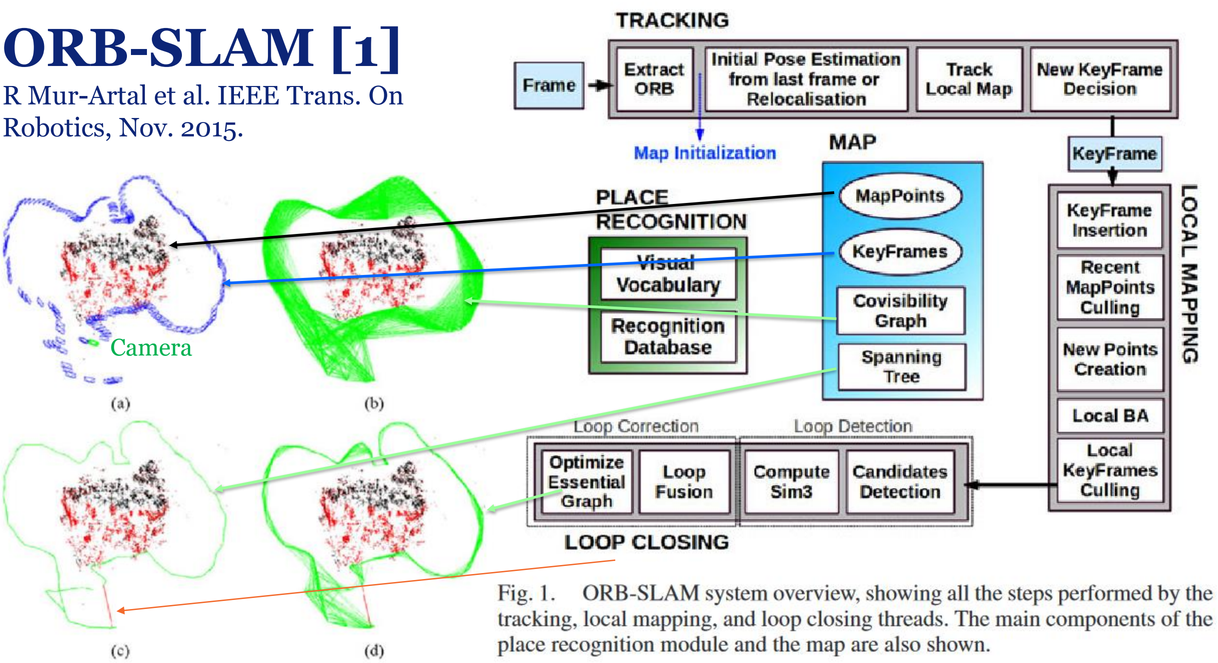
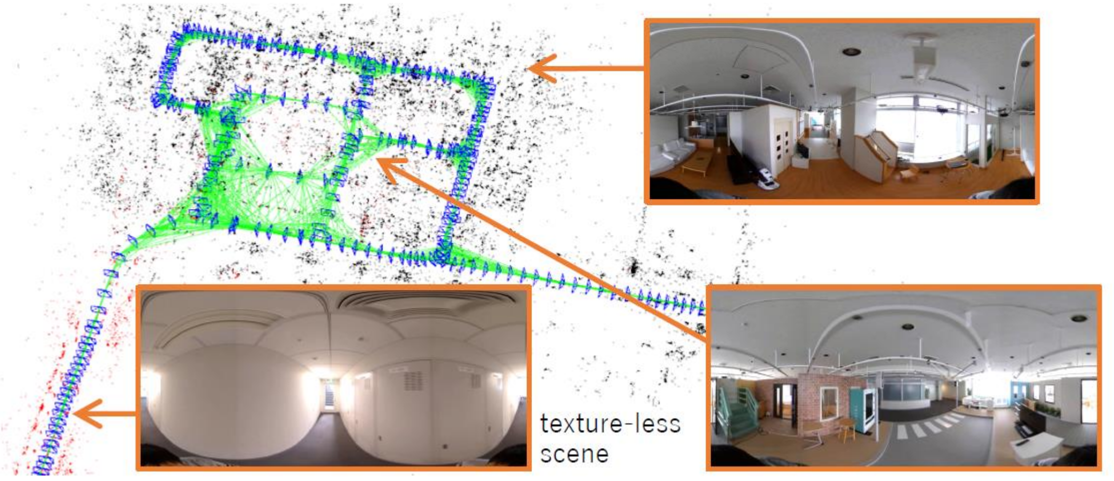


