

LiDAR-Based Robot Pose Estimation with Deep Learning

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Robotics 2

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Introduction

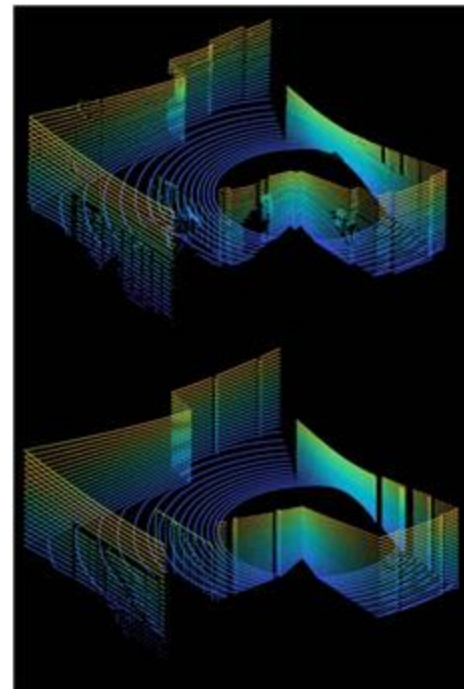
Project Group MyRob



Related Work

Indoor LiDAR relocalization based on Deep Learning using a 3D Model

- Localization based on 3D Model
- Real and Synthetic LiDAR Data
- Trained with known locations [1]



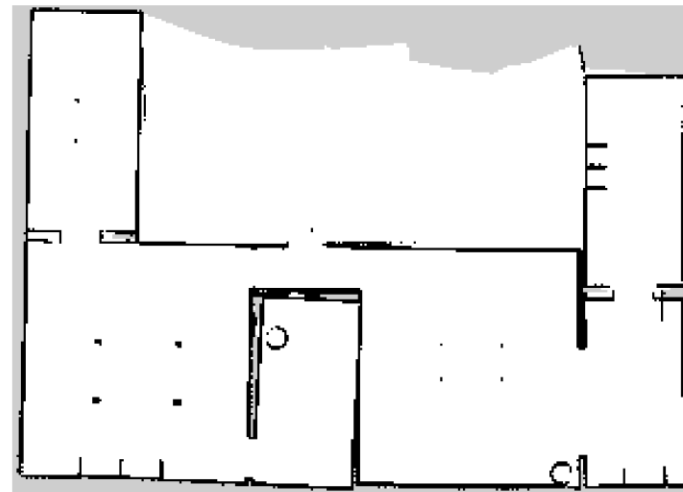
Real lidar point cloud (top) and synthetic point cloud (bottom)

[Zhao et al., 2020]

Related Work

SLAM

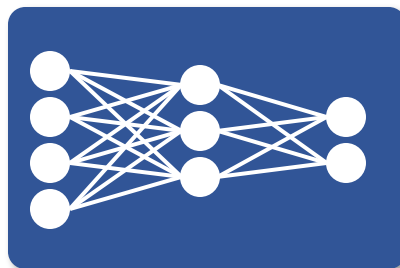
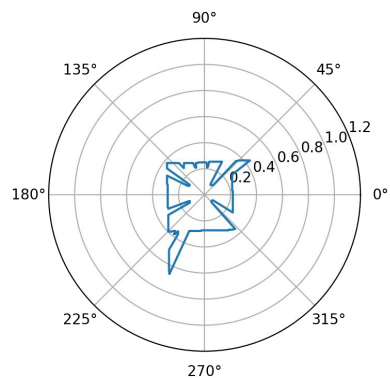
- Optical sensors (LiDAR)
- Odometry
- Generates a Map
- Estimates position with map and last location
- GMapping, Lama [2]



Map generated with Gmapping in Gazebo

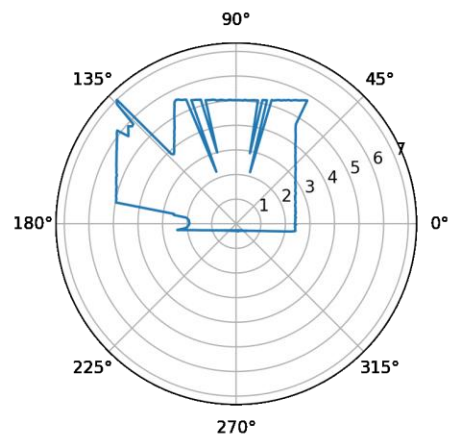
Concept

Our Approach



Concept

Gazebo Dataset Generator



Concept

Architecture: Convolution Block

Convolution [9, 64]

