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# Beam Management with Orientation and RSRP using Deep Learning for Beyond 5G Systems


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## Agenda

- Introduction
- Approach
- Experimental Results
- Conclusion

# Introduction

# Overview

- mmWave beam management can be challenging, particularly in highly dynamic scenarios.
- In this work, we use the orientation information coming from IMU for effective BM.
- We utilize a data-driven strategy that fuses the reference signal received power with orientation information using a RNN.
- The proposed data-driven strategy improves the beam-prediction accuracy up to 34% and increases mean RSRP by up to 4.2 dB when the UE orientation changes quickly.

# Related Studies

- 3D orientation of a hand-held UE could change quickly in daily usage, e.g., from the portrait to the landscape mode.

- The earlier work on using orientation information for BM has several shortcomings.
  - In particular, the strategy of Shim et al can work only if the AoA aligns with the best beam's peak, which is not guaranteed. As a result, any prediction based on AoA that is incorrect is also likely to be sub-optimal.
  - The beam steering method of Qi et al i.e. relative position/orientation tracking, is useful only in LOS. Furthermore, the beam steering ignores the hardware limitations of current mmWave systems.
  - Unlike this work, the previous techniques do not consider the 5G signaling and realistic beam codebooks.

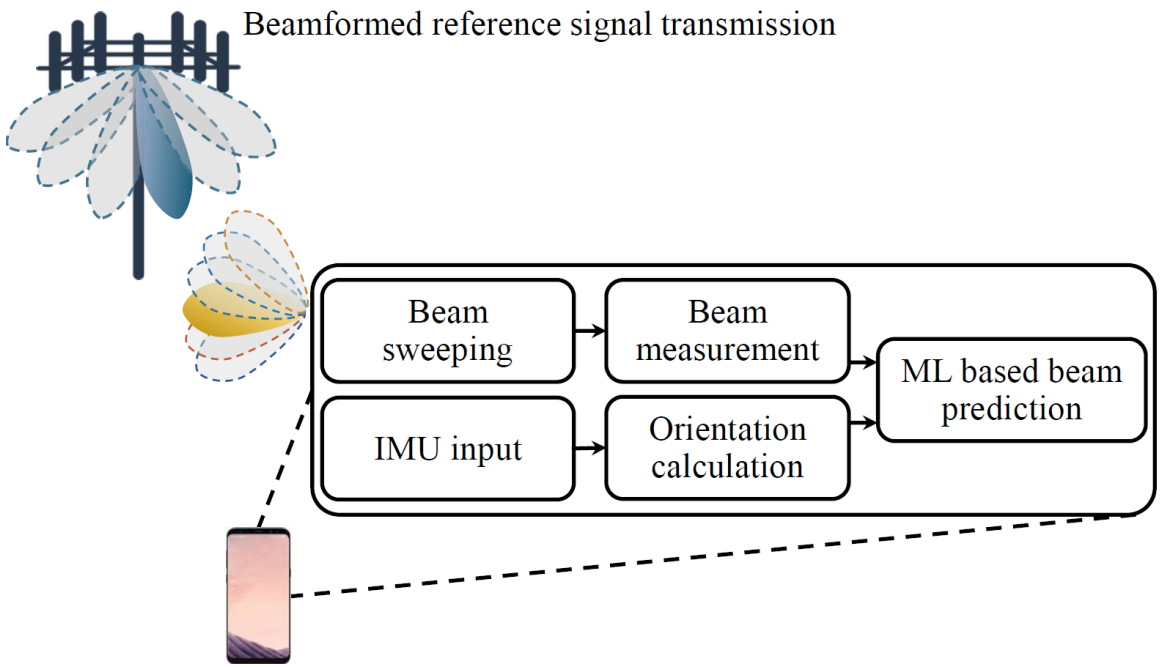

- *Shim, Duk-Sun, et al. "Application of motion sensors for beam-tracking of mobile stations in mmWave communication systems." Sensors 14.10 (2014): 19622-19638.*
- *Qi, Zichen, and Wei Liu. "Three-dimensional millimetre-wave beam tracking based on smart phone sensor measurements and direction of arrival/time of arrival estimation for 5G networks." IET Microwaves, Antennas & Propagation 12.3 (2018): 271-279.*

# Approach

# Overall of the System Model

RSRP: Reference signal received power
IMU: Inertial measurement unit

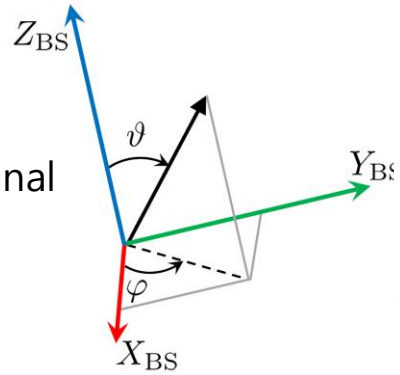
- We consider a communication system where beam prediction can be generated by using
  - The RSRP information is extracted from beam measurements.
  - The orientation information, is used at the UE side.



