ITUEvents

ITU-ML5G-PS-025: ML5G-PHY: Channel estimation (NC State University, USA) 3 July 2020

ITU AI/ML in 5G Challenge

Applying machine learning in communication networks

ai5gchallenge@itu.int

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NC STATE UNIVERSITY

ML5G-PHY [channel estimation]

ITU Challenge AI/ML for 5G

Site specific-channel estimation with hybrid mmWave MIMO systems Prof. Nuria González Prelcic

MIMO architectures @mmWave: analog vs. hybrid



antenna arrays and low resolution ADCs



MmWave MIMO: hybrid architecture



Split processing between analog and digital domains to reduce power consumption

Hybrid mmWave architecture is considered in mmWave cellular deployments

Main challenge is fast configuration of mmWave precoders and combiners [1]

5G beam training with analog architectures



Try different combinations of transmit and receive beams, pick best

5G has a beam-based design, challenging for high mobility

How to configure the arrays in hybrid architectures?



Beam training + Low dimensional channel estimation

Channel estimation

Reconstruct the channel and then design precoders and combiners

Overcoming large overhead in array configuration with model-based strategies



R. Méndez-Rial, C. Rusu, N. González-Prelcic, A. Alkhateeb and R. W. Heath, "Hybrid MIMO Architectures for Millimeter Wave Communications: Phase Shifters or Switches?," in IEEE Access, vol. 4, pp. 247-267, 2016.
 J. Rodríguez-Fernández, N. González-Prelcic, K. Venugopal, and R. W. Heath Jr, "Frequency-domain Compressive Channel Estimation for Frequency-Selective Hybrid mmWave MIMO Systems", IEEE Transactions on Wireless Communications, vol. 17, no. 5, pp. 2946-2960, May 2018.

[3] J. Rodríguez-Fernández and N. González-Prelcic, "Channel Estimation for Hybrid mmWave MIMO Systems with CFO Uncertainties", IEEE Transactions on Wireless Communications, 2019.

[4] N. González-Prelcic. H. Xie, J. Palacios and T. Shimizu. "Channel Tracking and Hybrid Precoding for Wideband Hybrid Millimeter Wave MIMO Systems," Submitted to IEEE Transactions on Wireless Communications, 2019.

[5] N. González-Prelcic, A. Ali, V. Va, and R. W. Heath Jr, "Millimeter Wave Communication with Out of Band Information", IEEE Communications Magazine, vol. 55, no. 12, pp. 140-146, Dec. 2017.

Overcoming large overhead in array configuration with ML



ML based approaches learn the structure of the propagation environment from data [1,2]

[1] Y. Wang, N. Jonathan Myers, N. Gonzalez-Prelcic, and Robert W. Heath Jr., "Site-specific online compressive beam codebook learning in mmWave vehicular communication," submitted to IEEE Transactions on Wireless Communications, May 2020, available in arXiv.

[2] A. Klautau, P. Batista, N. González-Prelcic, Y. Wang and R. W. Heath, "5G MIMO Data for Machine Learning: Application to Beam-Selection Using Deep Learning," in Proc. of the Information Theory and Applications Workshop (ITA), San Diego, CA, 2018, pp. 1-9.

Site-specific channel estimation: model-based vs. ML approaches

Collect channels and received training Consider a hybrid pilots to learn the environment or architecture at both the BS some of its features and the vehicles Test the trained network Test the adjusted model using a given number of based approach using a given received symbols at different number of received symbols SNR at different SNR

Raymobtime datasets



https://www.lasse.ufpa.br/raymobtime/

[6] A. Klautau, P. Batista, N. González-Prelcic, Y. Wang and R. W. Heath, "5G MIMO Data for Machine Learning: Application to Beam-Selection Using Deep Learning," in Proc. of the Information Theory and Applications Workshop (ITA), San Diego, CA, 2018, pp. 1-9.



Datasets



Collection of **10,000 channels** in HDF5 format obtained from **Raymobtime dataset** s004

9 collections of training pilots obtained at SNRs ranging from -20 to 0 dB and 1000 channels different from the ones in the training datasets, but corresponding to the same site

Participants must use for training 100 received pilots in the frequency domain for each one of the provided channels (Matlab code provided) at SNR=-15,-10,-5 dB

Test datasets correspond to different SNR ranges and different number of training pilots



Evaluation

Metric for the quality of the channel estimate is NMSE

 Few training symbols (20)

 / Lowest SNRs
 Highest SNRs

 PS=0.5(0.5NMSE(Test Dataset 1 SNR1)+0.3NMSE(Test Dataset 1 SNR2)+0.2NMSE(Test Dataset 1 SNR3))

+ 0.3(0.5 NMSE(Test Dataset 2 SNR1+0.3 NMSE(Test Dataset 2 SNR2)+0.2NMSE(Test Dataset 2 SNR3))

+ 0.2(0.5 NMSE(Test Dataset 3 SNR1)+0.3 NMSE(Test Dataset 3 SNR2)+0.2NMSE(Test Dataset 3 SNR3))

Many training symbols (80)

Obtained NMSE is weighted in a different way depending on the SNR range and training length, giving more weight to the more challenging settings

Timeline



Training and testing datasets are ready → https://research.ece.ncsu.edu/ai5gchallenge/

Registration → July 31, 2020, defined by ITU

Team enrollment: <u>ml5g.ncsu@gmail.com</u>

Submission (Global round) → October 2020, to be defined by ITU

Award (Global round) → October 2020, to be defined by ITU

Thanks!

NC STATE UNIVERSITY



https://research.ece.ncsu.edu/ai5gchallenge/

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ITUEvents

ITU-ML5G-PS-013: Improving the capacity of IEEE 802.11 WLANs through Machine Learning 10 July 2020 (Universitat Pompeu Fabra, Barcelona)

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