Concept

Architecture: Convolution Block

[2.42 2.39 2.38 2.40 2.41 ... 2.44 2.41 2.41 2.39 2.38]



Cyclic Padding: $\left\lfloor \frac{9}{2} \right\rfloor = 4$

2.41 2.41 2.39 2.38 2.42 2.39 2.38 2.40 2.41 ... 2.44 2.41 2.41 2.39 2.38 2.42 2.39 2.38 2.40]

Kernel of size 9



Convolution: 64 Kernels

Tensor with shape (360, 64)



Batch Normalization

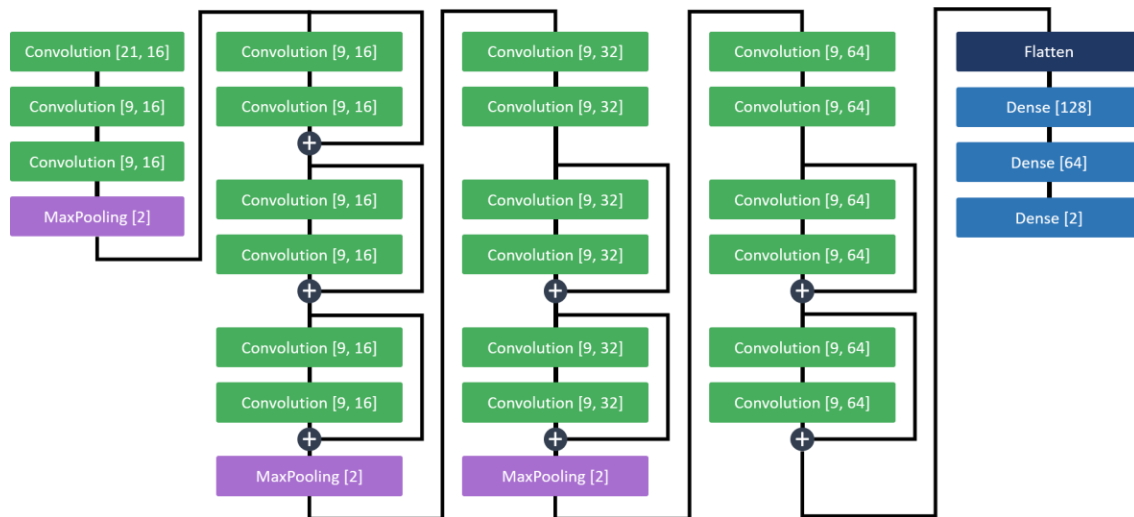
Activation: ReLU

Architecture A



857218 params

Architecture B

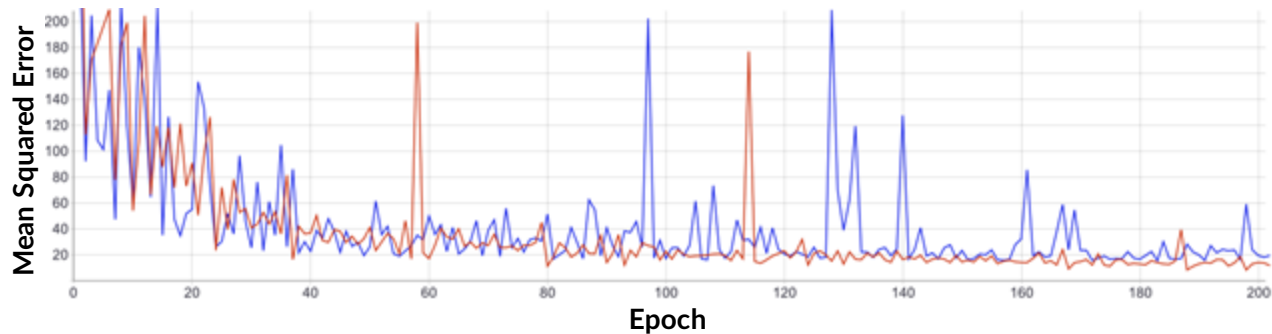


652946 params