Fig. 1. ORB-SLAM system overview, showing all the steps performed by the tracking, local mapping, and loop closing threads. The main components of the place recognition module and the map are also shown.

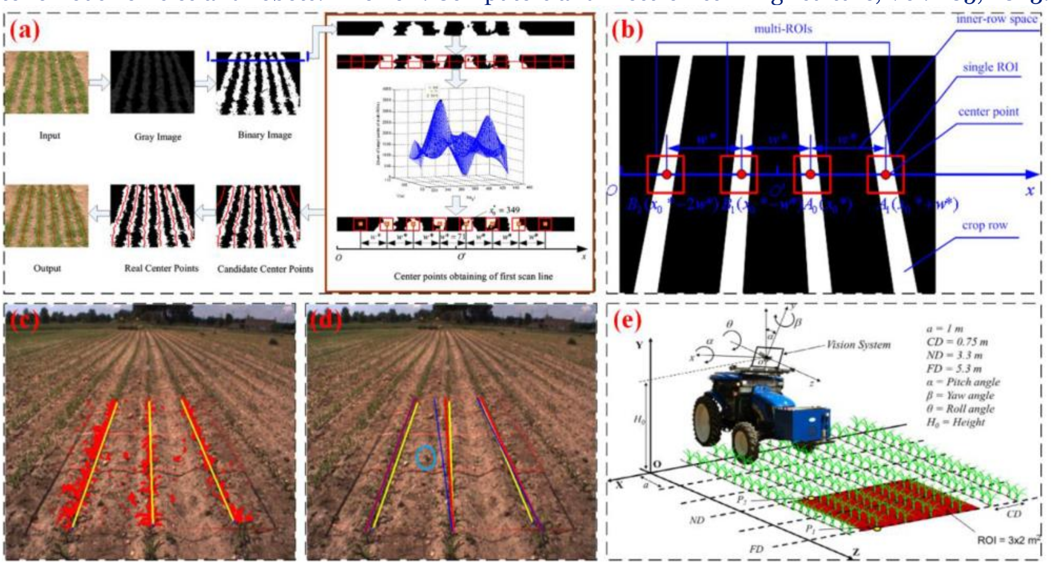
(Note: ORB, SIFT, SURF key-point detectors are available in OpenCV)

OpenVSLAM [3]

NB OpenVSLAM: termination of release because of concerns regarding similarities with ORB-SLAM2)
https://github.com/raulmur/ORB_SLAM2



- Bai, B. Zhang, N. Xu, J. Zhou, J. Shi, Z. Diao, Vision-based Navigation and Guidance fro agricultural autonomous vehicles and robots: A review. Computers and Electronics in Agriculture, Vol. 205, 2023.



automatic crop rows detection methods

- Bai, B. Zhang, N. Xu, J. Zhou, J. Shi, Z. Diao, Vision-based Navigation and Guidance fro agricultural autonomous vehicles and robots: A review. Computers and Electronics in Agriculture, Vol. 205, 2023.

