AI-Aided mmWave Beam Selection for Vehicular Communication

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Beam-selection

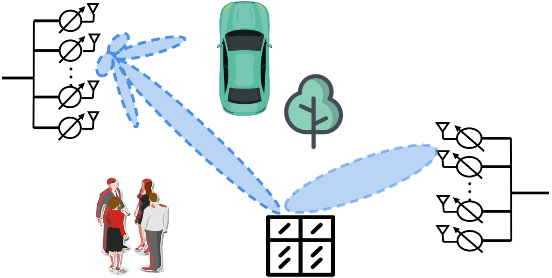
- Transmitter with N_t antennas and code-book

$$\mathcal{H} = \{\mathbf{h}_1, \dots, \mathbf{h}_{|\mathcal{H}|} : \mathbf{h}_i \in \mathbb{C}^{N_t \times 1}\}.$$

- Receiver with N_r antennas and code-book

$$\mathcal{D} = \{\mathbf{d}_1, \dots, \mathbf{d}_{|\mathcal{D}|} : \mathbf{d}_i \in \mathbb{C}^{N_r \times 1}\}.$$

- channel matrix $\mathbf{H} \in \mathbb{C}^{N_r \times N_t}$.



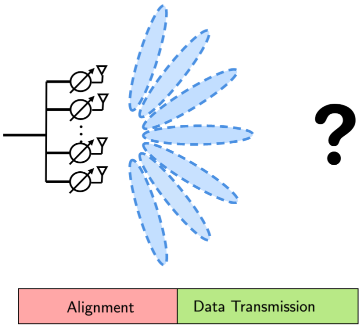
Goal:

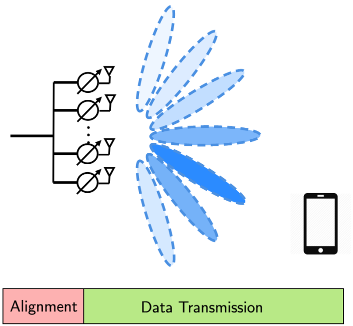
$$\underset{(i,j) \in |\mathcal{H}| \times |\mathcal{D}|}{\text{maximize}}\ g(i,j) = \left\| \mathbf{d_j}^T \mathbf{H} \mathbf{h_i} \right\|$$

In practice solved by sequential search procedures, possibly based on estimates of $\mathbf{H}$.

Beam-selection

Beam alignment overhead is proportional to the uncertainty about the beamformed channel gains, contextual information can reduce it.





Beam-selection in vehicular communication

In vehicular communication, efficient beam selection is imperative due to the shorter beam coherence times.

Channel Variability

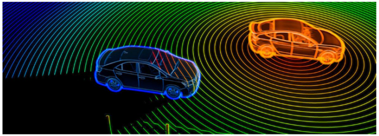
Alignment	Data Transmission	Alignment	Data Transmission	Alignment	Data Transmission	Alignment	Data Tr.

Taking advantage of multiple sensory information can enhance situational awareness

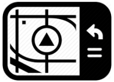
Roadside Cameras

Dash Cameras

LIDAR



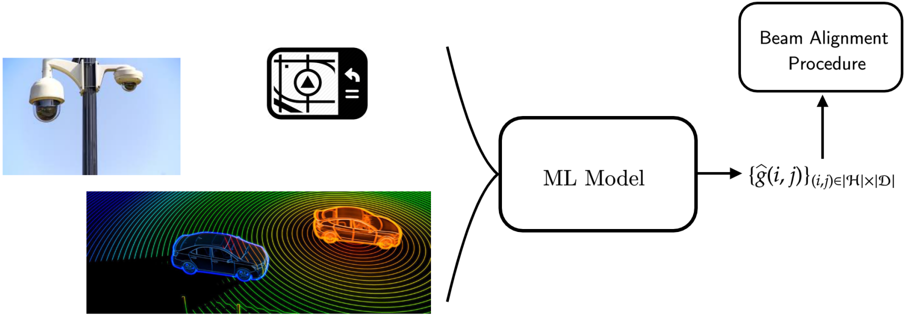
GPS



Role of deep learning

It is not clear how to intelligently use the high dimensional sensory data to guide the beam alignment procedures.

Is it possible to combine abundance of sensory data with deep learning techniques to guide the beam alignment procedure and reduce its overhead?



Problem statement

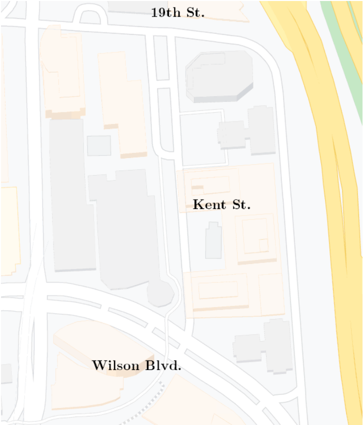
Communication scenario:

- mmWave (60GHz) vehicle to infrastructure (V2I) communication
- Single user analog MIMO architecture
- Transmitter (infrastracuture) has $N_t = 32$ antenna elements while the receiver (vehicle) has $N_r = 8$.
- N_t DFT beamforming vectors at transmitter and N_r at receiver. For a total of 256 different beam-formed channels.