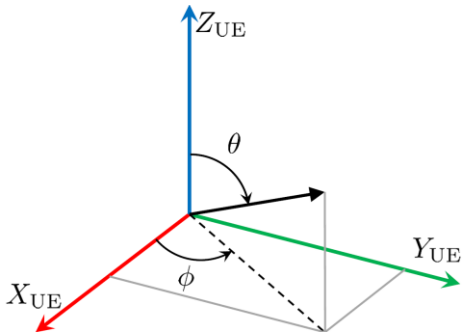
# RSRP Information

- For downlink (DL) BM in 5G NR, the BS sends the beam-formed synchronization signal blocks (SSBs) and CSI reference signals.

- The coordinate systems include
  - The local coordinate system of the BS.
  - The local coordinate system used at the UE.




BS Local coordinate system

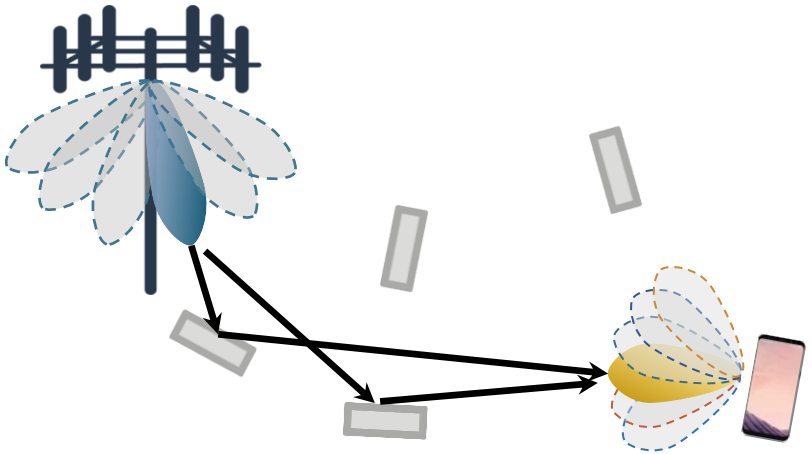



UE Local coordinate system

- The SSBs are transmitted with periodicity $T_{SS}$, and the time variable $t$ denotes the index of an SSB. The received RSRP at time $t$

$$s_t = P_T + 10\log_{10}\left(\frac{\mathrm{SCS}}{\mathrm{BW}}\right) + \mathrm{pow2db}\left(\sum_{c=1}^{C} \mathrm{db2pow}\left(p_t^{(c)} + F_{i_t}\left(\varphi_t^{(c)}, \vartheta_t^{(c)}\right) + G_{j_t}\left(\phi_t^{(c)}, \theta_t^{(c)}\right)\right)\right) + n_t$$

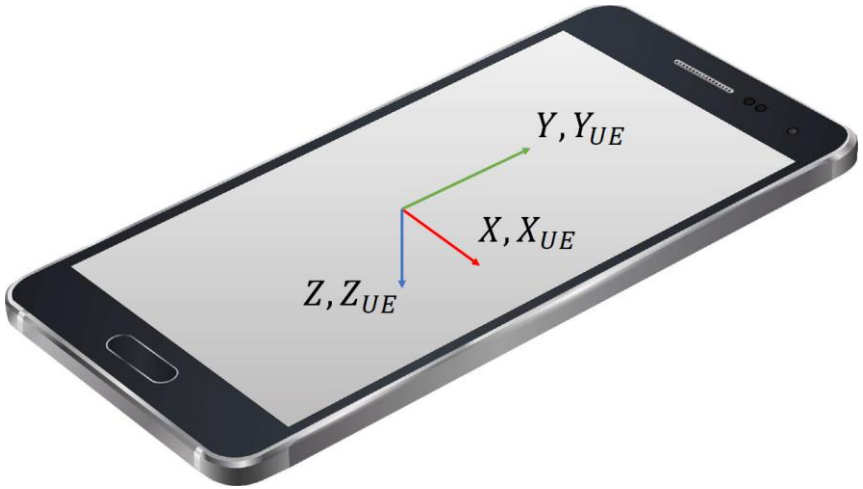
  - $P_T$: BS transmission power, 30 dBm
  - SCS: subcarrier spacing, 240kHz
  - BW: bandwidth: 100 MHz
  - $p_t^{(c)}$: c-th path's gain (dB)
  - $F_{i_t}\left(\varphi_t^{(c)}, \vartheta_t^{(c)}\right)$: BS beam gain (dB) at the c-th path's local angle of departure $(\varphi_t^{(c)}, \vartheta_t^{(c)})$
  - $G_{j_t}\left(\phi_t^{(c)}, \theta_t^{(c)}\right)$: UE beam gain (dB) at the c-th path's local angle of arrival $\left(\phi_t^{(c)}, \theta_t^{(c)}\right)$
  - $n_t$: RSRP measurement noise (dB)



