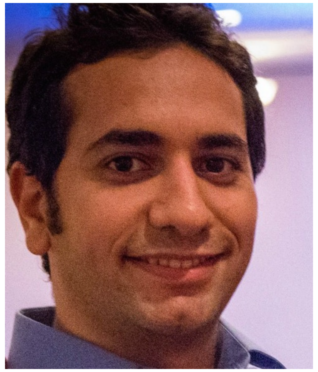
Millimeter Wave V2V Beam Tracking using Radar: Algorithms and Real-World Demonstration


Hao Luo
h.luo@asu.edu


Umut Demirhan
udemirhan@asu.edu


Ahmed Alkhateeb
alkhateeb@asu.edu

Wireless Intelligence Lab - Arizona State University

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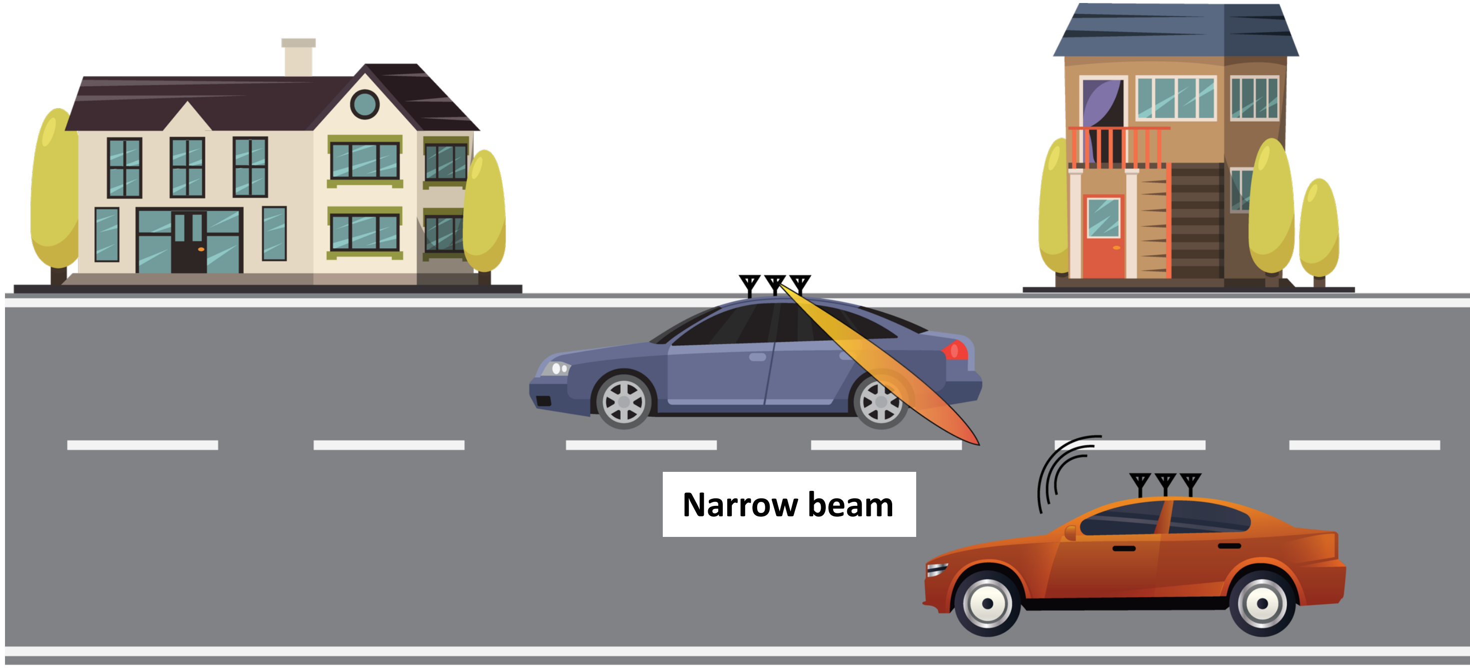
Wireless Intelligence Lab

Challenges with vehicle-to-vehicle (V2V) communications

- Envisioned V2V communications
  - Sensor-supported safety applications
  - Demand high data rate
- mmWave and THz communications
  - High data transfer speeds
  - Large antenna array and narrow beam
  - Accurate narrow beam alignment