Sensors:

- GPS coordinates
- Rooftop LIDAR
- 3 road side cameras

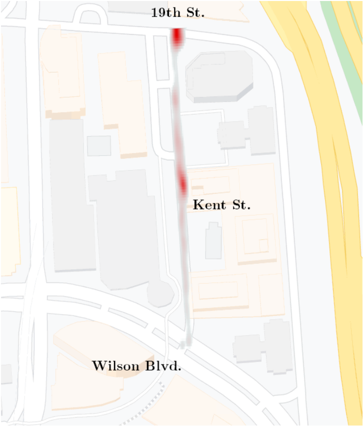
Rosslyn, Arlington



GPS data

- GPS coordinates provides a low dimensional (x,y,z) and extremely valuable information.[1]
- Simple, yet effective, ML models can be trained based on GPS only. [2]
- GPS coordinates do not distinguish between LOS/NLOS nor informs about the presence of reflectors

1-NN error magnitude

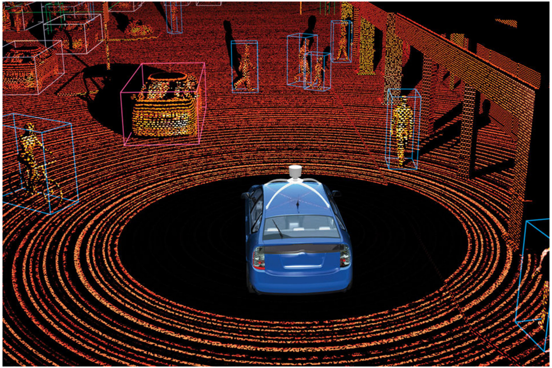


[1] Maschietti, Flavio, et al. "Robust location-aided beam alignment in millimeter wave massive MIMO." GLOBECOM 2017-2017 IEEE Global Communications Conference. IEEE, 2017.

[2] Heng, Yuqiang, and Jeffrey G. Andrews. "Machine Learning-Assisted Beam Alignment for mmWave Systems." 2019 IEEE Global Communications Conference (GLOBECOM). IEEE, 2019.

LIDAR Data

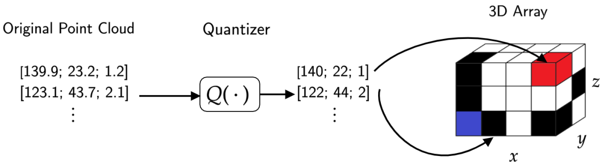
LIDAR is a radar using laser impulses to locate nearby objects.

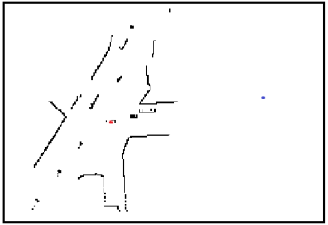


Returns a point cloud: a list of 3D coordinates of sampled points on surrounding object surfaces.

LIDAR Feature extraction

- There exist architectures processing directly cloud points (PointNet) [3]
- It is possible to transform the point cloud in an image like format. [4]
- The feature extraction block was tweaked in order to retain more info in NLOS scenarios.





[3] Qi, Charles R., et al. "Pointnet: Deep learning on point sets for 3d classification and segmentation." Proceedings of the IEEE conference on computer vision and pattern recognition. 2017.

[4] Klautau, Aldebaro, Nuria González-Prelcic, and Robert W. Heath. "LIDAR data for deep learning-based mmWave beam-selection." IEEE Wireless Communications Letters 8.3 (2019): 909-912.

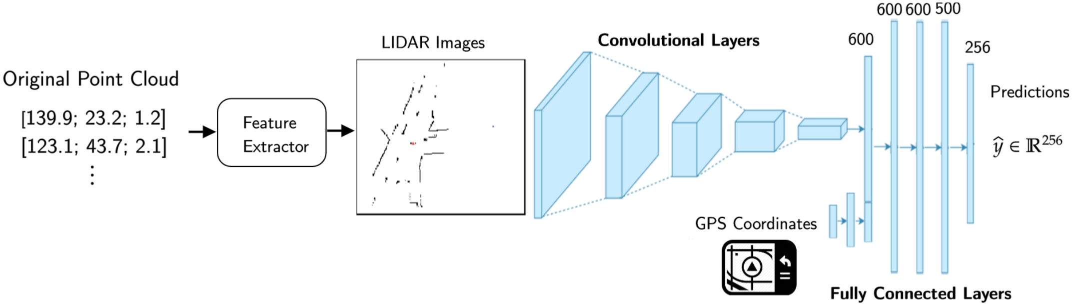
Roadside Cameras

- Image data is typically processed by convolutional neural networks (very successful models).
- However task at hand entails a problem that can be hard for humans too: inferring 3D geometry from 2D images

Ames room: the three men are equally tall!

