ACM MOBIHOC 2022

The University of Texas at Austin

EXTRACTING AND PREDICTING MULTIPATH PROFILES UNDER HIGH MOBILITY


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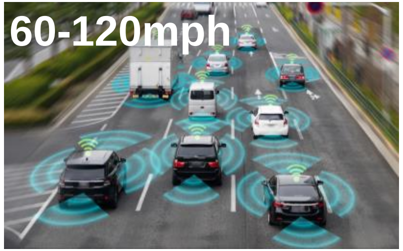
Motivation - Wireless Channel Prediction

- Wireless channel prediction extremely useful
  - Optimal spectrum management
  - Wireless performance optimization
  - Minimize channel feedback overhead
  - …
- 5G and beyond need to cater for high mobility

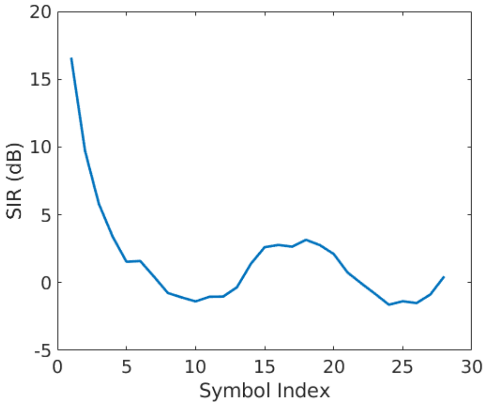


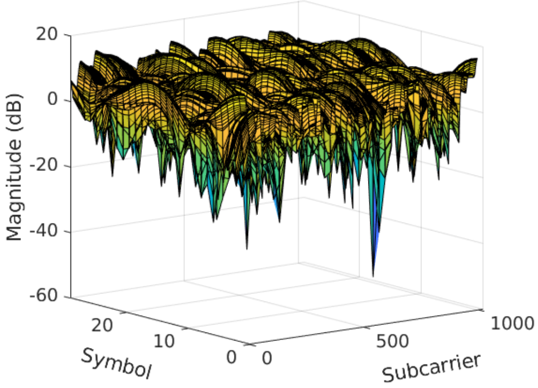
Are LTE **channel estimation & prediction** mechanisms reliable in **high mobility**?

Challenging to Predict Channel under High Mobility in LTE

Previous Channel → Future Channel

- Predicted channel quality sharply degrades
  - Reasons: Rich Multipath, Large Doppler spread, Highly dynamic channel (< 1 ms coherence time)





Current LTE channel prediction mechanisms **NOT** suitable for high mobility

Proposed Approach

- Instead of wireless channel, estimate and predict mobility
    - Very hard to do in current LTE PHY

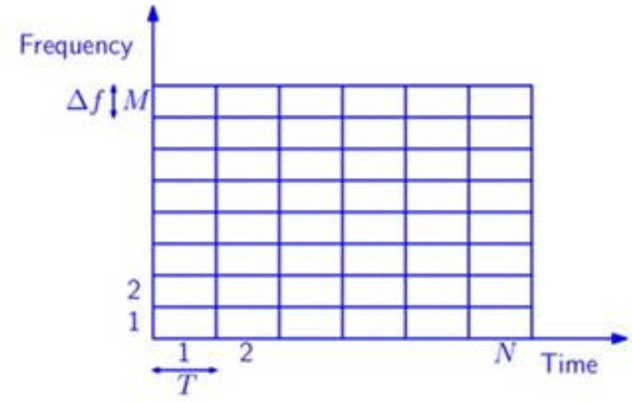
Mobility Related Parameters: Propagation Path Length, Doppler Shift, Amplitude

Intuition: Mobility has inertial and easier to predict

Idea: Directly estimate and predict channel in delay-Doppler domain

Delay-Doppler – Relationship with Time-Frequency Domain

- Alternative representation of signal

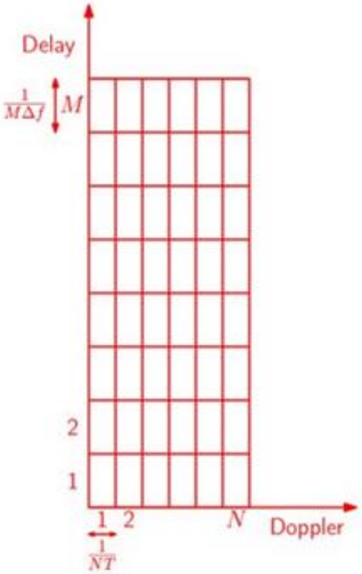


$$x[k,l] = \frac{1}{\sqrt{NM}} \sum_{n=0}^{N-1} \sum_{m=0}^{M-1} X[n,m] e^{-j2\pi\left(\frac{nk}{N} - \frac{ml}{M}\right)}$$

Symplectic FFT

Inverse Symplectic FFT

$$X[n,m] = \frac{1}{\sqrt{NM}} \sum_{k=0}^{N-1} \sum_{l=0}^{M-1} x[k,l] e^{j2\pi\left(\frac{nk}{N} - \frac{ml}{M}\right)}$$