Finding the optimal narrow beam results in a large training overhead

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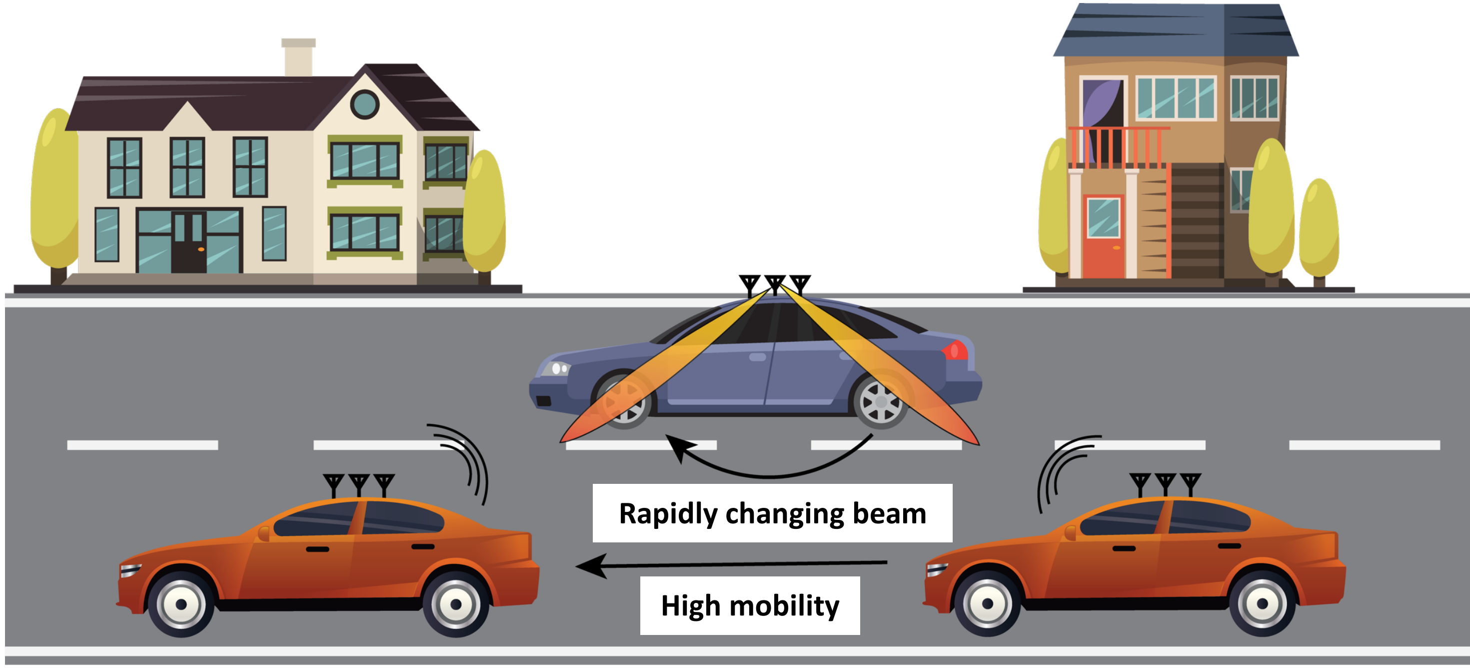
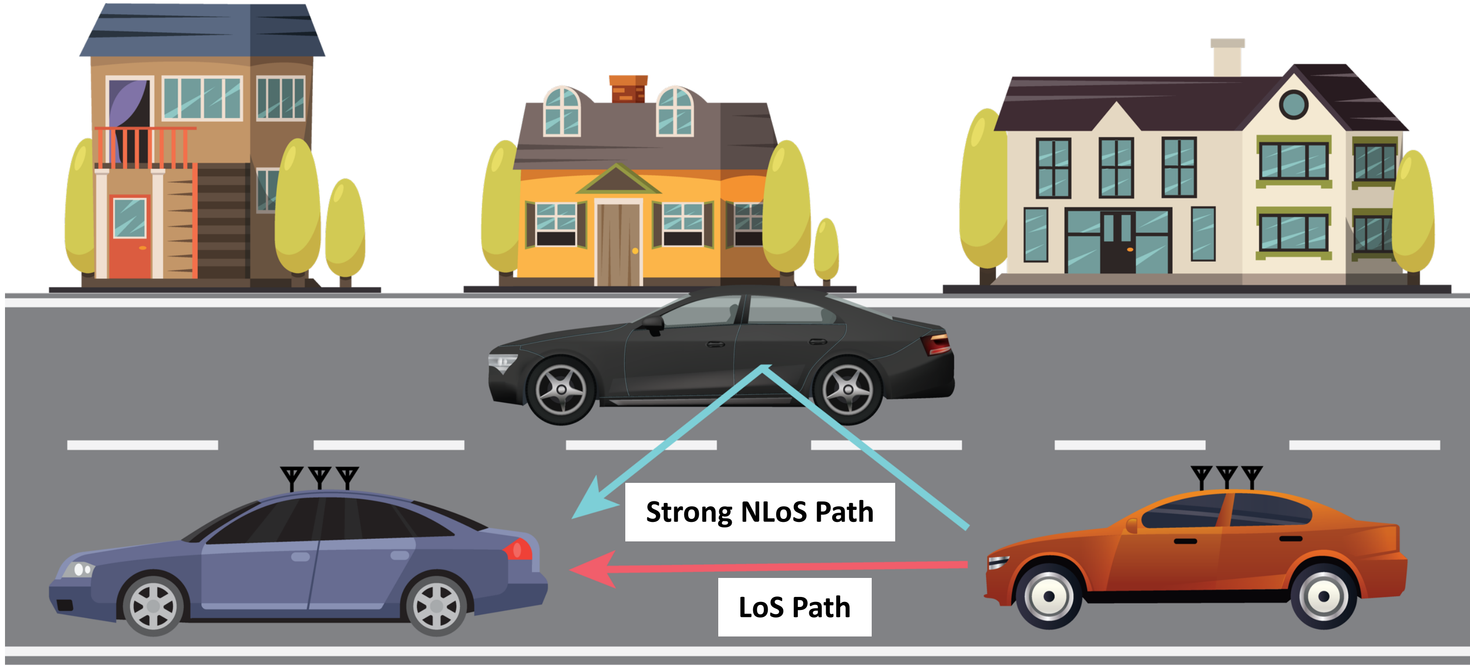


Finding the optimal narrow beam results in a large training overhead

It is challenging to support highly-mobile vehicular scenarios

Key idea: Radar-aided beam tracking

- Channels are the functions of
  - Geometry of the environment
  - Position/direction of the Tx/Rx
- Multi-modal vehicular sensors
  - Already available for other applications
  - Example: Automotive radar sensors



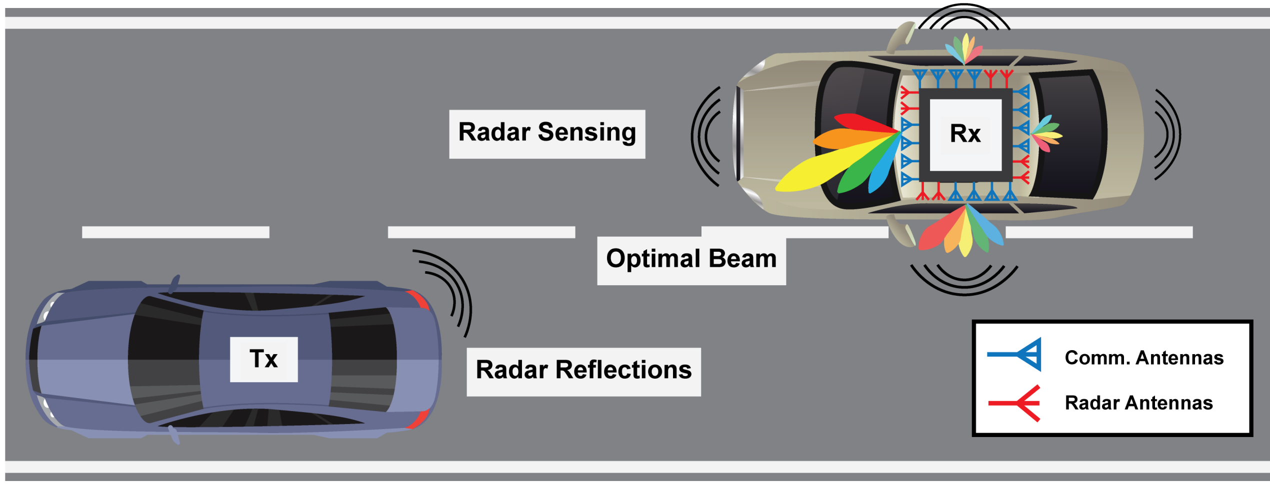
Can we use radar sensing for beam tracking in V2V scenarios?

