Data-Driven Protection Levels for Camera and 3D Map-based Urban Localization

#2006162, CAREER: High Integrity Navigation for Autonomous Vehicles, PI: *Grace Gao, Stanford University*

Overview

Objective:

- Reliably assessing the position error in an estimated vehicle position is integral for ensuring safety of the vehicle
- We develop a data-driven method for computing a probabilistic upper bound of position error, *protection level*, from camera images and a 3D LiDAR environment map

Protection Level:

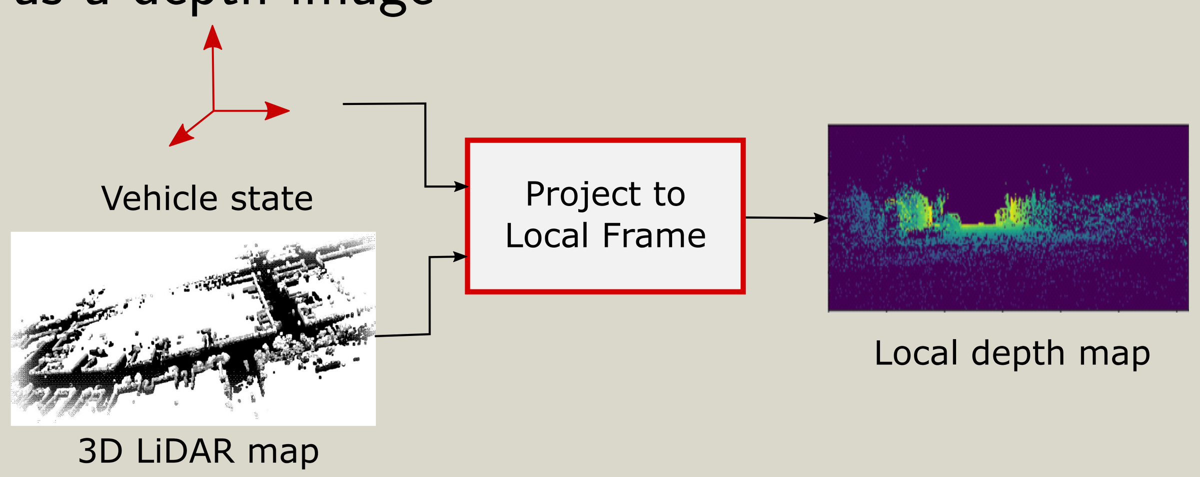
$$PL = \sup\{x \; : \; \Pr(\| \underbrace{\hat{s}}_{\text{Estimated position}} - \underbrace{s^*}_{\text{True position}} \| > x) \leq \underbrace{IR}_{\text{Integrity requirement}}\}$$

Contributions:

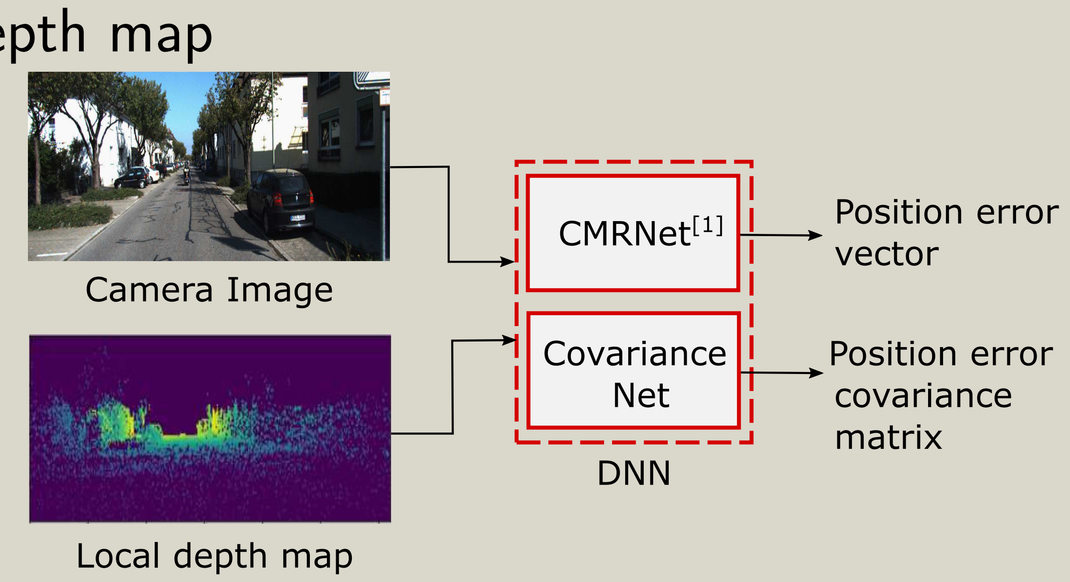
- Deep neural network (DNN)-based estimation of position error and its covariance in a vehicle state estimate from a camera image measurement and 3D environment map
- Method to characterize uncertainty in position error by computing multiple position error outputs from geometrically-related inputs to the DNN
- Outlier weighting scheme to mitigate the impact of large errors in DNN outputs