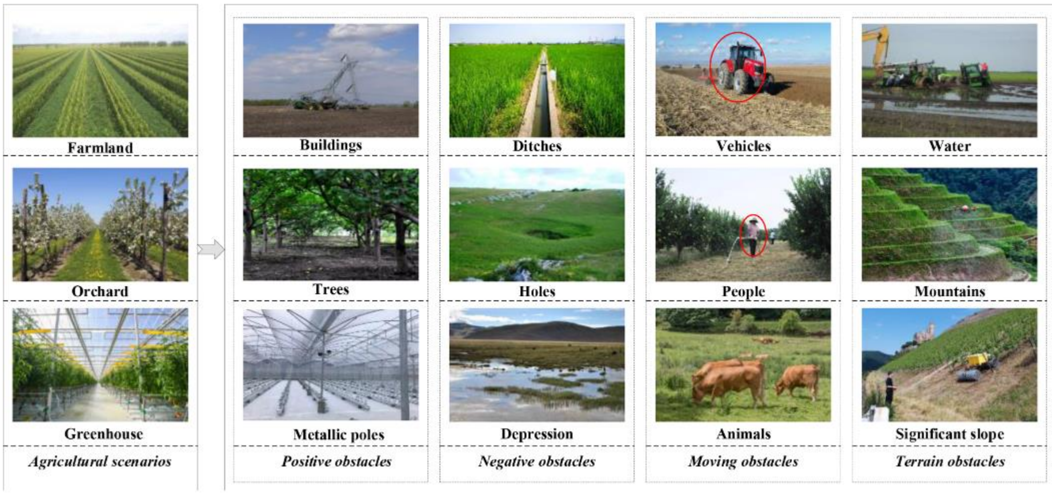
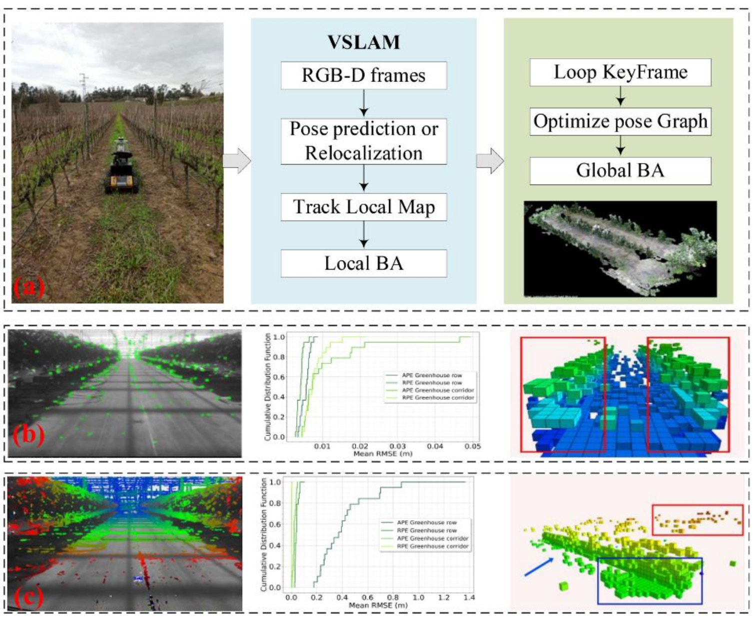