# ▶ Orientation Information

RSRP: Reference signal received power
IMU: Inertial measurement unit

- Our objective is to use orientation information coming from an IMU together with the RSRP information for BM.



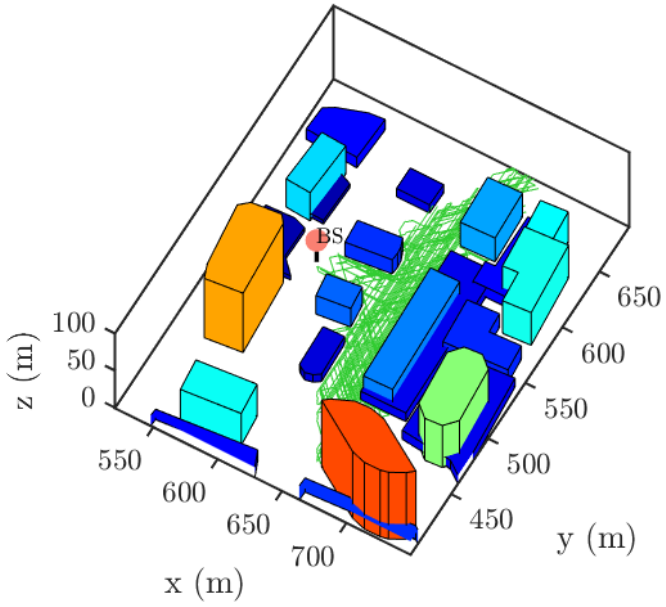

- The UE orientation at time t is determined by Euler angles $\alpha_t$, $\beta_t$ and $\gamma_t$.
  - UE has access to the erroneous estimates of Euler angles.

- $\mathrm{R}_Z(\alpha) = \begin{bmatrix} \cos\alpha & -\sin\alpha & 0 \\ \sin\alpha & \cos\alpha & 0 \\ 0 & 0 & 1 \end{bmatrix}$
- $\mathrm{R}_Y(\beta) = \begin{bmatrix} \cos\beta & 0 & \sin\beta \\ 0 & 1 & 0 \\ -\sin\beta & 0 & \cos\beta \end{bmatrix}$
- $\mathrm{R}_X(\gamma) = \begin{bmatrix} 1 & 0 & 0 \\ 0 & \cos\gamma & -\sin\gamma \\ 0 & \sin\gamma & \cos\gamma \end{bmatrix}$

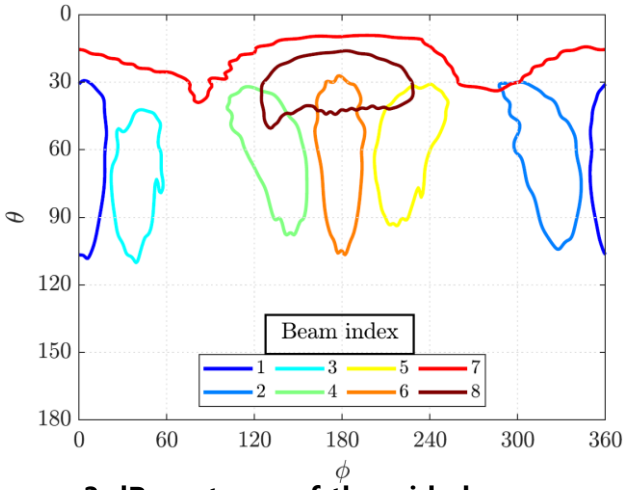
$$\mathrm{R}(\alpha,\beta,\gamma) \triangleq \mathrm{R}_Z(\alpha) * \mathrm{R}_Y(\beta)^* \mathrm{R}_X(\gamma)$$