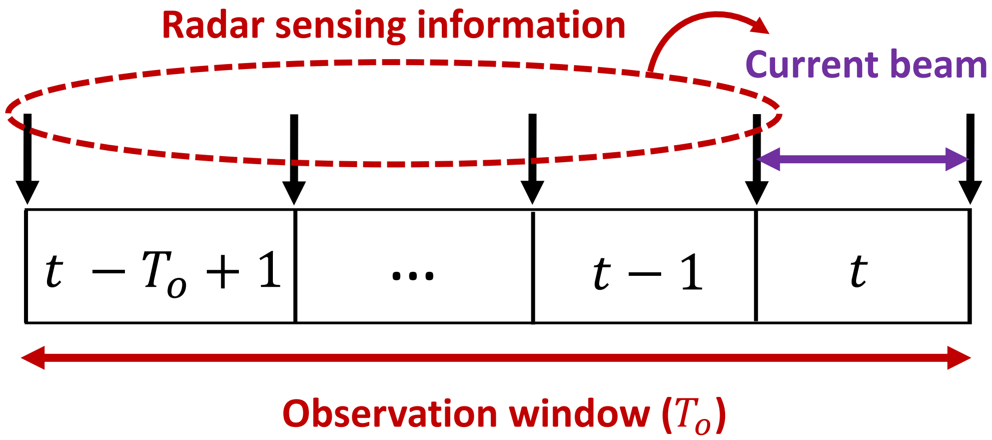
Can the developed solutions perform well in the real world?

System model

- A transmitter vehicle with a single antenna
- A receiver vehicle
  - A set of linear mmWave antenna arrays
  - A set of off-the-shelf FMCW radars
  - Cover the whole circular directions

    $d \in \{front, right, back, left\}$
- Radar-aided mmWave beam tracking
  1. Observe a sequence of radar measurements
  2. Predict the optimal beam





System model

Communication model

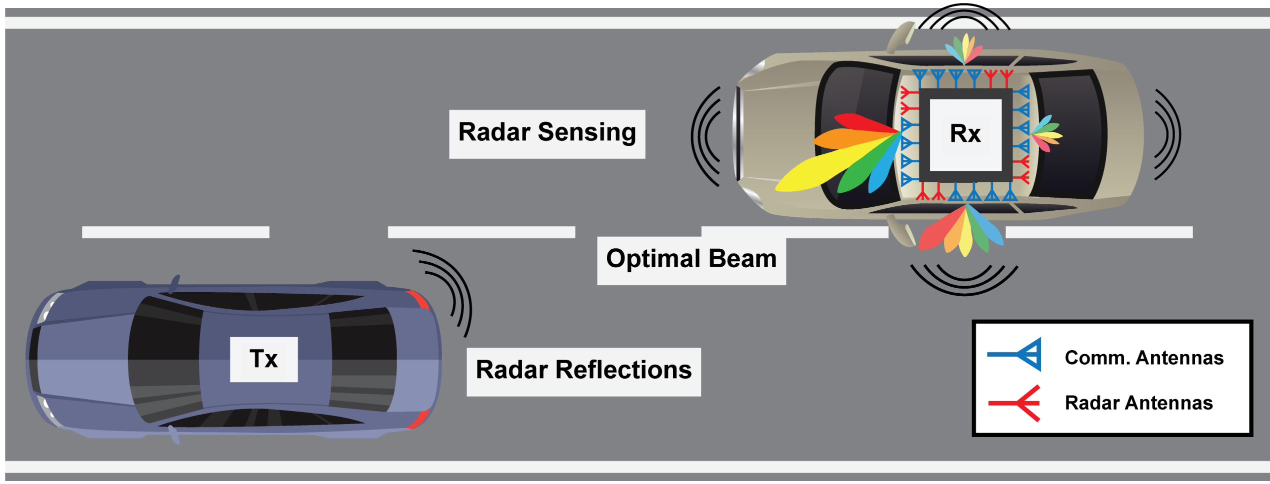
- Channel model

$$\mathbf{h}_d = \sum_{l=1}^{L_d} \alpha_{d,l} \mathbf{a}(\theta_{d,l}^{az}, \theta_{d,l}^{el})$$

Number of paths

Complex path gain

Array response vector



- Received signal

$$y_d = \sqrt{\mathcal{E}_c} \mathbf{f}_d^H \mathbf{h}_d s + n$$

Data symbol

Noise

Power gain

Combining vector

$$\mathcal{F}_d = \{\mathbf{f}_{d,1}, \ldots, \mathbf{f}_{d,B}\}$$

Pre-defined codebook

- Optimal direction and beam index

$$\begin{aligned} \max_{d,b} \quad & |\mathbf{f}_{d,b}^H \mathbf{h}_d|^2 \\ \text{s.t.} \quad & d \in \{front, right, back, left\}, \\ & b \in \{1, \ldots, B\}. \end{aligned}$$

System model

Radar model

- Chirp signal

$$s^{\text{tx}}_{\text{chirp}}(t) = \begin{cases} \sin\left(2\pi[f_0 t + \frac{S}{2}t^2]\right) & \text{if } 0 \le t \le T_{\text{active}} \\ 0 & \text{otherwise} \end{cases}$$

- Transmit signal (Radar frame)

$$s^{\text{tx}}_{\text{frame}}(t) = \sqrt{\mathcal{E}_t} \sum_{c=0}^{M_{\text{chirp}}-1} s^{\text{tx}}_{\text{chirp}}(t - c \cdot T_{\text{PRI}})$$