Estimating Position Error and Variance

- 3D map is projected to local reference frame of the vehicle state as a depth image



- A DNN estimates the position error vector and the associated covariance matrix from the camera image and local depth map

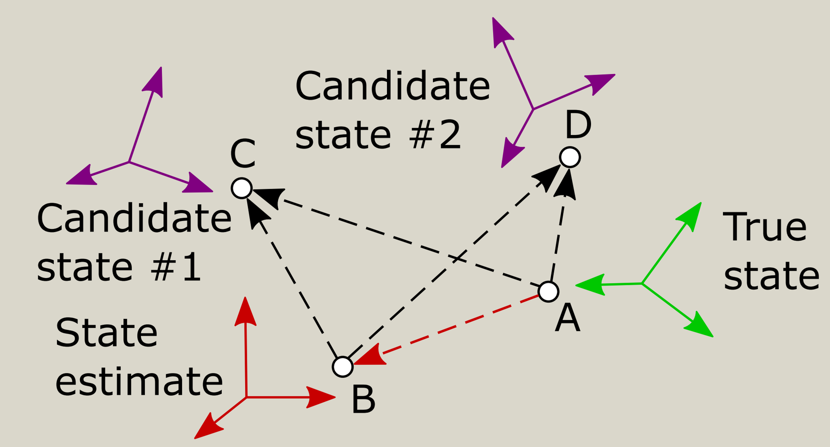


Characterizing Uncertainty in Position Error

Problems with DNN-based covariance:

- Overconfident measure of uncertainty
- No accounting of DNN model inaccuracy or large errors
- Local map inputs ignore many environment features

Idea: The state estimate position error AB can be computed from the linear combination of the position error AC or AD computed for a different candidate state and its relative position vector BC or BD.



Method:

- Determine multiple candidate states by selecting random positions and orientation from within a vicinity of state estimate
- Evaluate position error and covariance for candidate states from DNN
- Project the candidate state position errors into samples of the state estimate position error
- Weight each sample in x, y and z dimensions using robust Z-score to mitigate the effect of outliers

Computing Protection Levels

- Incorporate uncertainty from the projection of candidate state position errors in the DNN-based covariance matrix
- Construct a Gaussian mixture model (GMM) probability distribution in lateral x, longitudinal y and vertical z directions from position error samples, outlier weights and covariance matrix
- Protection levels computed from CDF of GMM using numerical line search methods

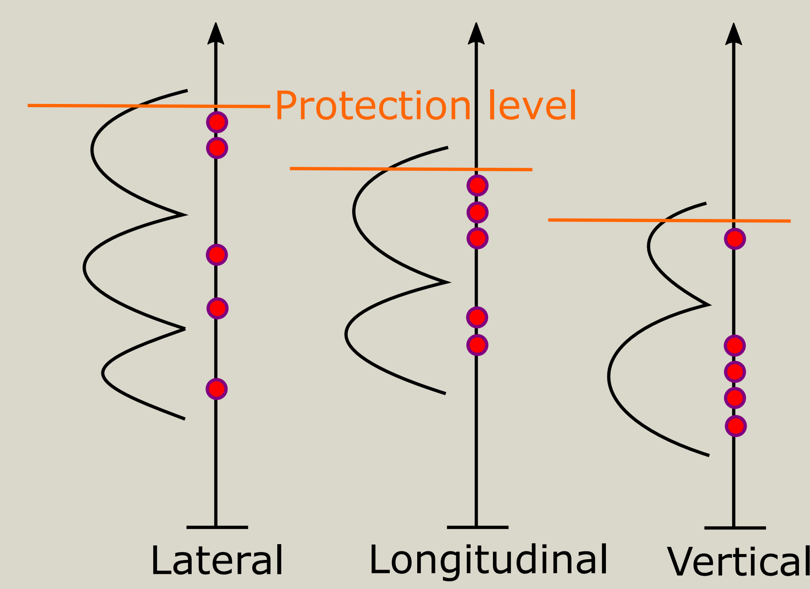


Figure: Protection level is computed as upper confidence interval of the GMM in lateral, longitudinal and vertical directions.