Concept

Architecture Performance Comparison

Architecture A



Architecture B



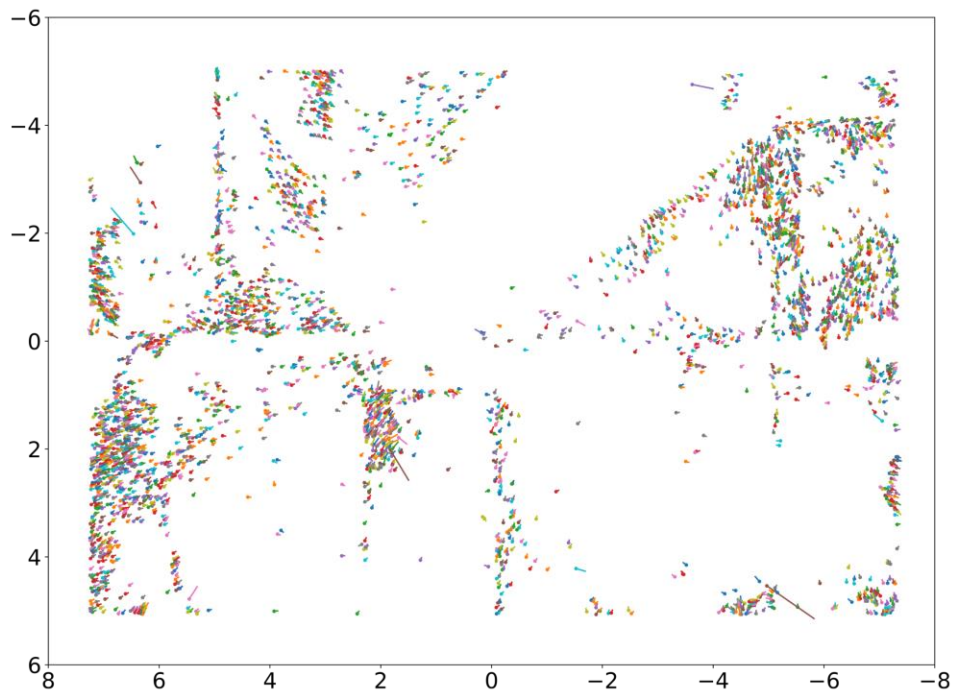
Concept

Architecture Performance Comparison

	Mean Squared Error	Mean Average Error	Mean Absolute Percentage Error	Average Error
Architecture A	0.0210	0.0332	4.3%	5.2cm
Architecture B	0.0006	0.0183	2.9%	2.8cm

Analysis

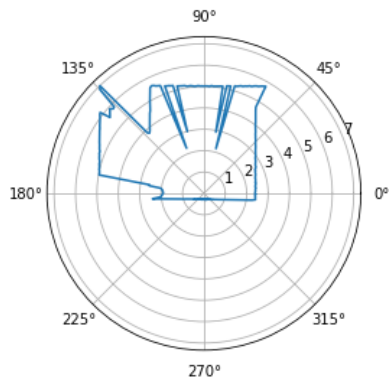
Problematic Regions



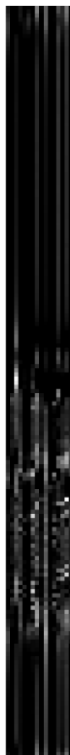
Coordinates with highest error (top 10%) from our dataset.