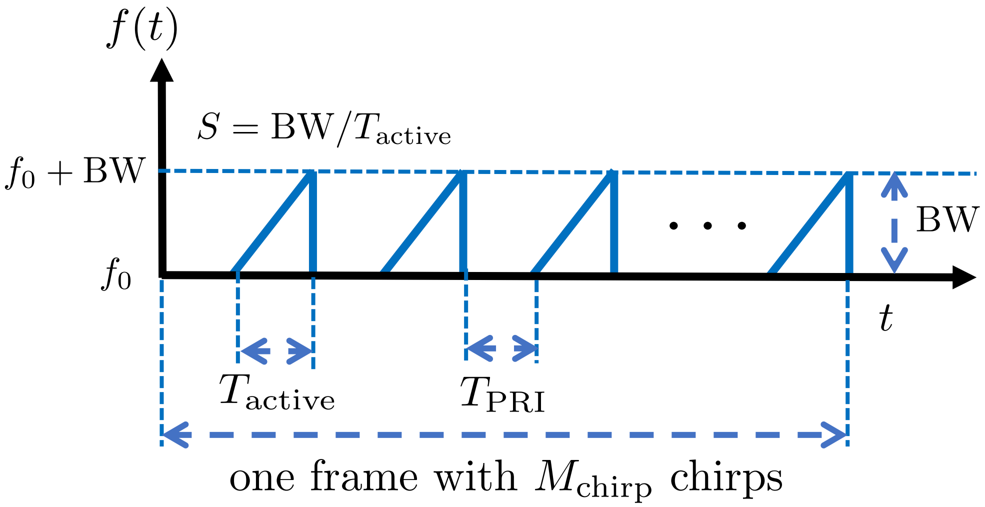
- IF signal of a chirp

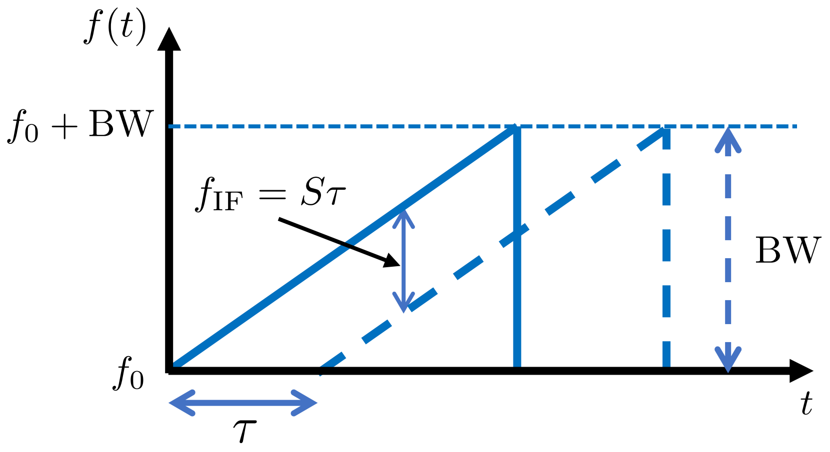
Round-trip time of sensing signal

$$s^{\text{rx}}_{\text{chirp}}(t) = \sqrt{\mathcal{E}_t \mathcal{E}_r} \exp\left(j2\pi\left[S\tau t + f_0\tau - \frac{S}{2}\tau^2\right]\right)$$

Transmission power gain

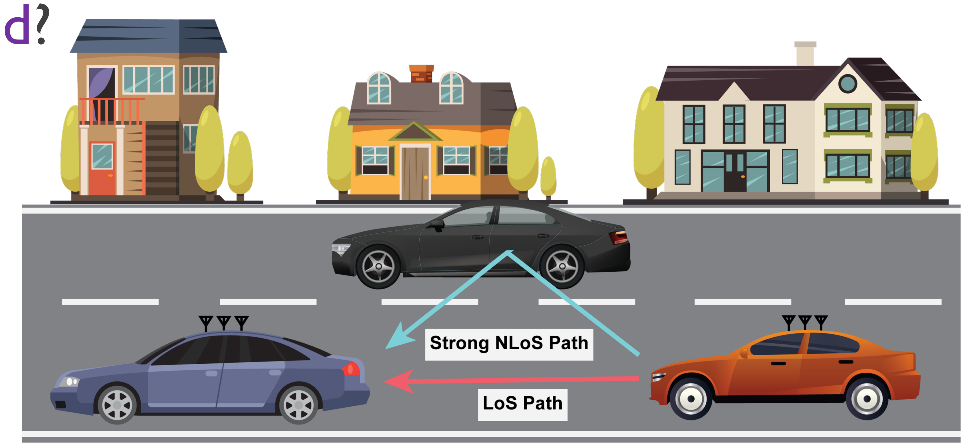
Reflection/scattering gain





Radar-aided V2V beam tracking problem

- In this work, we aim to answer the following questions
  - Can we use radar sensing for beam tracking in V2V scenarios?
  - Can the developed algorithms work well in the real world?



- Challenges in the real world
  i. Multiple objects in the highly dynamic environment
  ii. Noisy radar data from the mobile receiver/radar
  iii. Multiple potential directions of linear arrays

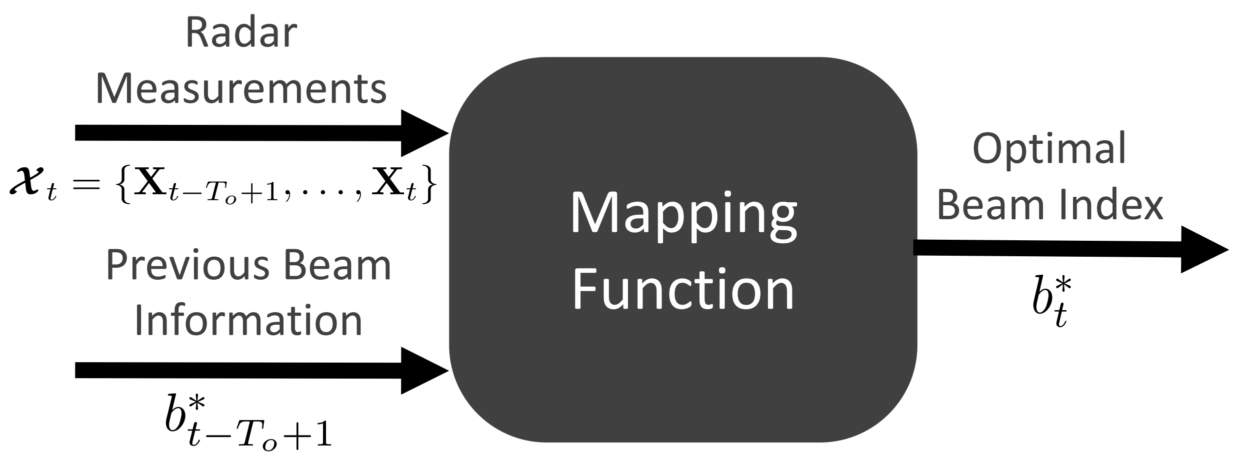
Simplify this challenge

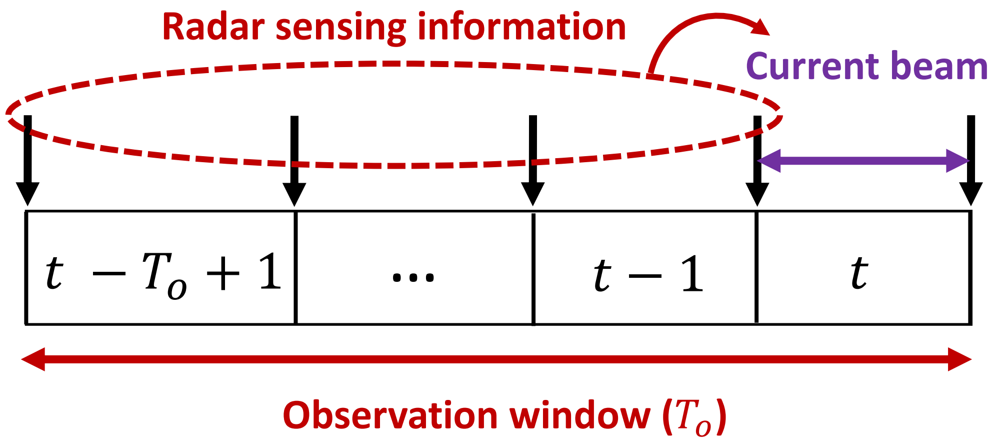
- Focus on the tracking within a single receive array/radar pair
- Assume the receive array/radar pair does not change within the sequence of samples