The neural network architecture

Goal: Transform the out-of-band information into good side information for the alignment phase.



Input: Lidar and GPS
Output: $\propto$ channel gains

The loss function

- The loss function servers as a proxy for learning and it is used to rank the network configurations (i.e. its free-parameters θ) based on training data.

$$\hat{L}(\theta) = \sum_{i=1}^{n} \ell^{\theta}(x_i, y_i), \quad x_i : \text{out of band info}, \quad y_i : \text{beam-formed channel gains}$$

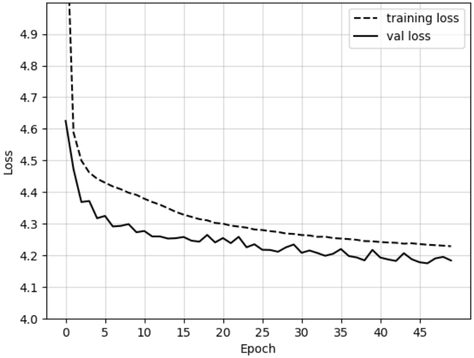
- The proposed loss is inspired by knowledge distilliation techniques and it interpolates between classification and regression

$$\ell^{\theta}(x, y) = \beta \mathsf{KL}\left(y^H, \bar{f}_\theta(x)\right) + (1 - \beta)\mathsf{KL}\left(\bar{y}, \bar{f}_\theta(x)\right), \ \beta \in [0, 1]$$

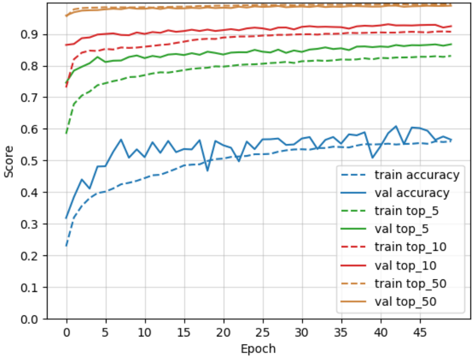
$\bar{f}_\theta(x)$: model output y^H: one-hot encoded best beam $\bar{y}$: normalized channel gain vector

Training

- Train for 50 epochs ($\approx$ 1 hour) using 11k samples for training and 1k for validation.
- L2 regularization + Gaussian input noise ($\sim$ sensor noise).



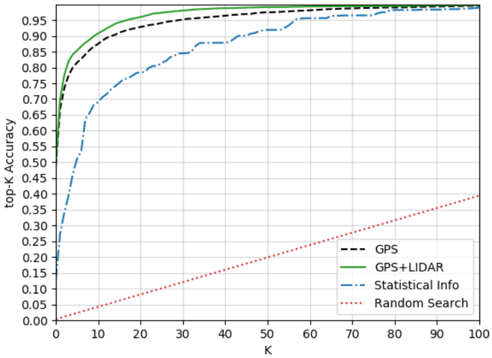
(a) Loss vs epoch



(b) top-K accuracy for $K = \{1, 5, 10, 50\}$ vs epoch

Testing performance

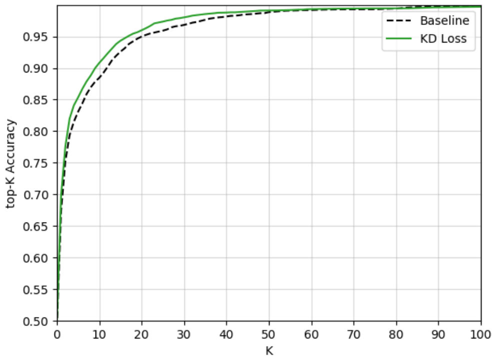
The trained model is tested on a new set of 7k *unseen* samples by computing the top-K performance

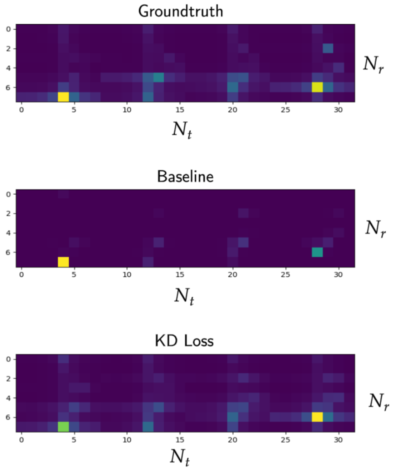


- Contextual information can only improve performance.
- If the beam alignment procedure is aided by LIDAR and GPS information, a 10 step training has a 92% confidence of getting the best beam.

Final remark: Loss Influence

The proposed loss yields higher top-K accuracy and more informative outputs.





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