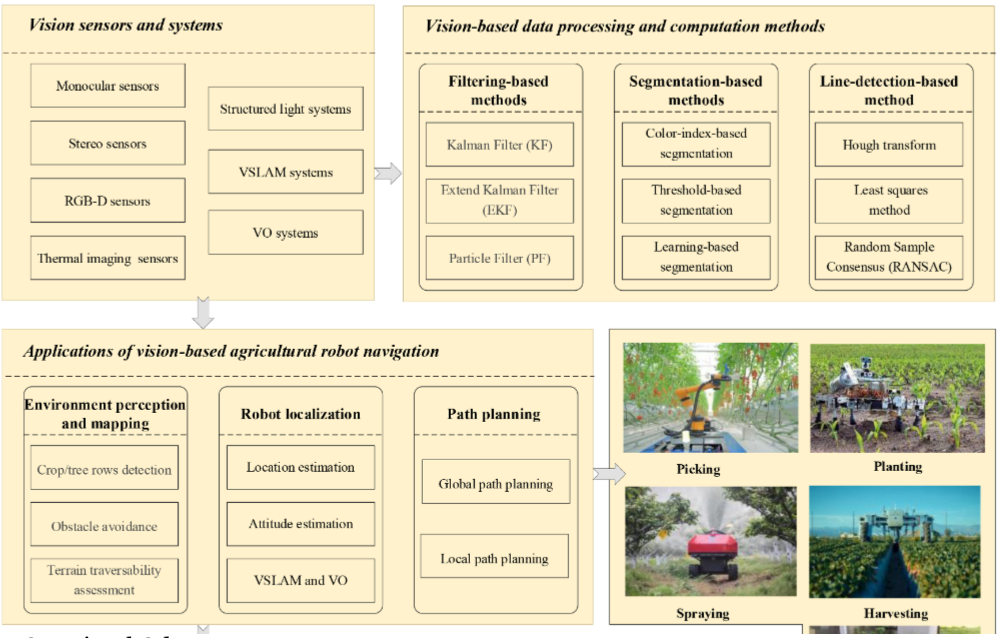
Fig. 3. Typical obstacles that can be encountered in agricultural environments.

Universiteit Leiden. Bij ons leer je de wereld kennen

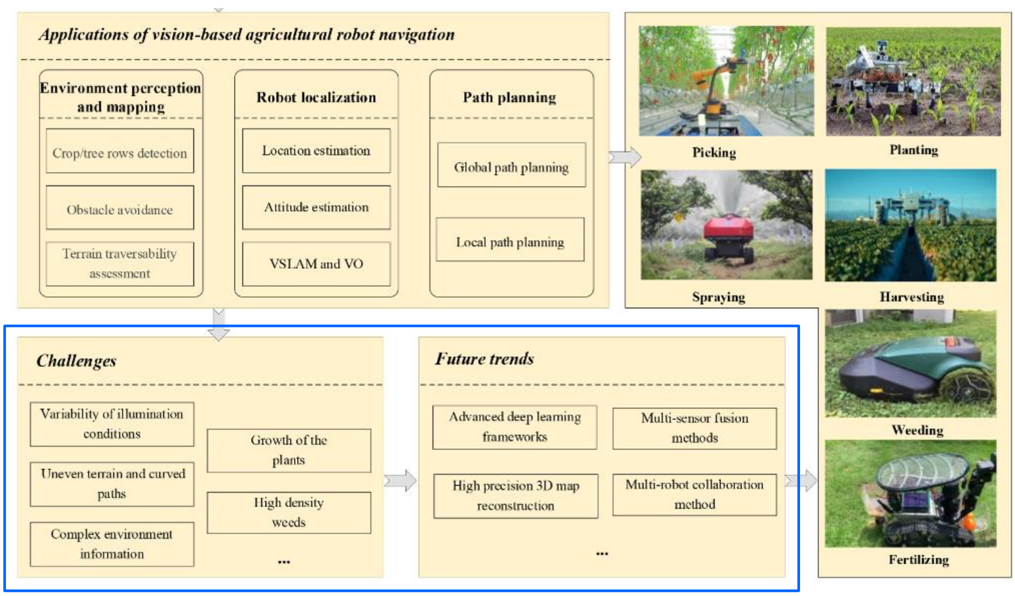
- Bai, B. Zhang, et al., 2023. [4]



Universiteit Leiden. Bij ons leer je de wereld kennen



VO = Visual Odometry



VO = Visual Odometry

References

1. R. Mur-Atal, J.M.M. Montiel, J.D. Tardos, ORB-SLAM: A Versatile and Accurate Monocular SLAM System. IEEE Transactions on Robotics, Vol. 31, Issues 5, 2015.
2. G. Liu, W. Zeng, B. Feng, F. Xu, DMS-SLAM: A General Visual SLAM System for Dynamic Scenes with Multiple Sensors. Sensors, 2019.
3. S. Sumikura, M. Shibuya, K. Sakurada, OpenVSLAM: A Versatile Visual SLAM Framework. MM'19 Open Source Software Competition, October 2019.
4. Y. Bai, B. Zhang, N. Xu, J. Zhou, J. Shi, Z. Diao, Vision-based Navigation and Guidance fro agricultural autonomous vehicles and robots: A review. Computers and Electronics in Agriculture, Vol. 205, 2023.