Induce additional difficulty

- The proposed algorithm needs to accommodate the data from different array/radar pairs

Radar-aided V2V beam tracking problem





- Mapping function – Convert the observed sensing and beam info. into the optimal beam index

$$f_{\boldsymbol{\Theta}}(\boldsymbol{\mathcal{X}}_t, b^*_{t-T_o+1}) = b^*_t$$

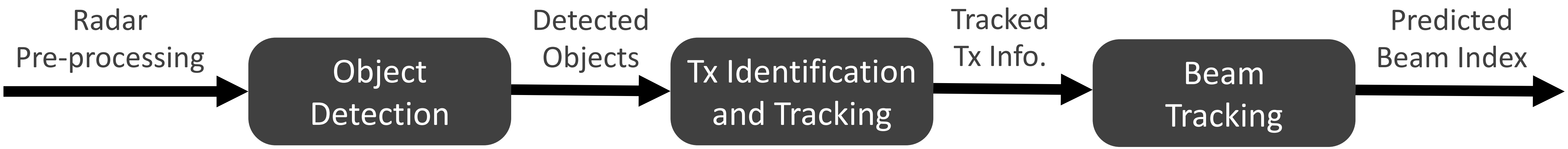
- Objective – Design a mapping function that targets optimal beam prediction

$$\hat{f}_{\hat{\boldsymbol{\Theta}}} = \underset{f,\boldsymbol{\Theta}}{\arg\max} \frac{1}{T} \sum_{t=1}^{T} \mathbf{1}_{\{b^*_t = f_{\boldsymbol{\Theta}}(\boldsymbol{\mathcal{X}}_t, b^*_{t-T_o+1})\}}$$

How can we develop an efficient solution for this problem?

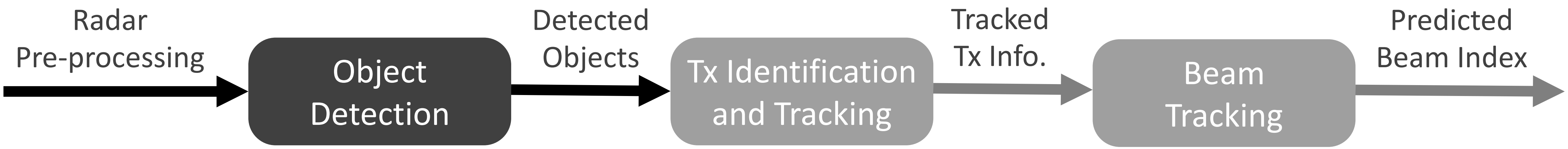
Approach 1: Beam tracking with transmitter identification

- Overview



Approach 1: Beam tracking with transmitter identification

Overview

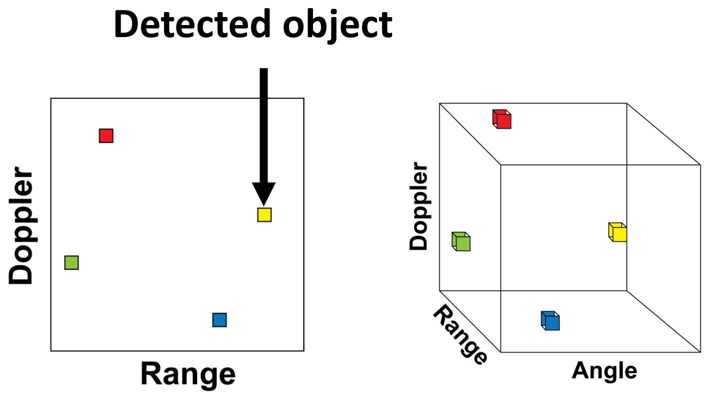


I. Radar pre-processing

Range-Doppler Map	$\mathbf{H}^{\mathrm{RD}} = \sum_{a=1}^{M_{\mathrm{ant}}} \lvert \mathcal{F}_{2\mathrm{D}}(\mathbf{X}_{a,:,:}) \rvert$
Radar Cube	$\mathbf{H}^{\mathrm{RC}} = \lvert \mathcal{F}_{3\mathrm{D}}(\mathbf{X}) \rvert$

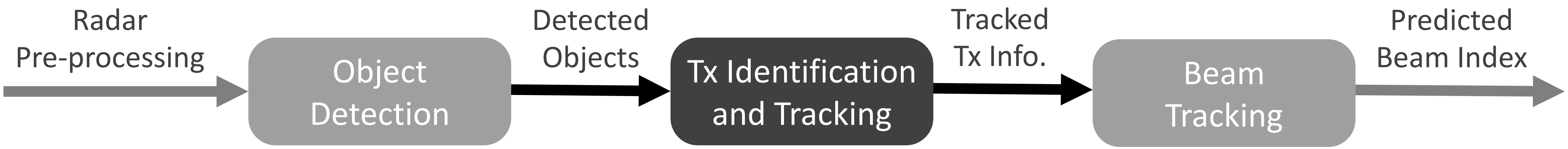
II. Object detection

- Apply CFAR method and clustering algorithm to range-Doppler maps
- Estimate the angle from the range and Doppler slice in the radar cube

