

# Timestamp Offset Determination between an Actuated Laser Scanner and its Corresponding Motor

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DFG Research Training Group (GRK2159)  
i.c.sens - Integrity and Collaboration in dynamic sensor networks



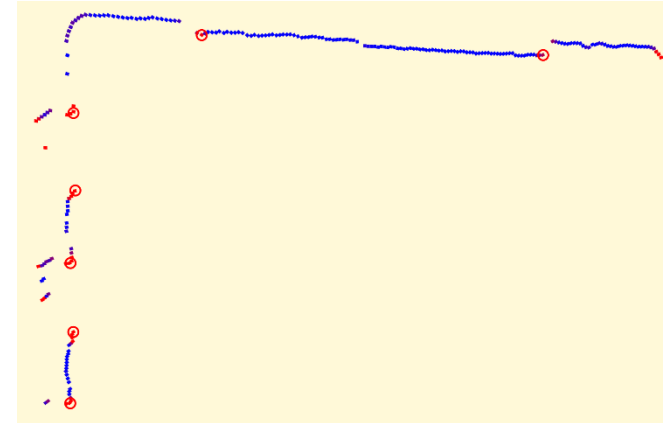
# Motivation

- Motor actuated 2D laser scanners
  - Wide ranging 3D data
  - Relative low cost
- Encoder values are required to transform 2D scan points into 3D space
  - Proper synchronization required
- Nonzero timestamp offset between encoder and laser scanner
  - Assumed to be constant
  - Leads to distortion in the resulting point cloud

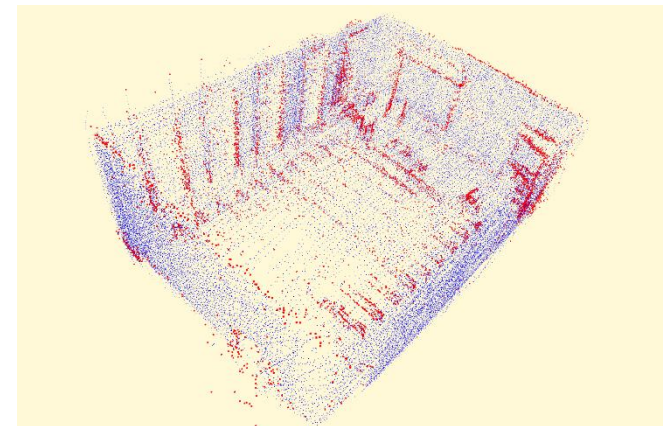


# Overview of the utilized SLAM approach [1]

- Approach by Zhang and Singh, 2014 [1]
- Two separate algorithms
- Lidar Odometry:
  - Motion estimation between consecutive sweeps to correct distortion
  - Sweep: rotation from  $-90^\circ$  to  $90^\circ$  (or inverse)
  - Feature extraction using curvature of scan points
  - Feature matching by identifying edges and planes
- Lidar Mapping:
  - Construct map and correct for drift over time
  - Map is composed of edge points and planar points
  - Feature matching by finding correspondences for edges and planes



Feature extraction based on scan points curvature



Resulting map of a lecture room

## Our approach: Prior to data acquisition

- Idea: Execute Lidar Odometry while standing still
  - Calculated movement should be zero
  - Wrong timestamp offset leads to erroneously transformed point clouds
  - Algorithm compensates for errors by nonzero motion estimation
- Approach: Run Lidar Odometry multiple times on small dataset
  - Calculate the magnitude of motion  $d$  for different timestamp offsets
  - Find the timestamp offset that induces the smallest magnitude of motion

$$d = \sqrt{t^2 + c \cdot \theta^2}$$

Translation:

$$t = \sqrt{t_x^2 + t_y^2 + t_z^2}$$

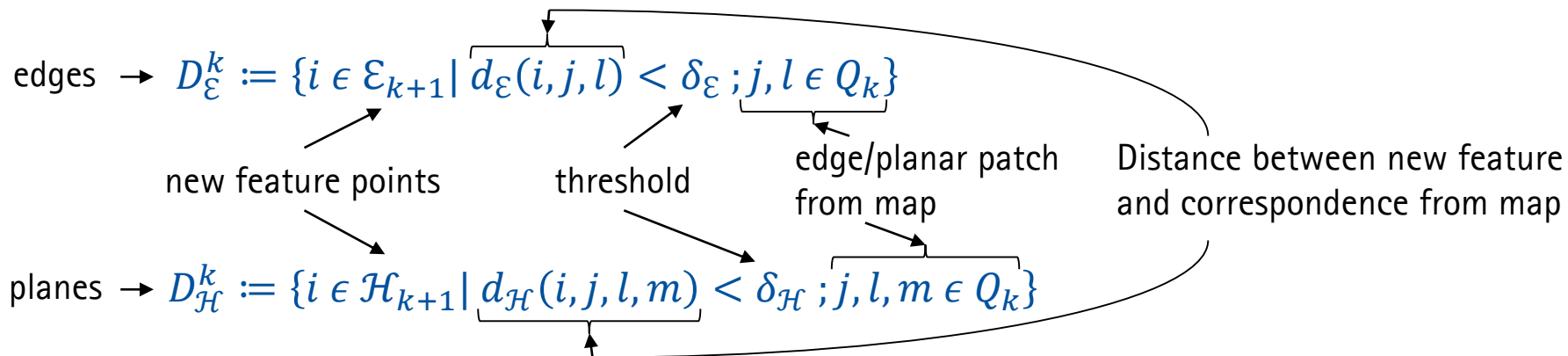
Rotation:

$$\theta = \sqrt{\theta_x^2 + \theta_y^2 + \theta_z^2}$$

# Our approach: After data acquisition

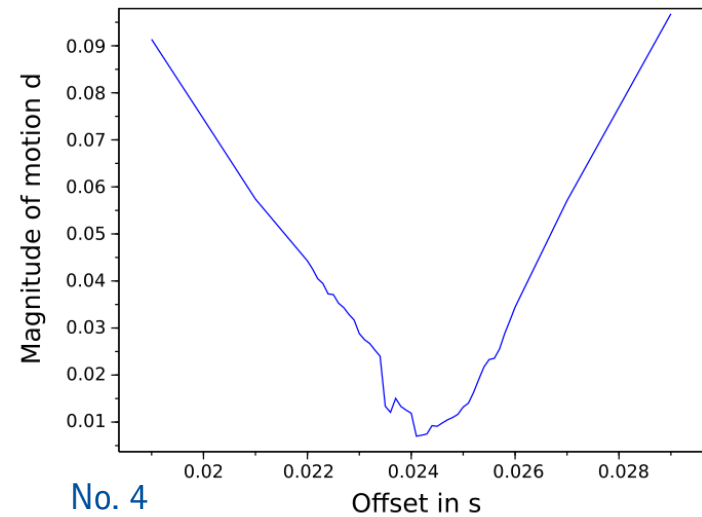
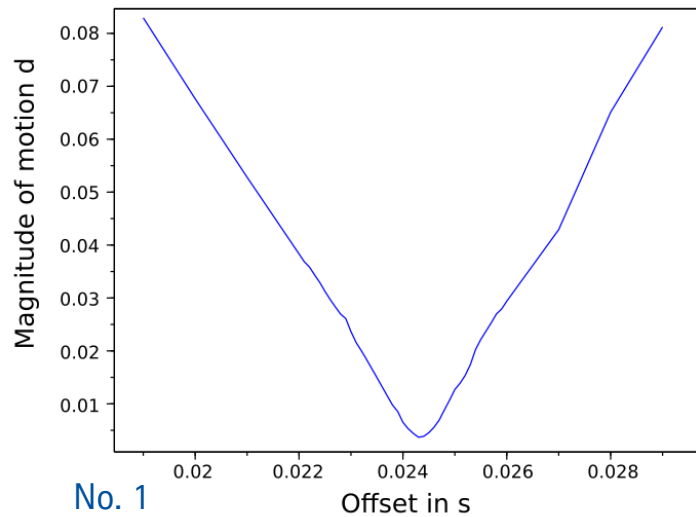
- Idea: Execute both Lidar Odometry and Lidar Mapping for a dataset
  - Wrong timestamp offset leads to distortion in resulting point cloud
- Criteria to evaluate "Clarity" or "Crispness" of said point cloud:

- Amount of matches  $n = \sum_{k \in S} (|D_{\mathcal{E}}^k| + |D_{\mathcal{H}}^k|)$  ← Accumulated sweeps
- Average error per match  $e = \frac{\sum_{k \in S} (\sum_{i \in D_{\mathcal{E}}^k} d_{\mathcal{E}}(i, j, l) + \sum_{i \in D_{\mathcal{H}}^k} d_{\mathcal{H}}(i, j, l, m))}{n}$