Organization and Overview

Lecturer:
Dr Erwin M. Bakker (erwin@liacs.nl)
Room 126a and LIACS Media Lab (LML)

Teaching assistants:
Xia Tian
Aristidou Kyriakos
Dimitrios Kourntidis
Ruilin Ma

Period: February 5th - May 21st 2024
Time: Monday 15.15 - 17.00
Place (Rooms):
a) LMUY Havingazaal

2nd Session for ACS students and upon individual request:
Time: 17.15 – 19.00
Place: Room 4.02 Snellius Building

Schedule (tentative, visit regularly):

Date	Subject
5-2	Introduction and Overview
12-2	Locomotion and Inverse Kinematics
19-2	Robotics Sensors and Image Processing
26-2	No Class
4-3	SLAM + Workshop@Home
11-3	Robotics Vision + Intro Mobile Robot Challenge
18-3	Project Proposals I (by students)
25-3	Project Proposals II (by students) *
1-4	No Class (Eastern)
8-4	Robotics Reinforcement Learning + Workshop@Home
15-4	Project Progress Reports I
22-4	Project Progress Reports II
29-4	Mobile Robot Challenge I
6-5	Mobile Robot Challenge II
13-5	Project Demos I -
20-5	No Class (Whit Monday)
27-5	Project Demos II
7-6	Project Deliverables

Grading (6 ECTS):
- Presentations and Robotics Project (60% of grade).
- Class discussions, attendance, assignments (pass/no pass) 2 workshops (0-10) (20% of the grade).

Mobile Robot Challenge (0-10) (20% of the grade)
- ***It is necessary to be at every class and to complete every workshop and assignment.***

Next week INTRODUCTION MOBILE ROBOT CHALLENGE

Groups of 4 to 5 students

Website: http://liacs.leidenuniv.nl/~bakkerem2/robotics/

Robotics Project Proposals Presentations

Monday 18-3 and 25-3 2024

Present your Robotics Project Proposal during a **5 minute (max)** talk. Clearly state the title of your project, the team members, your goals, how you will pursue them, what are the challenges and what at least can and should be delivered on the demo day on May 13th and May 27th 2024.

Note: Groups of 1-5 members are allowed.
Please form your project group in the coming week.

The presentation should contain slides for:
1. Title and group members.
2. Goal of the project: what is novel? Refer to at least one relevant and published research paper!
3. How will you pursue these goals: division of work per group member
4. What are the challenges.
5. What at least can and should be delivered on the demo days on May 13th and May 27th 2024.

The LIACS Media Lab can support your project with some materials for your project. Please clearly state any materials that you would need for your proposal. Note that these materials are limited so project goals may need to be adjusted accordingly.
Each presentation will be followed by a short class discussion.