Analysis

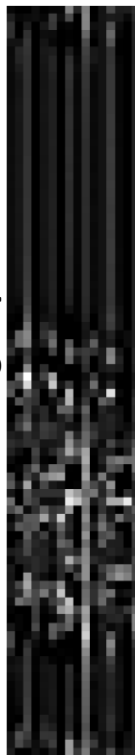
CNN Activations



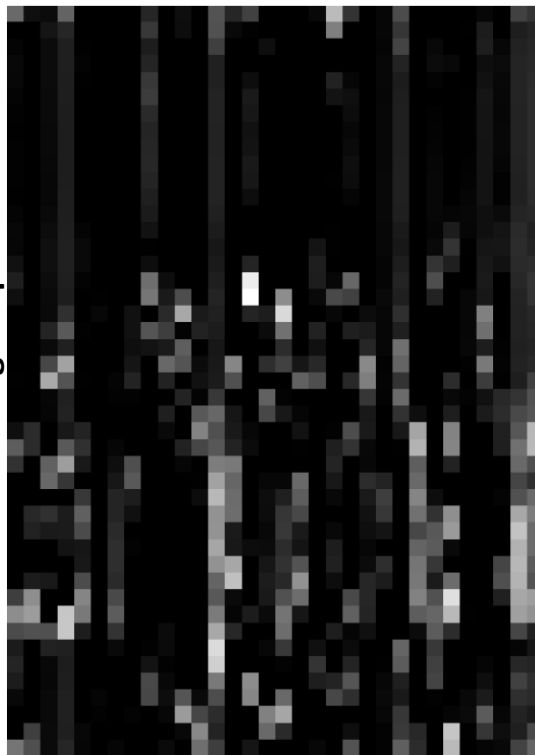
MaxPooling Output 1



MaxPooling Output 2

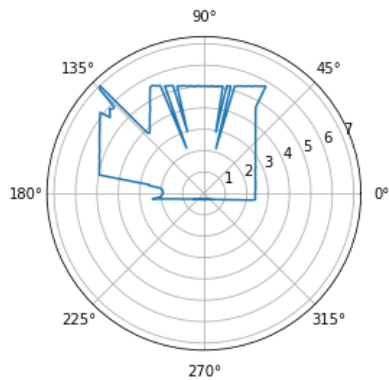


MaxPooling Output 3

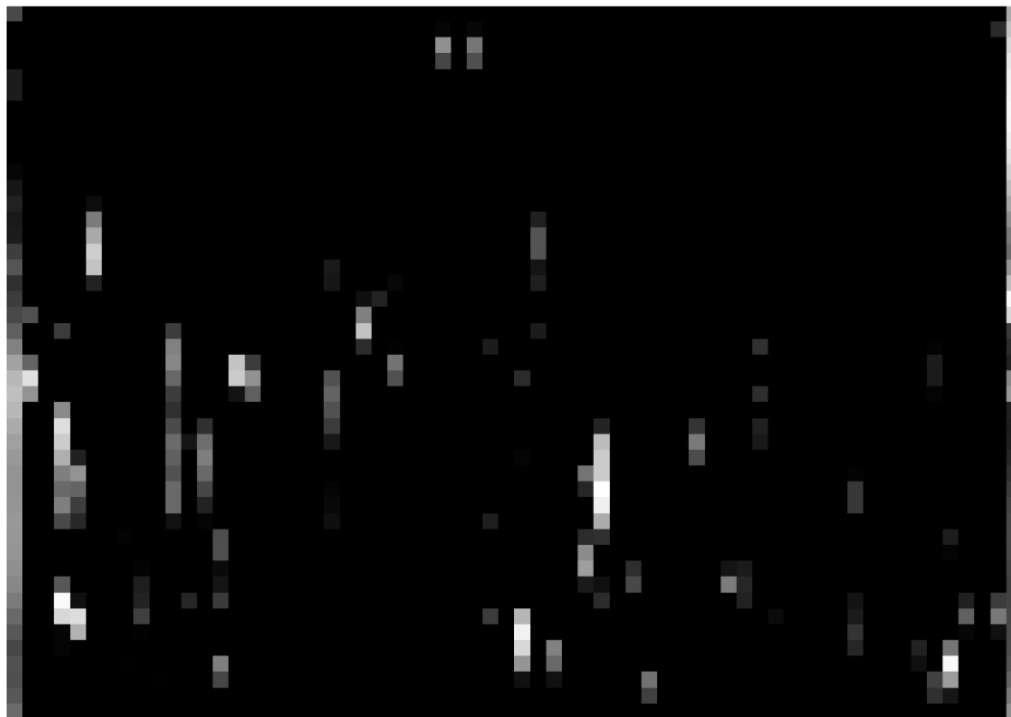


Analysis