# Simulation Setup (1/2)

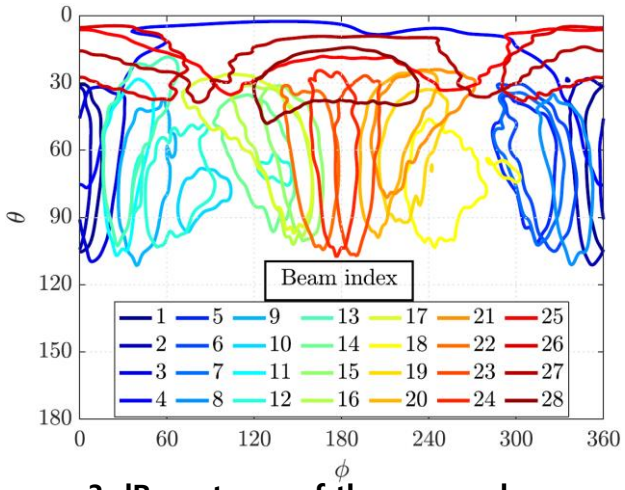
- The ray-tracing channels are generated for downtown Rosslyn, VA, USA, using Wireless InSite® software.
- The $A^*$ search algorithm is used to find a short route from one randomly picked destination point to the next.
- The operating frequency is 28 GHz, BW is 100MHz, SCS is 240 kHz, and the transmit power $P_T = 30$ dBm.
- Single isotropic antenna. The UE either uses
  - $M_{UE}^{W} = 8$ wide beams.
  - $M_{UE}^{N} = 28$ narrow beams.
- The codebooks are designed assuming 3-bit phase-shifters with no amplitude scaling.




**Downtown Rosslyn VA**
**Green curve stands for the UE trajectory on the ground.**




**3 dB contours of the wide beams**

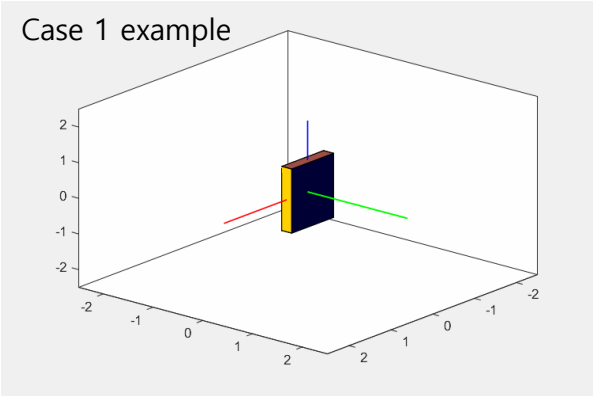


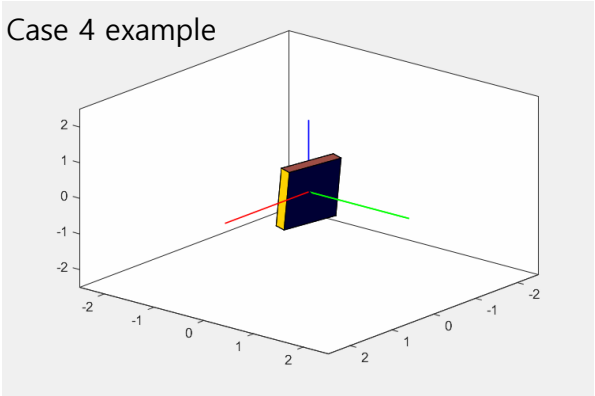

**3 dB contours of the narrow beams**

# Simulation Setup (2/2)

TABLE I: The four cases with slow or fast rotation speed, normal or sporadic RSRPs information, and smooth or non-smooth rotation.

| Case | Rotation speed ($\sigma_r$) | RSRP information rate ($f$) | Rotation smoothness ($K$) |
|---|---|---|---|
| 1 | Slow (1°) | Normal (1) | Smooth (21) |
| 2 | Fast (10°) | Normal (1) | Smooth (21) |
| 3 | Fast (10°) | Sporadic (3) | Smooth (21) |
| 4 | Fast (10°) | Sporadic (3) | Non-smooth (5) |



