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Mounting Position based Lidar Domain Gap Analysis

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Motivation



- A domain gap describes the difference in the Input data between two domains
 - Different mounting positions of Lidars have geometric implications on the input domain
 - Two commonly used positions
 - An important part is the analysis and identification of the domain shift
 - As well as a quantification of changes in the input data to evaluate procedures for the gap closure



Contribution



- Analysis of the domain gap in LIDAR data cross-sensor domain adaption
 - > Focus on change in measurement distribution with respect to sensor position
 - Focused on class based measurement distributions
 - Shared coordinate system measurement accumulation
 - > Enable comparative analysis of the gaps
 - > Show adaption strategies and the corresponding limitations
 - > Provide insights into classical voxel domains

Lidar Data Domain



We used the Lyft Level 5 data which uses different Lidar sensors in different mounting positions



R. Kesten, M. Usman, J. Houston, T. Pandya, K. Nadhamuni, A. Ferreira, M. Yuan, B. Low, A. Jain, P. Ondruska, S. Omari, S. Shah, A. Kulkarni, A. Kazakova, C. Tao, L. Platinsky, W. Jiang, and V. Shet. *Lyft level 5 perception dataset 2020.* https://level5.lyft.com/dataset/, 2019.

Data Accumulation



- For a comparative analysis we used a scale invariant coordinate system.
 - Extract points from annotation bounding box using the extra margin 10 cm in all dimensions to provide a common space for all data points to a surrounding rectangle.



Scheel, Alexander, and Klaus Dietmayer. "Tracking multiple vehicles using a variational radar model." IEEE Transactions on Intelligent Transportation Systems 20.10 (2018): 3721-3736.

Data Accumulation



> We accumulated Histogram over all annotations of type car perceived by the sensors



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-1.00 -0.75 -0.50 -0.25 0.00 0.25 0.50 0.75 1.00

Data Accumulation

To mitigate this bias conditionals on the aspect angle were generated.

And found a data bias with respect to the aspect angles and the sensor position





Lidar Front Left

This provides side based measurement distribution

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Model Generation



How to use and compare the accumulated data?

- > We use the data for the training of a representative distribution model
 - Gaussian mixture
- These models provide a likelihood for new measurements and our assumption is that the likelihood is an indicator that new data was emitted by the respective sensor setup.
- We want to evaluate this hypothesis by comparing the likelihood functions with respect to different sensor data

Model Generation



Mixture models based on for the respective aspect angles



Trained conditional mixture models. Normalized equidistant slices from the 3d mixture are provided for 2 of the aspect conditionals. Color scale (blue - red)

Model Comparision







Trained conditional mixture models. Normalized equidistant slices from the 3d mixture are provided for 2 of the aspect conditionals. Color scale (blue - red)

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Likelihood difference



Model Comparision

- The models likelihood provides a measure, that describes measurement distribution and is comparative.
 - The difference in likelihood on a new sample may be used
 - A negative value indicates the low mounted sensor
 - A positive value indicates



Likelihood difference



Model Comparision



- The model's likelihood provides a measure for the measurement distribution and is comparative.
 - > The difference in likelihood on a new sample may be used
 - A negative value indicates the low mounted sensor
 - A positive value indicates

Lidar_Front_Left data : Top and side view



Likelihood difference -0.121

Lidar_Top data : Top and side view





Likelihood difference 0.562

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Domain Adaption via Auto-Encoders

- We considered using the GMM as a generative model or use autoencoders
 - This cannot encode scan structure or a concrete number of measurements
- Leads us to the final question of this talk: How different are the domains in the voxel space?
 - The comparison of a high dimensional voxel feature space is complicated
 - > As a baseline, we compare the base occupancy of a voxel grid
 - > We count the number of cells occupied in one frame in comparison







Voxel Occupancy

- Consider frame by frame comparison in the data set
- Simple delta per frame: #(occupied(Top) and not occupied(Front Left))



- Lidar Top Lidar Front Left
- ★ Occupancy Top
- Occupancy Front Left

Birdseye view for sensor measurements and sensor occupancy a sensor pair



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Voxel Occupancy

- Resulting distribution as histograms over all frames in which all sensors receive measurements on the target
- Similar distribution between low and high mount
- Distribution as a measure of the delta



Sensor Sensor Delta Matrix for grid size 0.25m



Summary



- > We provided a comparative analysis of the distribution of cars in lidar sensors in different domains
- Investigated the generation of data and found limitations regarding real data
- > Looked into discretization effects that a neural network may face when discretising the domain
- > All analysis parts provide indicators to use in analysing the plausibility of abstraction methods





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