CNN Activations

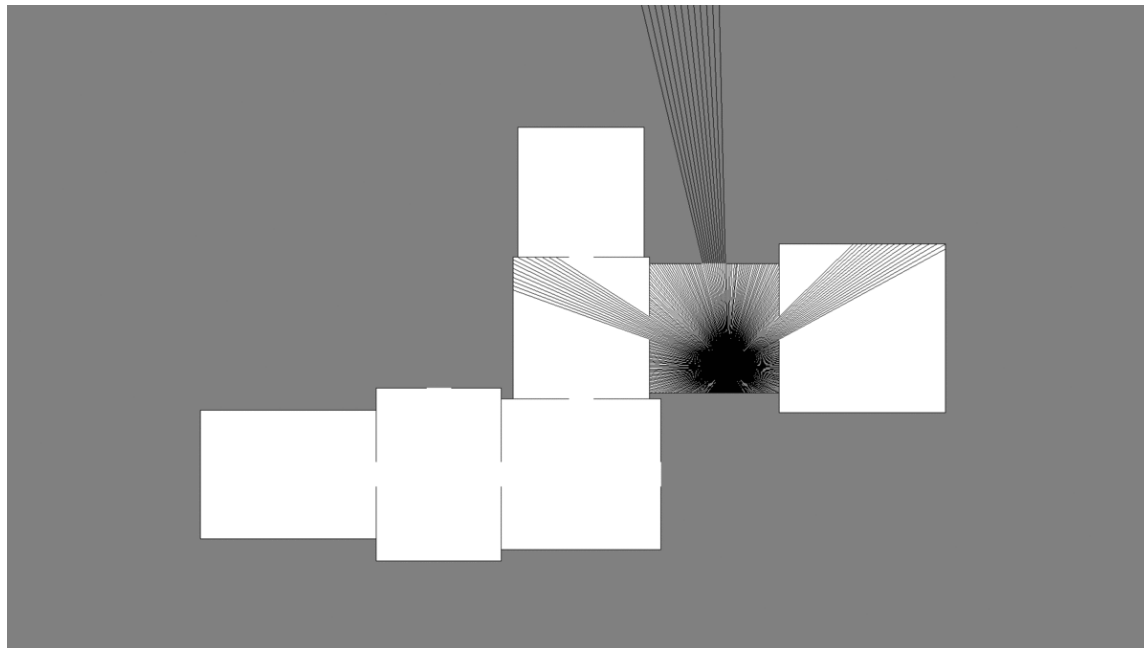


CNN Output before Flatten



Evaluation

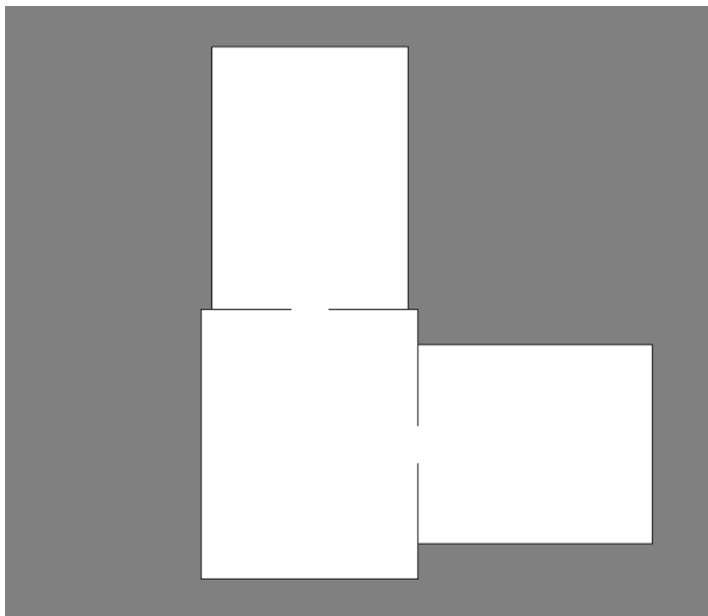
Performance Testing with different Layouts



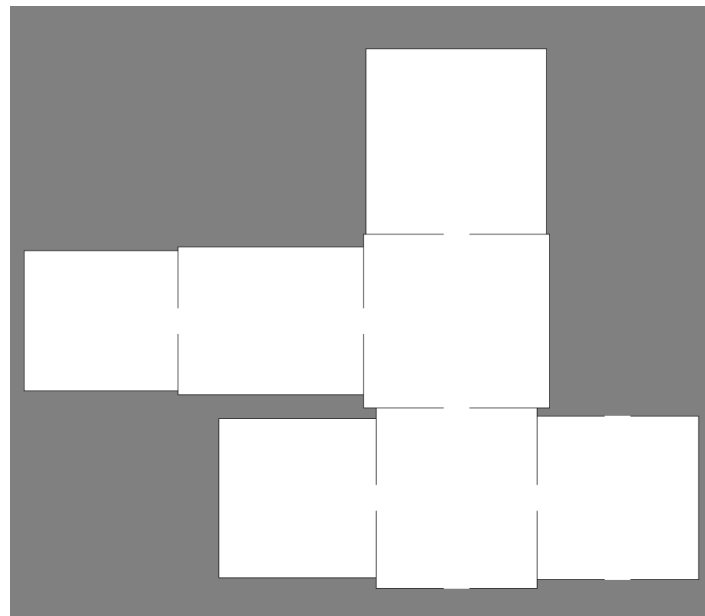
Sample Random Layout with Random Robot Position