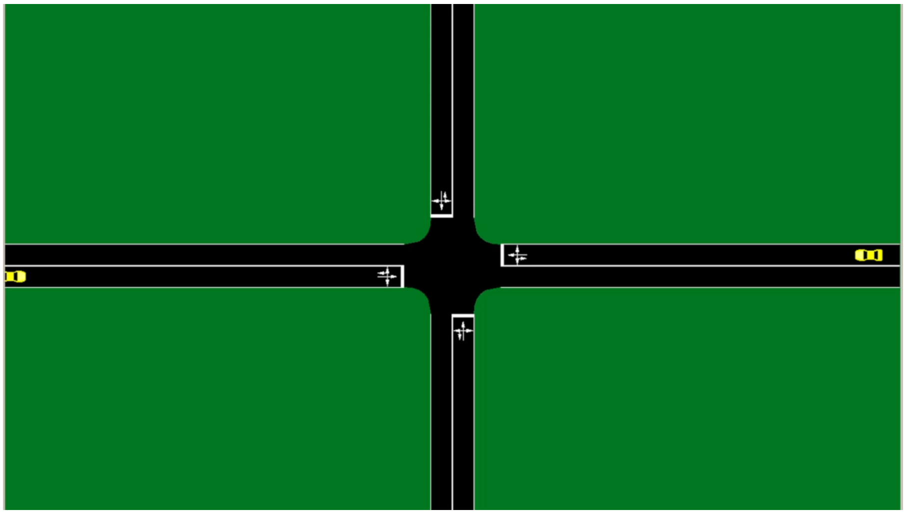
Previous Projects

1. Evolutionary Locomotion
2. Nao plays Tic-Tac-Toe
3. Slam Robot Project.
4. Dolphin Drone: Drone Recognition and Maneuvering with Hoops.
5. Delivery Drone.
6. Programming a NAO to play a tune using a xylophone.
7. Floor mapping with Swarm Robotics
8. Tootballing Yetiborg
9. Cat Flap Opening Based on Audio/Video/RFID
10. DrawBot
11. Traffic coordination (simulation).
12. Plane filling curves (simulation).

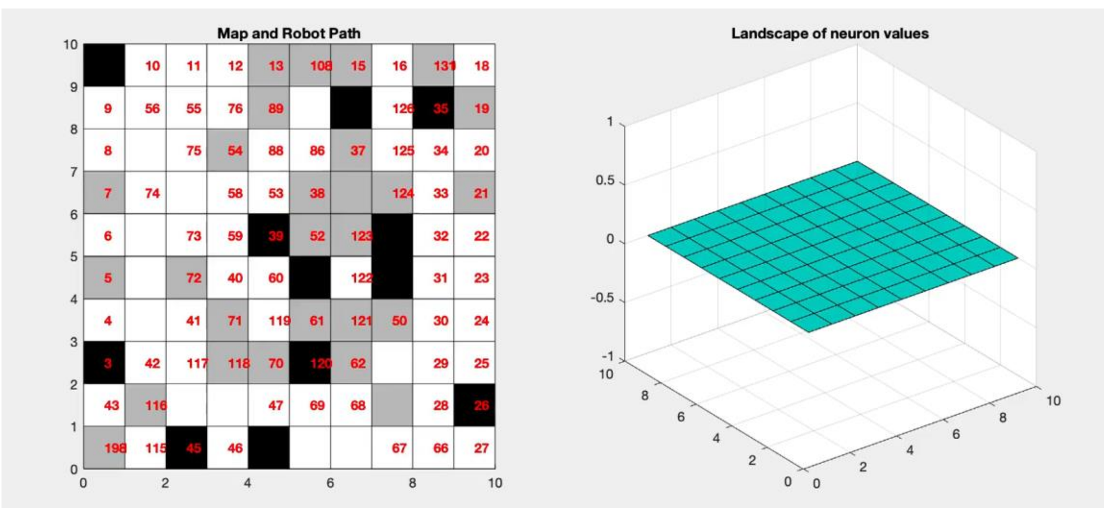
1. AimBot
2. Artificial Muscles
3. Ball Tracking Car
4. BorrelBot
5. Fetch Bot
6. Floor Mapping Robot
7. Gesture Control Pachenko
8. Hexapod
9. Nao Pose
10. Position Estimation
11. Race Car Training
12. Face Touch

1. Autonomous driving copilot
2. Self Balancing robot
3. Tennis playing robot
4. Etc.

Traffic coordination (simulation).