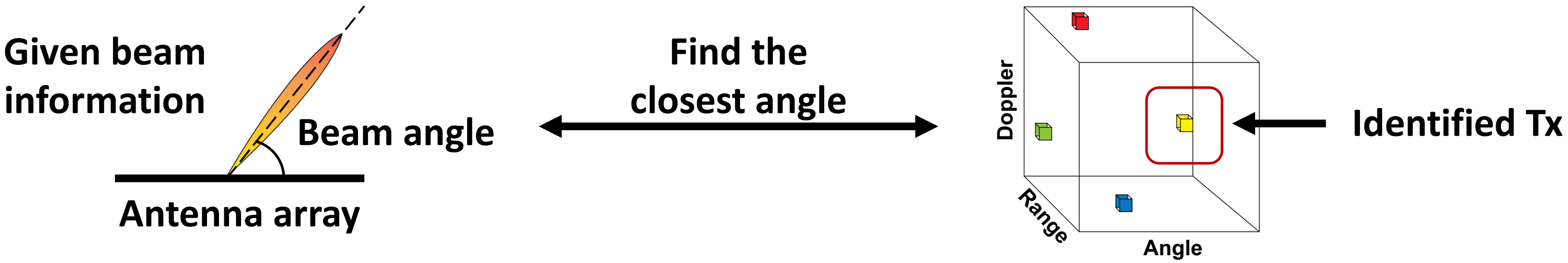


Approach 1: Beam tracking with transmitter identification

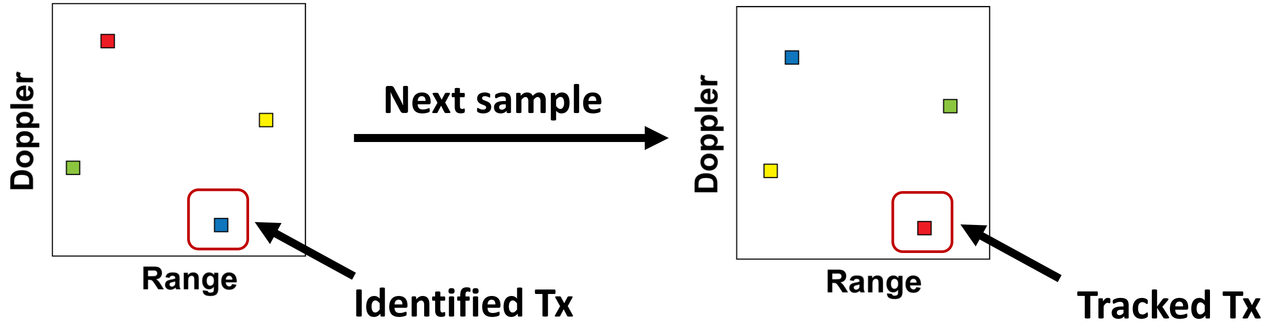
- Overview



III. Transmitter identification with the first radar measurement

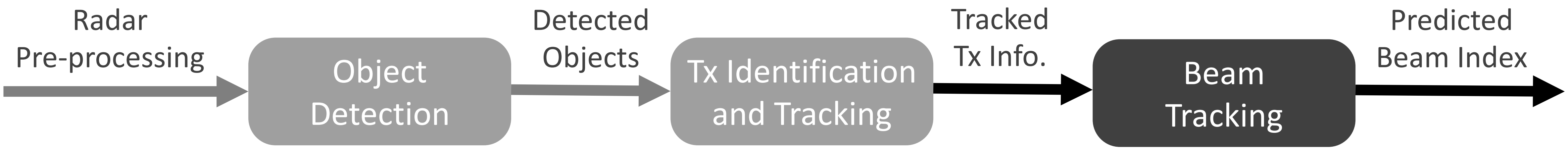


IV. Transmitter tracking – Find the closest object



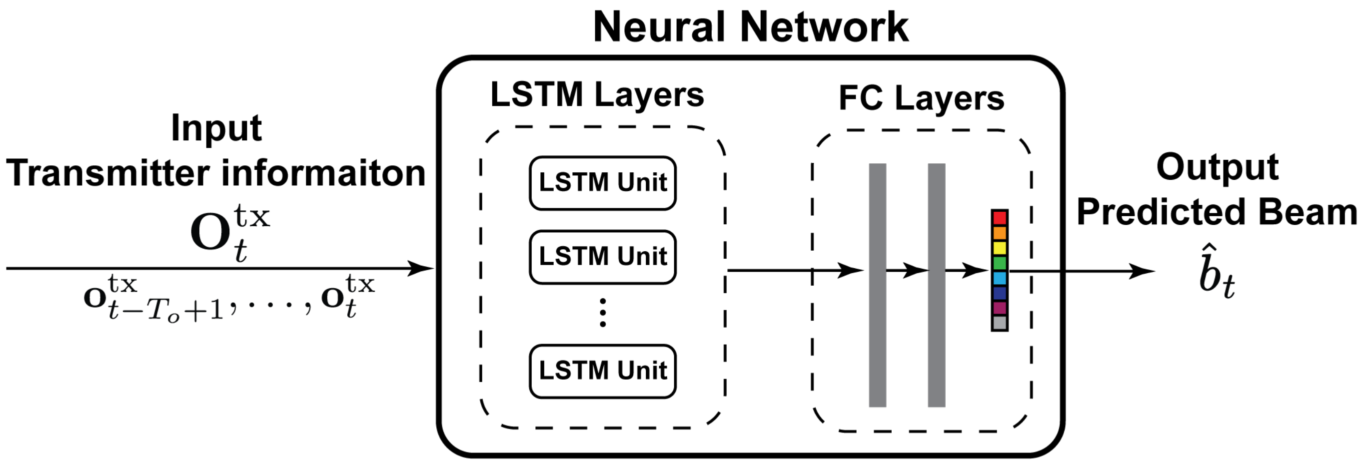
Approach 1: Beam tracking with transmitter identification

Overview



V. Beam tracking

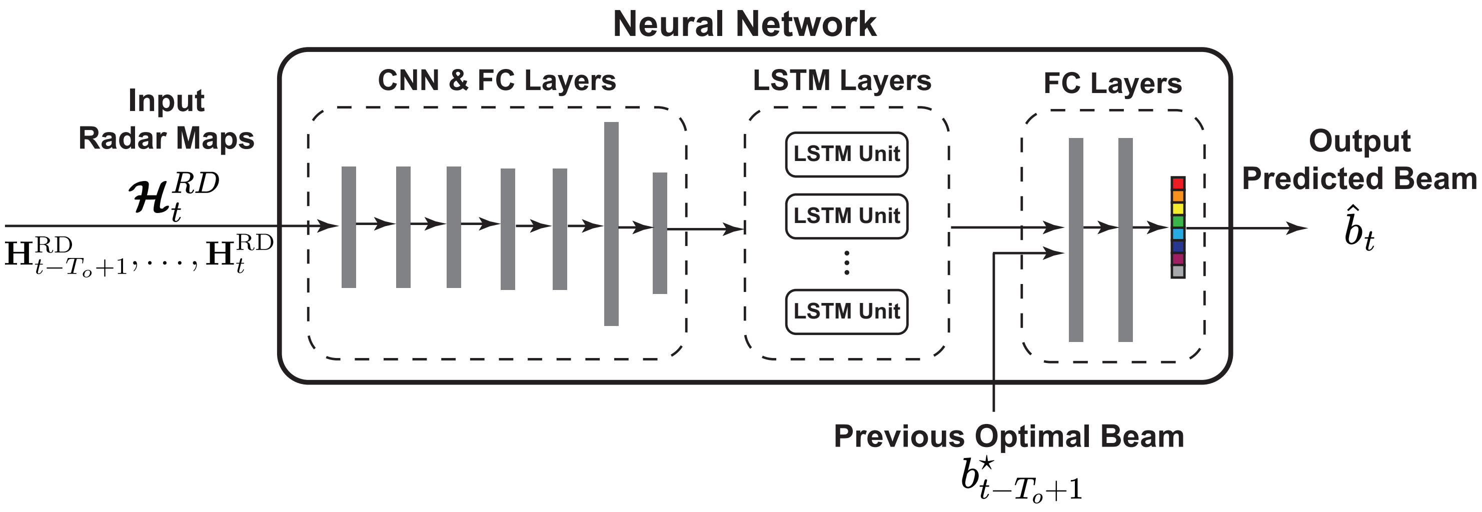
- Input: Tracked transmitter information (range, Doppler, angle)
- Output: Prediction of current optimal beam index