Evaluation

Performance Testing with different Layouts



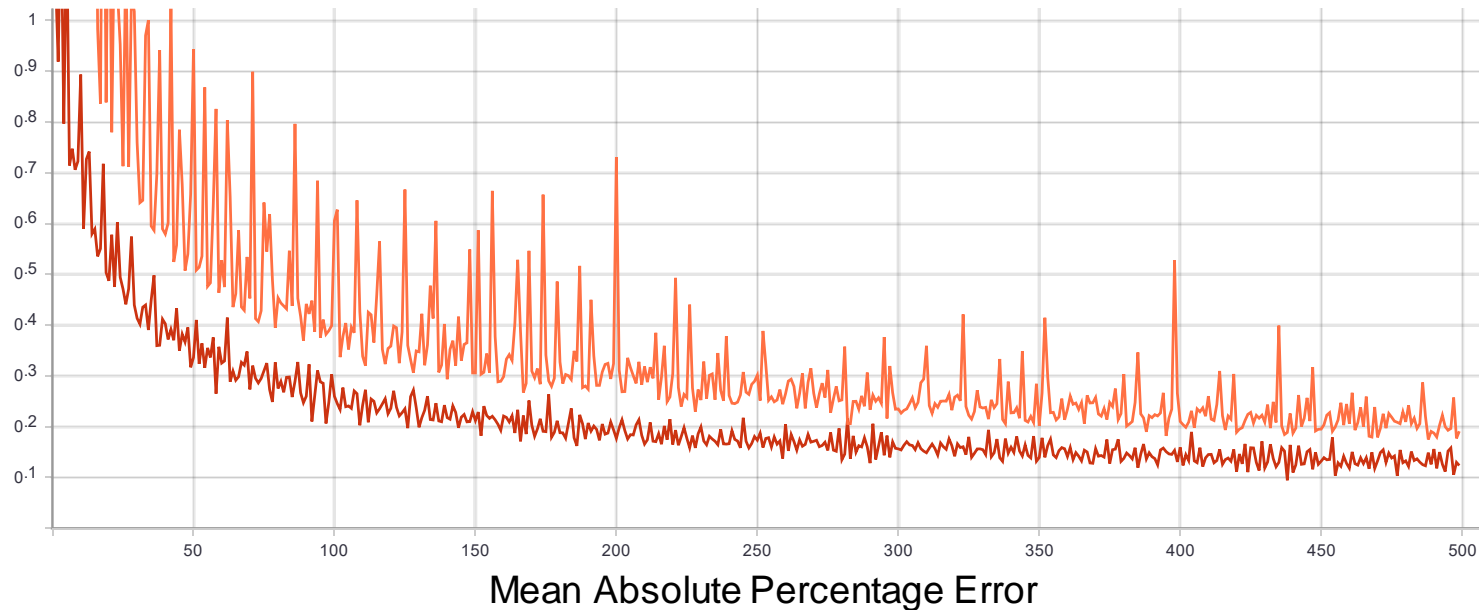
3 Room Apartment



7 Room Apartment

Evaluation

Performance Testing with different Layouts