Selected References

[1] Cattaneo, D., *et al.*, IEEE, 2019.
[2] Gupta, S. and Gao, G. X., ION GNSS+, 2020

Experimental Results

- Camera images from KITTI visual odometry dataset
- Randomly selected state estimates within ± 2 m translation and $\pm 5°$ rotation of the ground truth
- 3D map from LiDAR point clouds combined using SLAM poses

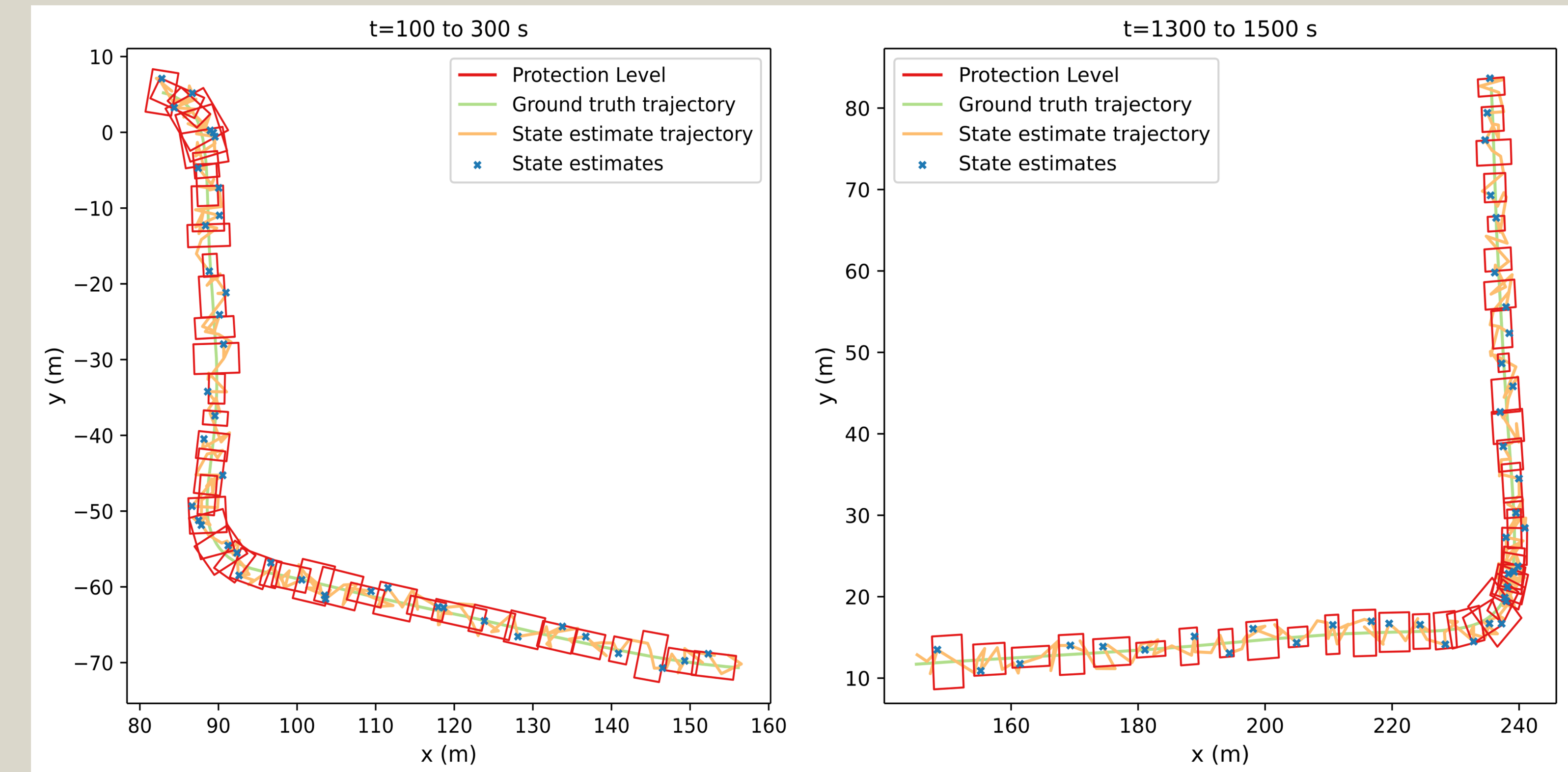


Figure: Horizontal (lateral and longitudinal) protection levels along two subsequences from the test trajectory for integrity requirement of 0.01.

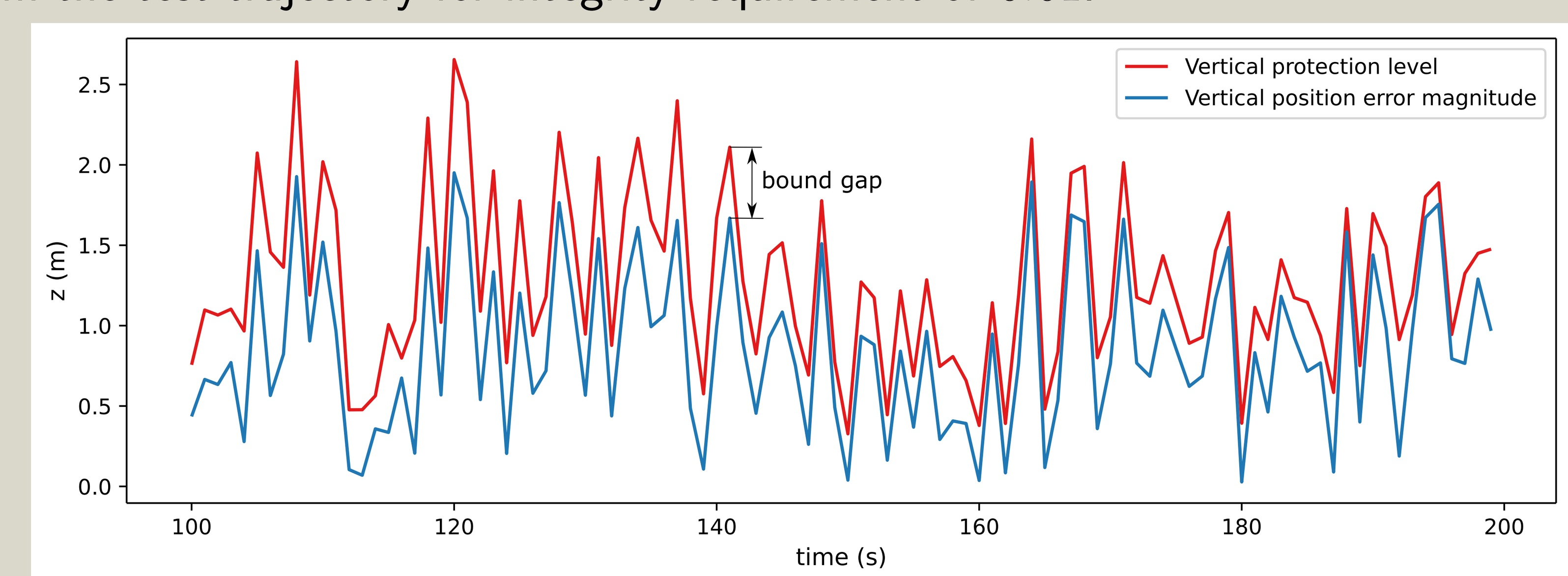


Figure: Vertical protection levels along subsequence from the test trajectory for integrity requirement of 0.01.

	Lateral PL	Longitudinal PL	Vertical PL
AL(m)	0.85	1.50	1.47
BG(m)	0.49	0.77	0.38
FR	0.01	0.01	<0.01
FAR	0.47	0.40	0.14

Table: Performance metrics of bound gap (BG), failure rate (FR) and false alarm rate (FAR) on KITTI dataset sequence 00 for integrity requirement of 0.01 and specified alarm limit (AL).

Conclusion

- Novel method to compute protection levels from camera image measurements and 3D LiDAR map
- Protection levels enclose the position error with low failure rate
- Bound gap is smaller than quarter the width of standard US lane