Approach II: Beam tracking with end-to-end ML

- Overview

- End-to-end learning
  - Input: Range-Doppler maps, previous optimal beam index
  - Output: Prediction of current optimal beam index



Evaluation setup: DeepSense 6G dataset

DeepSense 6G Dataset

- A large scale real-world multi-modal dataset
- Co-existing sensing and wireless data

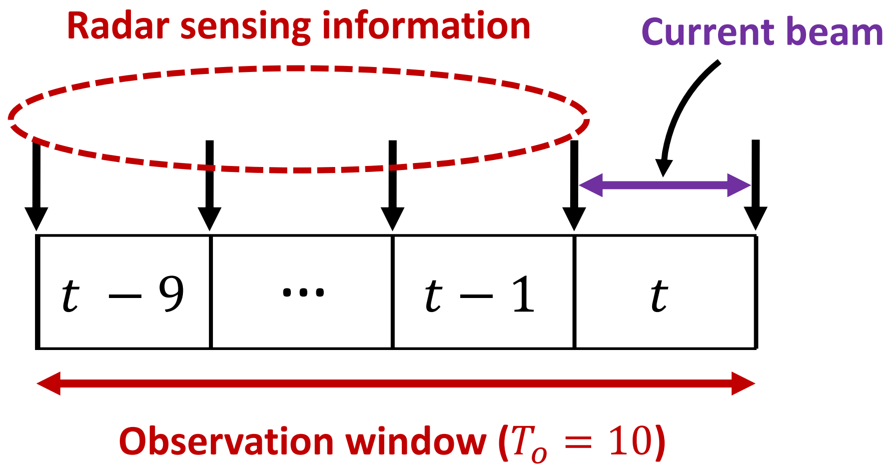
V2V Testbed

- Mobile receiver (Unit 1)
  - Four FMCW radars – Each radar employs one transmit antenna and four receive antennas
  - Four 60GHz mmWave antenna arrays – Each array has an ULA structure with 16 antennas
  - Oversampled beamforming codebook with 64 beams
  - FMCW radars operate at a different frequency band (Starting frequency: 77GHz) than the communication
- Mobile transmitter (Unit 2)
  - 60GHz omnidirectional antenna

Evaluation setup: AI-ready dataset and metric

AI-Ready Dataset

- Max observation window length: $T_o = 10$
- Keep the sequences with changing beam indices
- Number of data sequences: 3649
- Data split (Train/Test): $70/30\%$



Evaluation Metric

- Top-k accuracy

$$Acc_{\text{top-k}} = \frac{1}{N_{\text{sample}}} \sum_{i=1}^{N_{\text{sample}}} \sum_{j=1}^{k} \mathbf{1}_{\{b_i^* = \hat{b}_{i,j}\}}$$

Optimal beam index

Predicted beam index with the j highest confidence score

Results: Top-k accuracy of beam tracking

Beam-hold method (Baseline)

- Previous beam is used as the predicted beam

$$\hat{b}_t = b^{\star}_{t-T_o+1}$$

- ±1 and ±2 indices are used for top-3 and -5 predictions

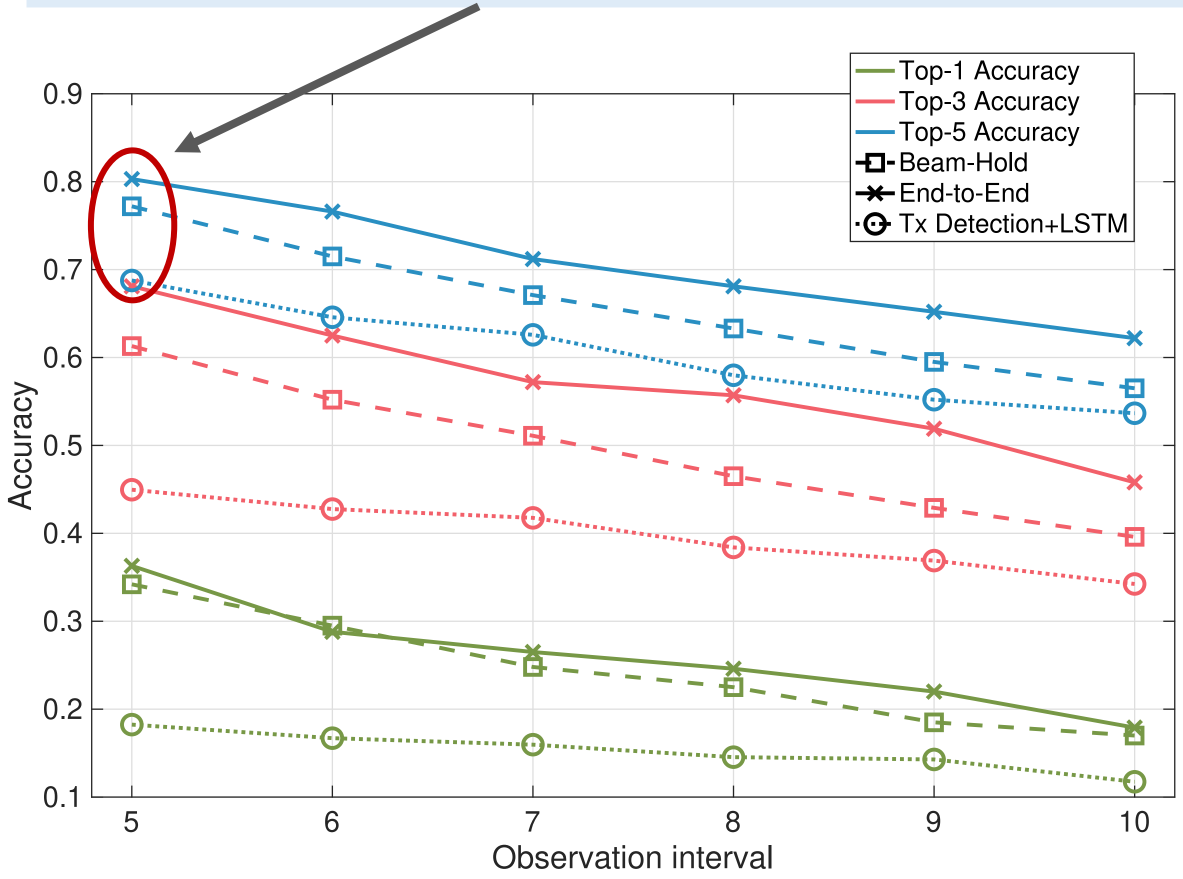
End-to-end solution

- Outperform the baseline method
- Provide gain by using the radar-aided beam tracking