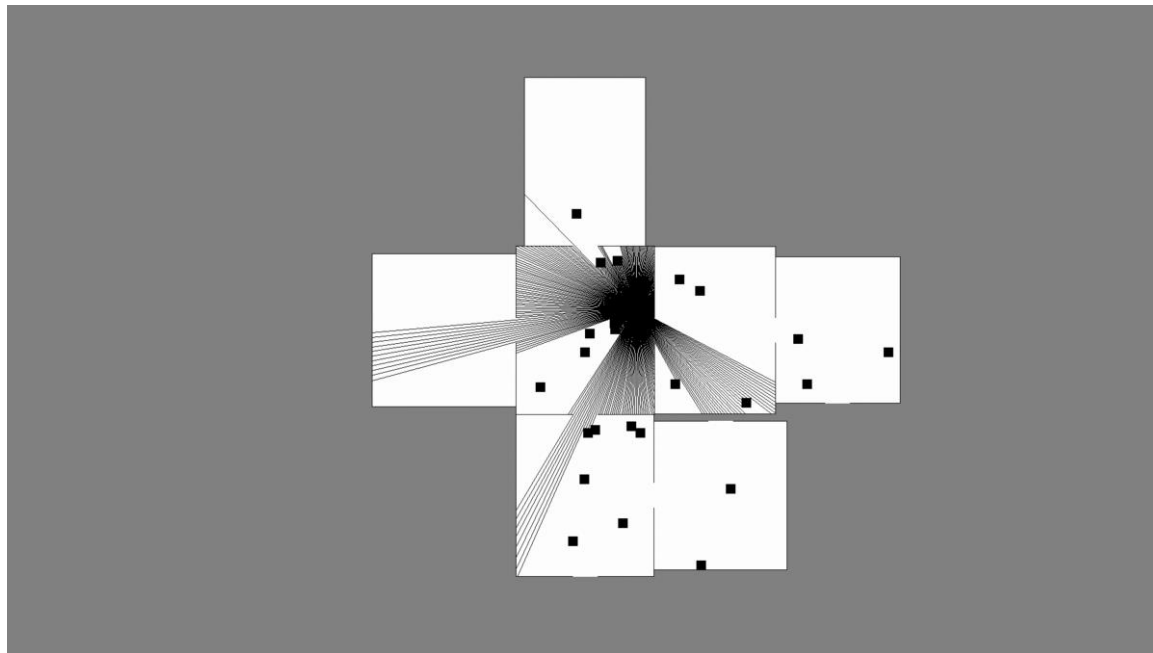


orange: large apartment (7 room)

red: small apartment (3 room)

Evaluation

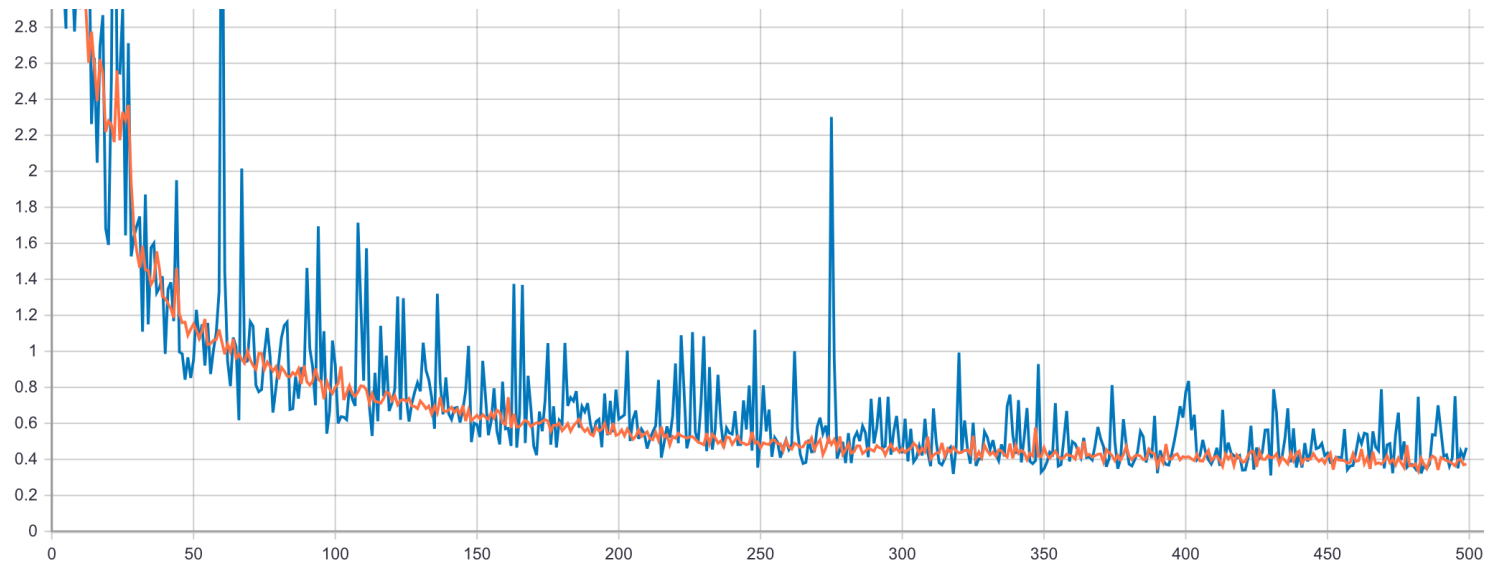
Performance Testing with different Layouts