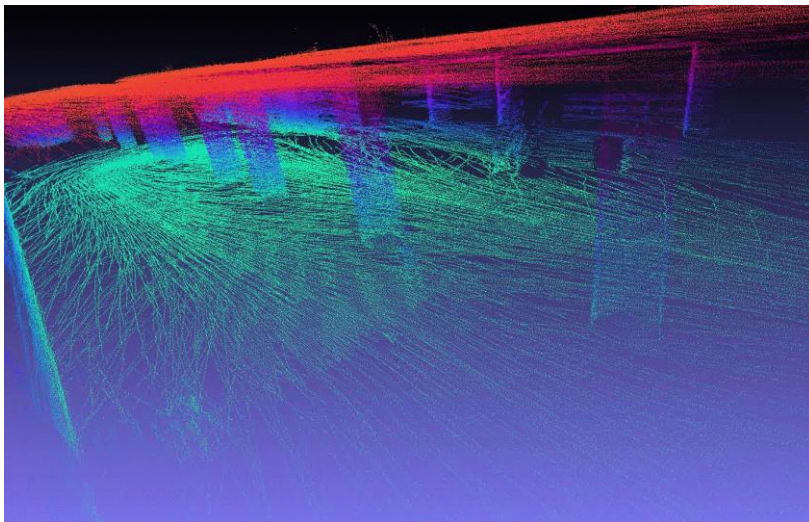
# Results: Prior to data acquisition

No.	Offset [ms]	Magnitude of motion d
1	24.3	0.0037
2	23.4	0.0314
3	23.9	0.0203
4	24.1	0.0070
5	23.8	0.0220
6	24.6	0.0194

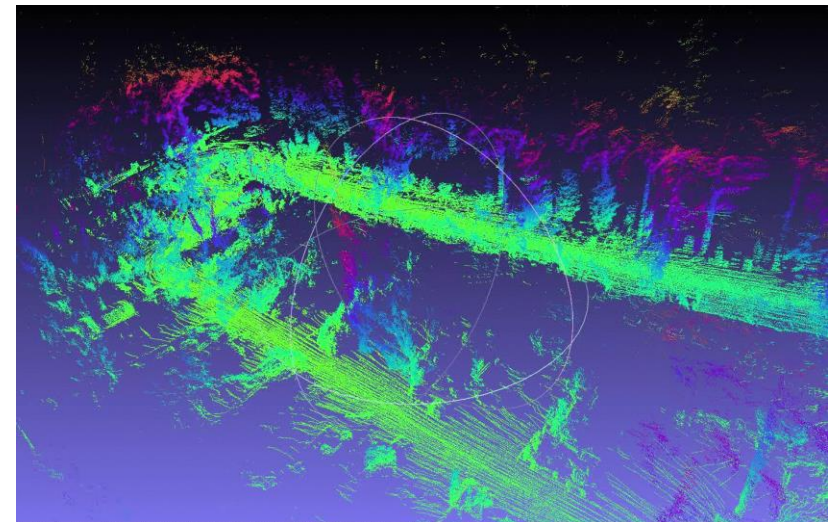


# Datasets

Description	Duration [s]	Distance covered [m]
Abandoned metro station	159	117
Parking area	208	155
Empty cemetery with lots of vegetation	287	236
Starts in empty lecture room; finishes outside the building under trees	274	184



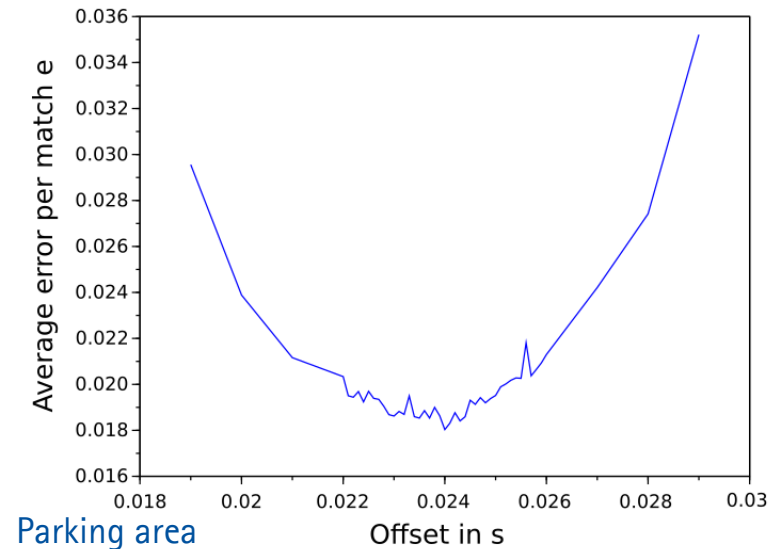
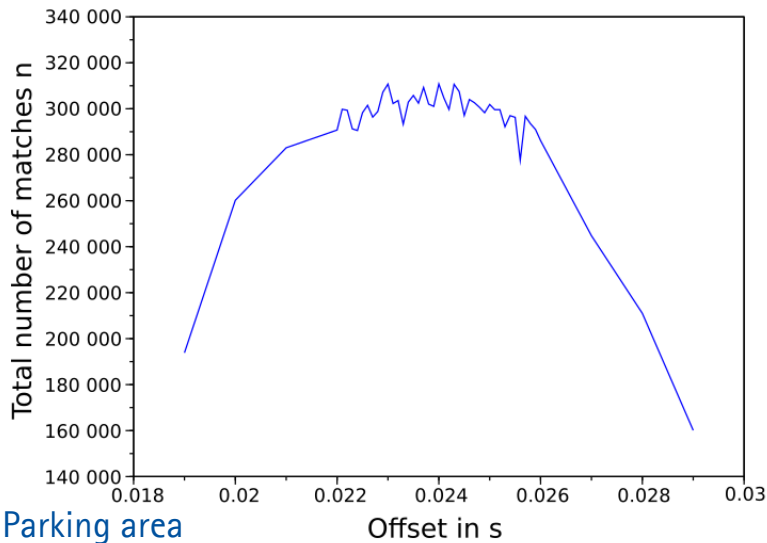
Metro station