Roombas with Brains: Neural Networks for Coverage Path Planning



Gesture Controlled Pachenko

Gesture Controlled Pachinko Game

Aaron Dunlea, Nathan van der Putten, Malte Wilhelm

liacs Leiden Institute of Advanced Computer Science

Universiteit Leiden The Netherlands

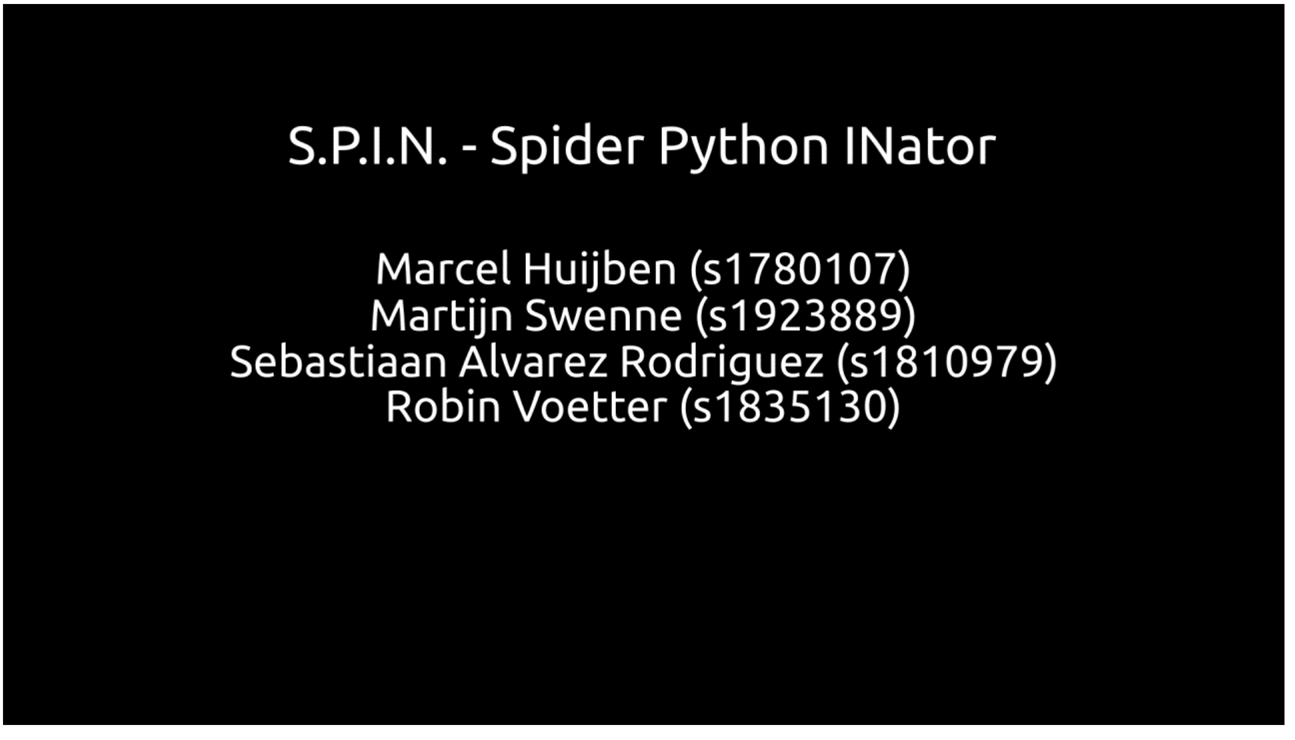
Traffic coordination (simulation).

DrawBot
AimBot
FetchBot

Cellular Automaton: https://youtu.be/maC1eo8_-lI
Dragon Curve: https://youtu.be/9ilDP_pvDEk

https://vimeo.com/425043774

Universiteit Leiden. Bij ons leer je de wereld kennen



Autonomous driving copilot

Gesture control and autonomous driving system

Siwen Tu, Chenyu Shi, Shupei Li, Lin He , Ruilin Ma

Universiteit Leiden. Bij ons leer je de wereld kennen

Universiteit Leiden. Bij ons leer je de wereld kennen