Sample Layout with Obstacles

Evaluation

Performance Testing with different Layouts

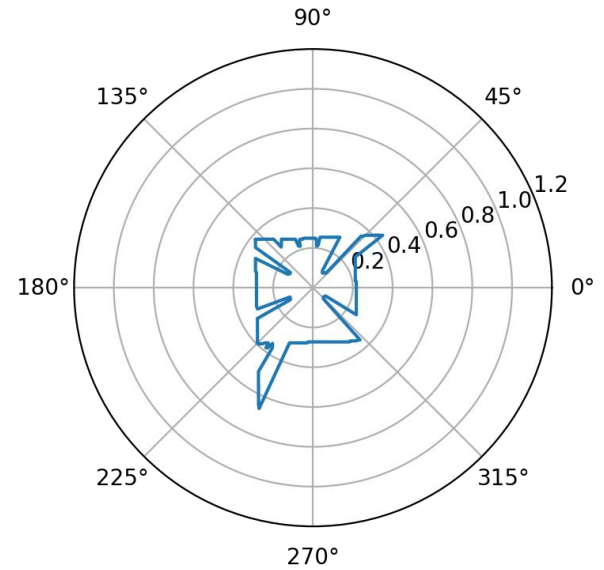
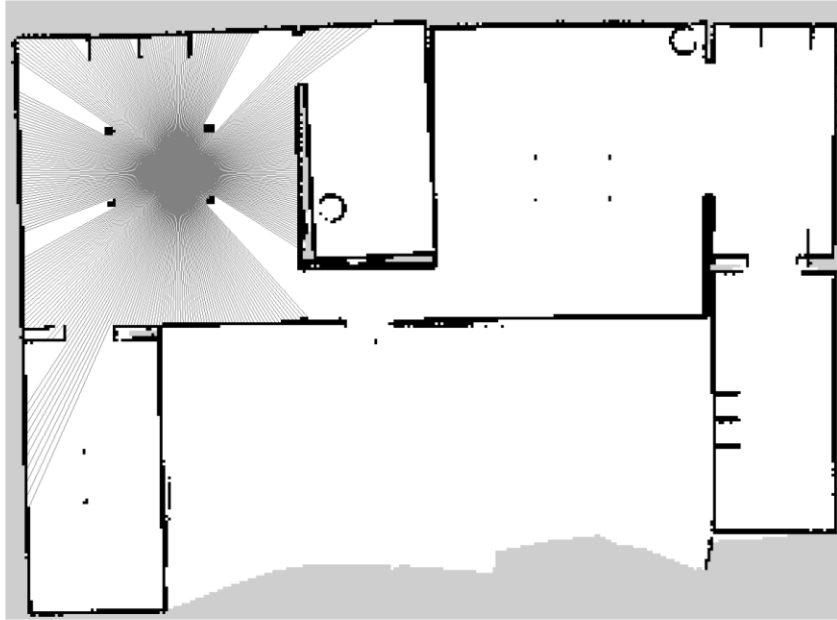


Mean Absolute Percentage Error of Apartment with Obstacles

blue: Testdata
orange: Trainingsdata

Application

Combination with GMapping



Discussion

Use-Cases

Combination with SLAM

- Determine initial position
- Detect errors (e.g. faulty odometry, drifting)

Stateless Localization

- Reliable: errors do not add up
- No odometry required
- Low computation cost
- Problems
 - Setup is complicated and expensive in real world
 - Effected by dynamic changes in environment (e.g. moved furniture)

Conclusion

Summary

- Dataset generated in Gazebo
- Model architecture based on ResNet [3]
- Trained with LiDAR data
- Compared networks against each other
- Evaluated with different techniques
 - Problematic regions
 - CNN Activations
 - Apartments of different complexity

Conclusion

Future Work

Real-world application

- Different types of LiDAR
- Indoor Positioning System (e.g. Bluetooth Beacons) to create dataset
- Orientation-invariant estimation
- Evaluate robustness of model against perturbations
 - e.g. humans moving around in the apartment

Any Questions?

References

Bibliography

1. Zhao, H., Acharya, D., Tomko, M., & Khoshelham, K. (2020). Indoor LIDAR Relocalization Based on Deep Learning Using a 3d Model. *The International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences*, 43, 541-547.
2. Scott Martin. (2019). *What Is Simultaneous Localization and Mapping?* SLAM is a commonly used method to help robots map areas and find their way. <https://blogs.nvidia.com/blog/2019/07/25/what-is-simultaneous-localization-and-mapping-nvidia-jetson-isaac-sdk/>
3. He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep residual learning for image recognition. In *Proceedings of the IEEE conference on computer vision and pattern recognition* (pp. 770-778).