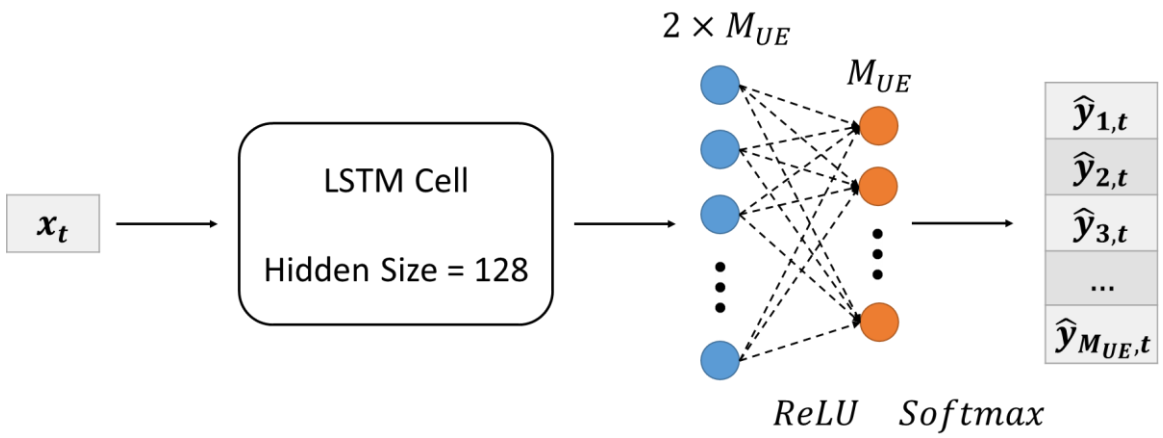




- We create 4 test cases to concretely capture the different levels of rotation speed, RSRP information rates, and orientation smoothness.
- The RSRP information rate $f$ is either
  - "Normal", $f = 1$ and we get an RSRP measurement every $T_{SS}$.
  - "Sporadic", $f = 3$ and we get an RSRP measurement every $3T_{SS} = 60\,ms$.
- The rotation speed $\sigma_r$ is either
  - Slow $\sigma_r = 1°$ per 20 $ms$.
  - Fast $\sigma_r = 10°$ per 20 $ms$.
- The rotation smoothness $K$ is either
  - "Smooth", $K = 21$.
  - "Non-smooth", $K = 5$.
- A higher case index is a more favorable scenario for orientation-information use.

# Data-driven Beam Management

- Our motivation of using ML to tackle the BM problem comes from the fact that
  - It is a tracking problem and using ML technique such as RNN can help capture the temporal information in the sequential input that can lead to an improved performance compare to other approaches.
  - With a strong fitting ability, Deep Learning has been adopted as a promising solution for mmWave beam alignment, which is inherently a complex nonlinear problem.

# Deep Learning Architecture




- The architecture includes
  - LSTM cell with a hidden size of 128 neurons.
  - FC layer of size $2 \times M_{UE}$ with a ReLU activation.
  - Another FC layer of size $M_{UE}$ with a soft-max activation.

# Data Preparation

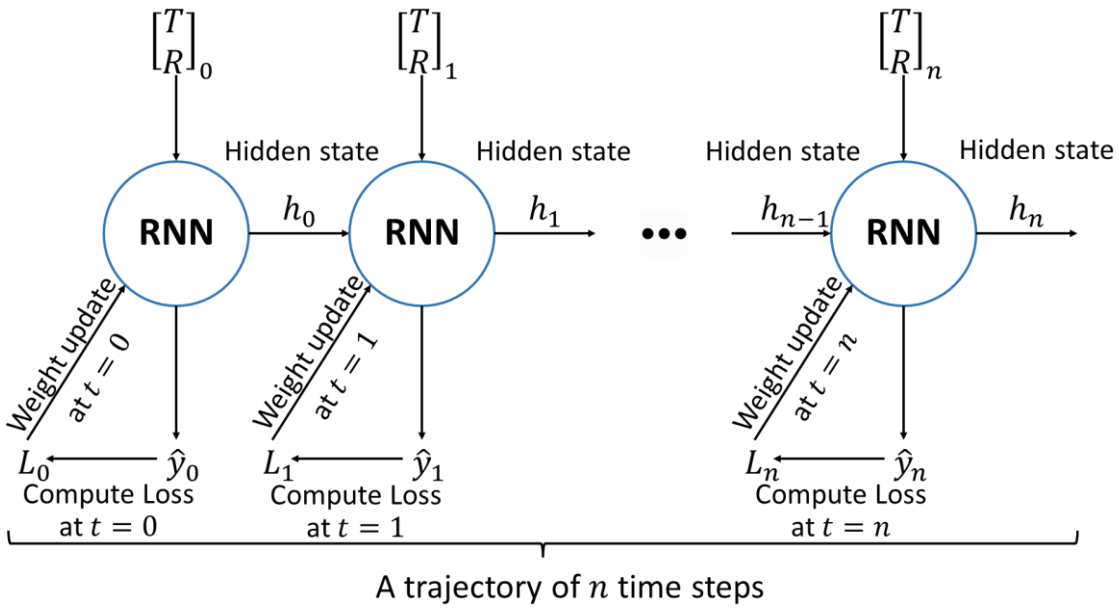
- Input for one time step is a vector with a shape of $[1 \times (M_{UE} + 9)]$. It consist of the following 2 components:
  - $T$ – A table with a size of $M_{UE}$. The RSRP value of the last measured beam is store at that beam index. The values at other entries are set to 0
  - $R$ – $[3 \times 3]$ matrix computed from the current IMU orientation. It is flatten to become a vector with a shape of $[1 \times 9]$