Transmitter identification based solution

- Limited by the low angular resolution of the radar

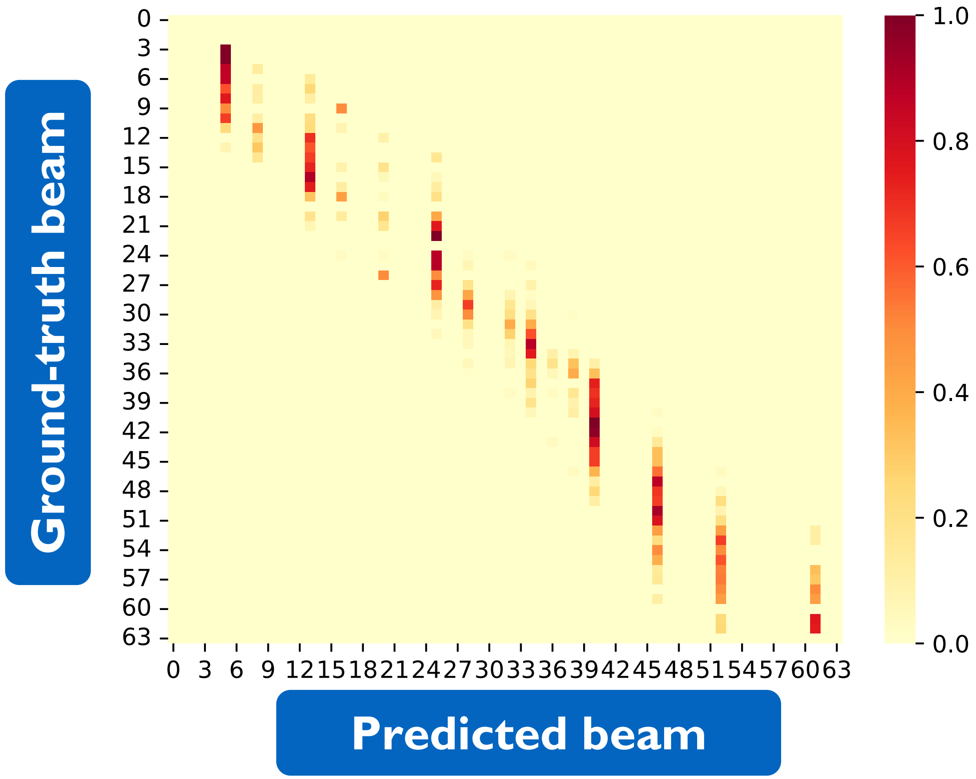
Gain provided by end-to-end solution in top-5 prediction



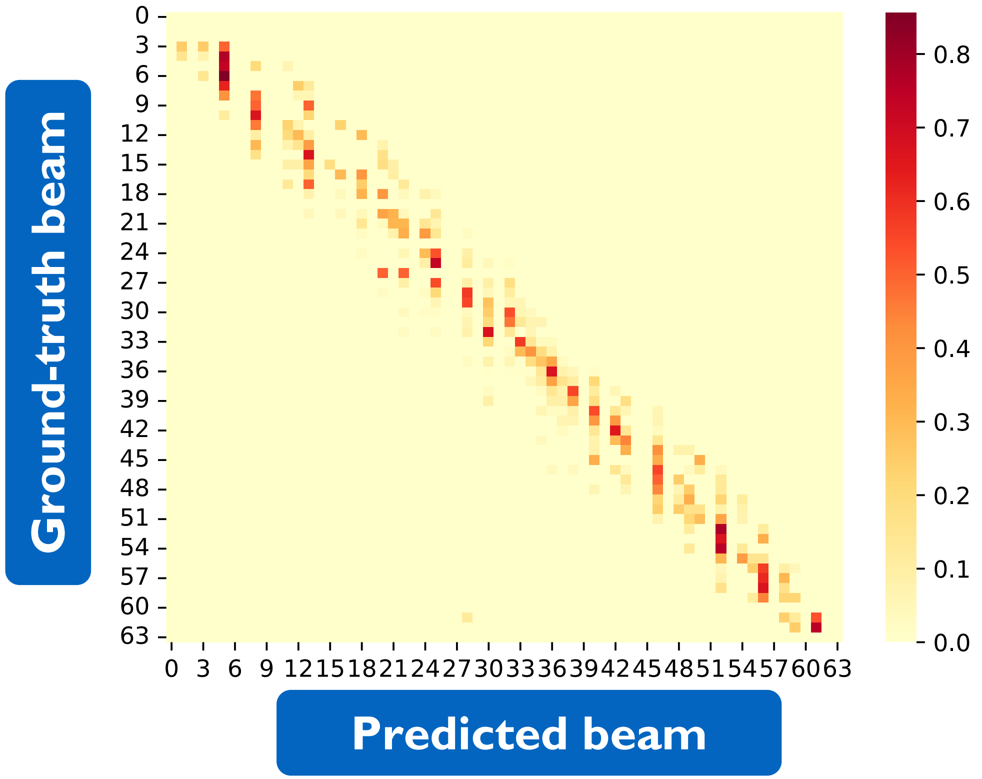
The end-to-end solution shows the potential of radar-aided beam tracking

Results: Confusion matrix of predictions

Approach I: Transmitter Identification



Approach II: End-to-End Learning



- The low resolution of the radar causes a bias towards specific bins in the Tx tracking
- The end-to-end learning refines the given beam index with the radar information

The end-to-end solution is able to overcome the low radar resolution

Conclusions and future work

- Radar sensing and machine learning can improve the V2V communication

- Radar-aided beam tracking in V2V scenarios
  - We developed machine learning based approaches for beam tracking with radar measurements
  - We evaluated the performance on the data collected with a real-world V2V testbed
  - The results highlight the potential of the end-to-end solution in radar-aided beam tracking

- Future work
  - Generalization of the proposed radar-aided beam tracking framework
  - Extension to multi-modal sensing-aided beam tracking in V2V scenarios

The dataset and implementation are available at deepsense6g.net

Thank you