Cemetery

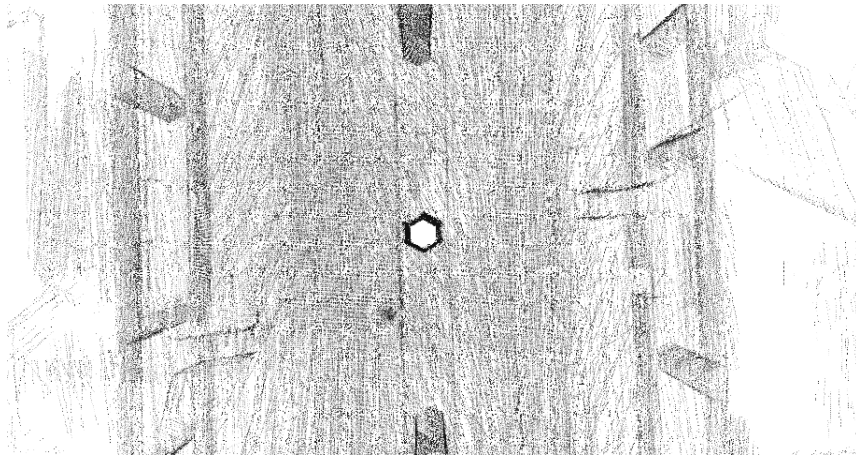
# Results: After data acquisition

Dataset	Offset using the total number of matches $n$ [ms]	Offset using the average error per match $e$ [ms]
Metro station	23.9	24.2
Parking area	24.0	24.0
Cemetery	23.8	23.8
Lecture room	24.1	24.1



## Results: Influence of timestamp offset

- Top view of metro station dataset
  - Pillar in the shape of a hexagon
  - Stairs to both sides
- Adjustment of merely 5 ms leads to a lower perceived clarity



Appropriate timestamp offset of 24 ms



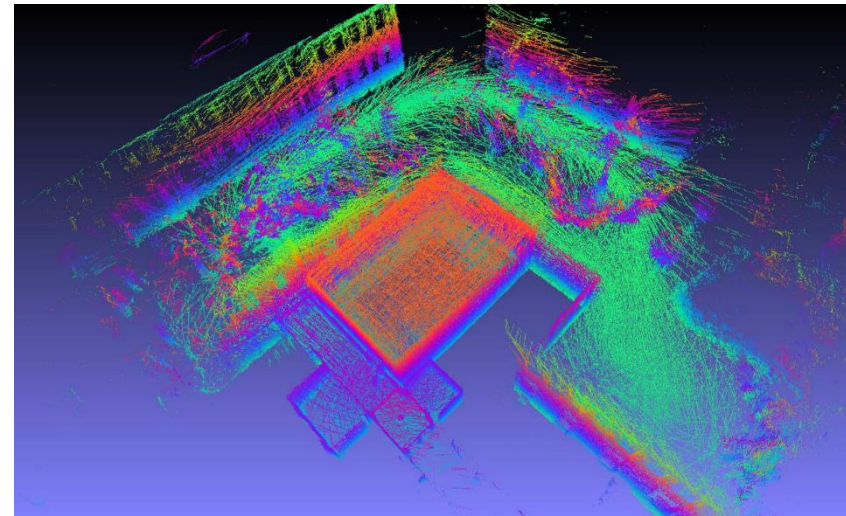
Inappropriate timestamp offset of 19 ms

# Conclusion

- Both approaches yield the same result of 24 ms
- Different datasets were evaluated
- Influence of incorrect timestamp offset was demonstrated

## Future Work

- Develop an approach similar to our first one (prior to data acquisition) for other sensor combinations
- Use the second approach (after data acquisition) to determine the timestamp offset for arbitrary sensor combinations



Lecture room

Thank you for your attention! Any questions?

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i.c.sens – Integrity and Collaboration in dynamic sensor networks.

## References

- [1] Zhang, J. and Singh, S., 2014. LOAM: Lidar Odometry and Mapping in Real-time. In: Robotics: Science and Systems Conference (RSS).