- We partitioned the data across the trajectory
  - The training, validating, and test data split is around 70%, 20%, and 10%.

- We combine all the data to increase the training data size for RNN including
  - 3 different UE speeds
  - 2 different rotation speeds
  - 2 different RSRP information rates
  - 2 levels of smoothness

# Training Process

- The RNN adopts the categorical cross-entropy loss function
  - $L_t = -\sum_{m=1}^{M_{UE}} y_{t,m} \log \hat{y}_{t,m}$
    - $y_{t,m}$ is the target value at time $t$ of class $m$.
    - $\hat{y}_{t,m}$ is the predicted probability at time $t$ of class $m$.
- Adam optimizer with a learning rate of 0.001 was used.
- The training took 10,000 epochs to converge with a batch size of 6 trajectories

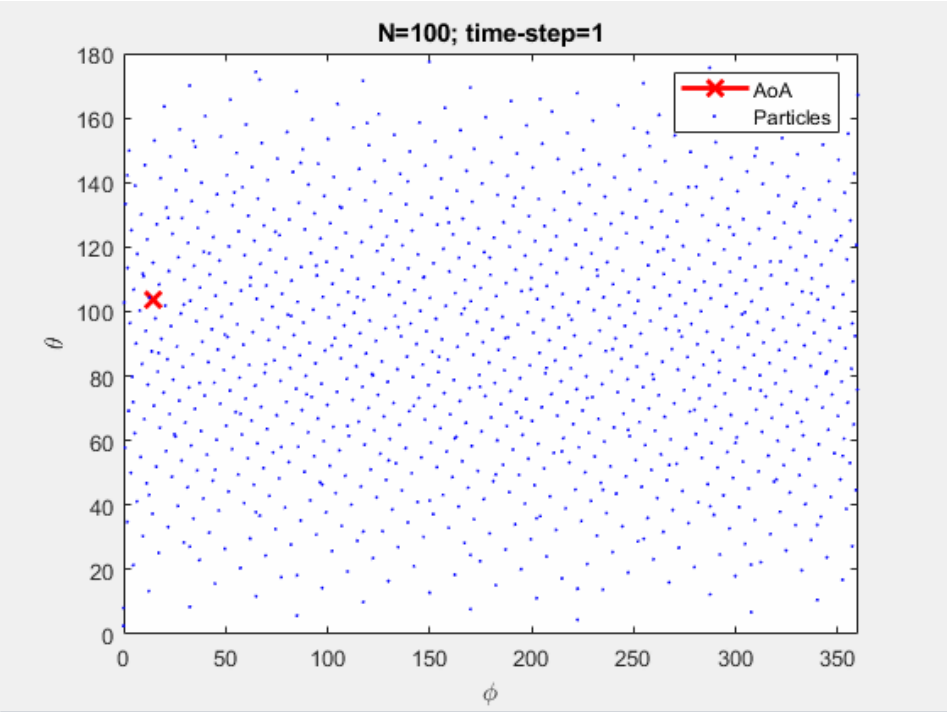



Unrolling the RNN

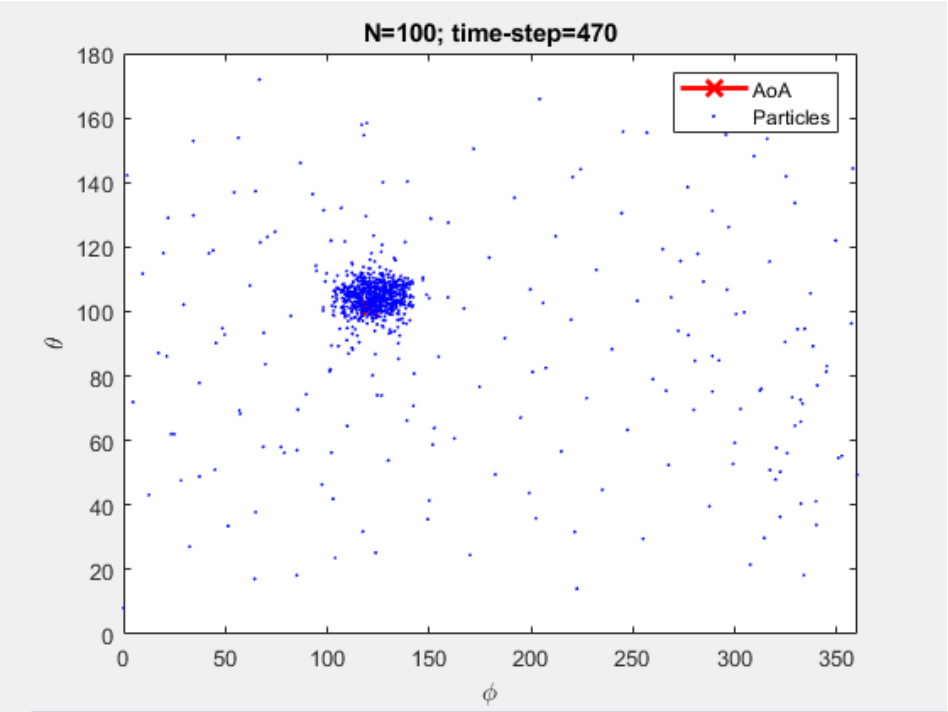
# Experimental Results

# Experimental Results

## ▶ Particle Filter as a baseline




In the initial phase (time-step 1-100), particles converge to a region close to the true AoA.




PF can track the sudden AoA change at time-step 495 due to change from LOS to NLOS.

Setup:

$\{\sigma_r = 10°,$

Low sensor error,

Normal measuremen

Filter length=21,

8 WBs,

100 random filters}

- The baseline particle filter method was proposed by Ali et al (IEEE Access 2021).
  - It fuses the RSRP and IMU information to track the AoA.
  - Its non-deterministic characteristic might lead to wrong predictions when uninformative sensor readings are collected for an extended period.
  - Its computational intensive requirement (a good filter requires a significant amount of particles) will put quite a burden on the UE.

# Experimental Results

## ▶ Comparison of Strategies

TABLE I: The four cases with slow or fast rotation speed, normal or sporadic RSRPs information, and smooth or non-smooth rotation.

| Case | Rotation speed ($\sigma_r$) | RSRP information rate ($f$) | Rotation smoothness ($K$) |
|---|---|---|---|
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| **4** | Fast (10°) | Sporadic (3) | Non-smooth (5) |

| Case | | | 1 | | | 2 | | | 3 | | | 4 | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Metric | | | AC | RSRP | Loss | AC | RSRP | Loss | AC | RSRP | Loss | AC | RSRP | Loss |
| $20\,\mathrm{km\,h^{-1}}$ | WB | *RSRP-only* | **90.16** | **-101.9** | **0.17** | 75.60 | -102.57 | 0.83 | 49.10 | -104.91 | 3.17 | 40.43 | -105.90 | 4.15 |
| | | PF | 73.42 | -102.57 | 0.84 | 70.65 | -102.84 | 1.10 | 54.80 | -104.53 | 2.78 | 50.58 | -104.97 | 3.22 |
| | | RNN | 88.88 | -101.9 | 0.17 | **80.71** | **-102.22** | **0.47** | **80.71** | **-102.22** | **0.47** | **60.45** | **-103.69** | **1.93** |
| | NB | *RSRP-only* | **63.49** | **-100.98** | **0.86** | 28.55 | -104.51 | 4.42 | 13.11 | -107.63 | 7.54 | 11.14 | -108.04 | 7.94 |
| | | PF | 37.14 | -102.99 | 2.87 | 33.05 | -103.38 | 3.29 | 21.72 | -105.56 | 5.47 | 21.41 | -105.66 | 5.57 |
| | | RNN | 57.52 | -101.02 | 0.90 | **43.99** | **-101.98** | **1.88** | **30.08** | **-103.51** | **3.42** | **26.69** | **-103.99** | **3.90** |
| $60\,\mathrm{km\,h^{-1}}$ | WB | *RSRP-only* | **85.36** | -102.59 | 0.41 | 72.20 | -103.06 | 1.09 | 44.16 | -105.65 | 3.68 | 36.87 | -106.53 | 4.56 |
| | | PF | 69.06 | -103.36 | 1.18 | 67.83 | -103.30 | 1.33 | 49.75 | -105.28 | 3.31 | 47.19 | -105.56 | 3.60 |
| | | RNN | 84.53 | **-102.55** | **0.36** | **78.18** | **-102.63** | **0.64** | **78.18** | **-102.63** | **0.64** | **57.09** | **-104.24** | **2.26** |
| | NB | *RSRP-only* | **53.39** | -102.21 | 1.76 | 26.36 | -105.10 | 4.84 | 10.74 | -108.33 | 8.07 | 9.53 | -108.73 | 8.43 |
| | | PF | 31.62 | -103.93 | 3.48 | 30.31 | -103.95 | 3.69 | 18.73 | -106.46 | 6.20 | 18.34 | -106.50 | 6.20 |
| | | RNN | 51.58 | **-101.91** | **1.44** | **41.35** | **-102.47** | **2.20** | **28.03** | **-104.10** | **3.84** | **25.40** | **-104.53** | **4.22** |
| $100\,\mathrm{km\,h^{-1}}$ | WB | *RSRP-only* | **81.07** | -102.43 | 0.66 | 69.31 | -103.22 | 1.30 | 41.12 | -106.03 | 4.11 | 34.52 | -106.78 | 4.86 |
| | | PF | 67.46 | -103.12 | 1.35 | 65.03 | -103.52 | 1.60 | 45.29 | -105.76 | 3.84 | 42.98 | -106.02 | 4.10 |
| | | RNN | 80.65 | **-102.34** | **0.54** | **74.36** | **-102.80** | **0.86** | **74.36** | **-102.80** | **0.86** | **52.33** | **-104.68** | **2.74** |
| | NB | *RSRP-only* | **46.73** | -102.66 | 2.47 | 23.86 | -105.60 | 5.26 | 9.88 | -108.52 | 8.17 | 9.45 | -108.86 | 8.48 |
| | | PF | 29.24 | -104.28 | 4.09 | 27.79 | -104.64 | 4.30 | 17.00 | -106.97 | 6.63 | 15.98 | -107.14 | 6.76 |
| | | RNN | 45.38 | **-102.11** | **1.89** | **37.09** | **-103.00** | **2.64** | **25.02** | **-104.69** | **4.33** | **23.07** | **-105.08** | **4.68** |

The performance comparison of orientation-assisted BM strategies (PF is Particle Filter and RNN is Recurrent Neural Network) in comparison with RSRP-only BM in terms of beam prediction accuracy-AC (%), mean RSRP (dBm), and RSRP loss (dB).

# Experimental Results

## Observations

TABLE I: The four cases with slow or fast rotation speed, normal or sporadic RSRPs information, and smooth or non-smooth rotation.

| Case | Rotation speed ($\sigma_r$) | RSRP information rate ($f$) | Rotation smoothness ($K$) |
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- For Case 1, the accuracy and the mean RSRP of the orientation-assisted classical signal processing method is lower compared to RSRP-only.
- In Case 2, the RNN performs better than the RSRP-only, whereas the PF does not.
- In Case 3 and 4, the RSRP information rate is lower than the orientation information rate and the benefit of using the orientation-assisted strategies for BM becomes clear.
- Overall, the performance of the proposed deep learning strategy is consistently better than the PF strategy across all the scenarios.

# Conclusions

# Conclusions

## Summary

- We proposed a data-driven BM strategy that **jointly utilizes the RSRP and orientation information through an RNN** which outperforms the conventional BM.
  - **Improve BM accuracy by 34% and boost the mean RSRP by 4.2 dB** in challenging environments of high mobility and fast rotation UE and sporadic RSRP measurement.
- The **4.2 dB** gain is significant at the UE because it is equivalent to a cut of uplink transmission power by 62%, which substantially improves the UE battery life.
- When both RSRP measurement and orientation information are utilized, the data driven strategy performs consistently better than the model based PF strategy.
- Lastly, the high-complexity RNN training is done offline, and the data-driven strategy is more efficient than PF for online BM.

# Future Works

- More training data from other deployment areas, for example, suburban, rural, can be obtained from simulation and used to train a more robust RNN for different propagation environments.

- Another future direction is to implement and evaluate the proposed strategy in a mobile device.

  - The 5G mmWave devices may have a different number of mmWave antenna arrays and mount them in different locations, thus the WB and NB radiation patterns will be different.


**Fig from**

SPR21587 - RF - Apple 5G mmWave Chipset (systemplus.fr)

There are 3 mmWave antenna modules in S20, and 2 mmWave antenna modules in S21.

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# Thank You