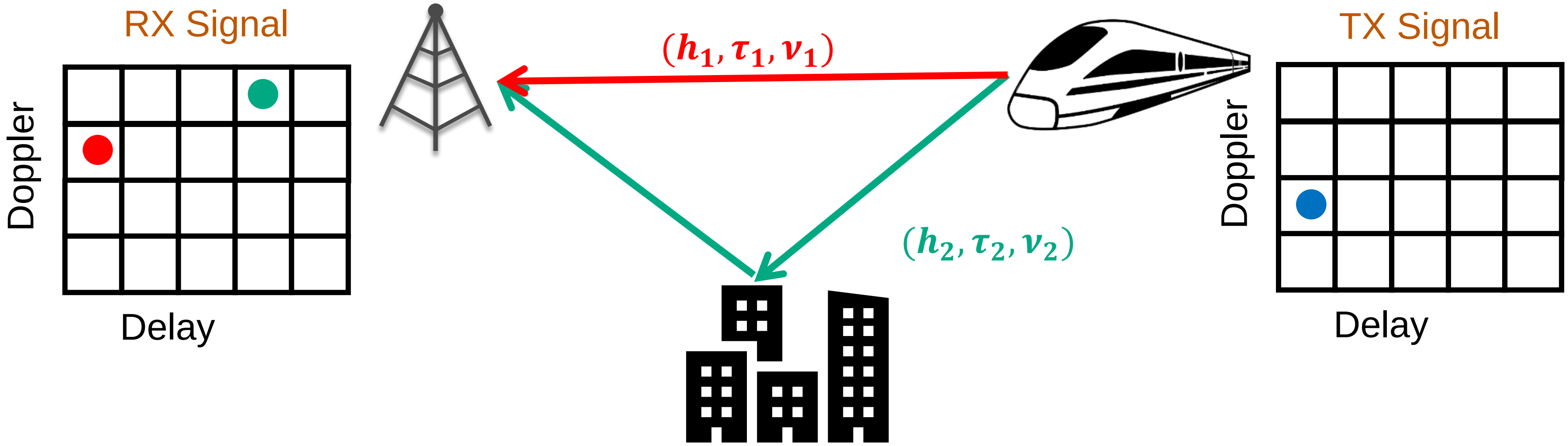


Delay-Doppler signaling can be implemented on top of LTE PHY layer by adding Precoding/Decoding blocks

Estimate Mobility

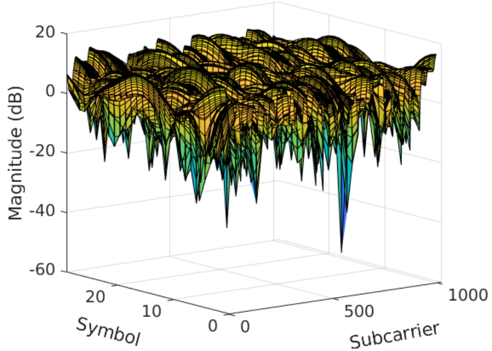
Estimate Mobility - Delay-Doppler Channel Estimation

- Transmit single pilot symbol in delay-Doppler domain
- Received signal
  - Multi-path geometry and Doppler shift between client and cell

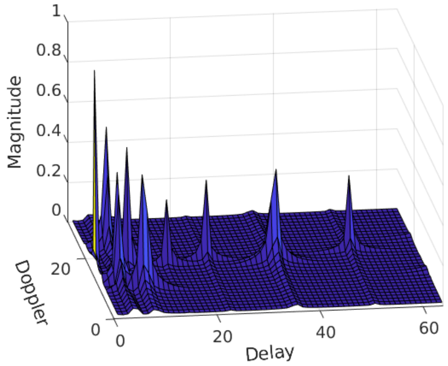


Delay-Doppler Channel - Benefits

- Physically meaningful
  - Directly estimate physical parameters
- Inertial correlation over time
  - Easier to predict
- Stable over time
  - Less frequent measurement
- Same over different frequencies
  - No feedback required



Time-Frequency Domain



Delay-Doppler Domain

Problem Statement

How can we precisely estimate mobility parameters for every path from the Delay-Doppler channel representation

Challenges

- Actual Delay and Doppler will not be aligned with taps

$$\tau_i = (\alpha_i + a_i)\frac{1}{M\Delta f}, \ \alpha_i \in \mathbb{Z}, \ -1/2 < a_i < 1/2,$$

$$\upsilon_i = (\beta_i + b_i)\frac{1}{NT}, \ \beta_i \in \mathbb{Z}, \ -1/2 < b_i < 1/2.$$

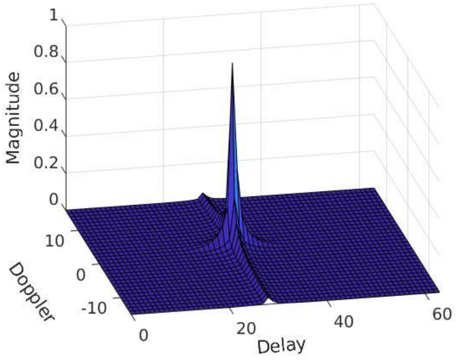
- Results in Inter-Delay and Inter-Doppler Interference

$$y[k,l] = \sum_{i=1}^{P}\sum_{q=0}^{M-1}\sum_{r=1}^{N-1} \overbrace{\left(\frac{e^{j2\pi(-q-a_i)}-1}{Me^{j\frac{2\pi}{M}(-q-a_i)}-M}\right)}^{\text{Inter-Doppler Interference}} \overbrace{\left(\frac{e^{-j2\pi(-r-b_i)}-1}{Me^{-j\frac{2\pi}{N}(-r-b_i)}-N}\right)}^{\text{Inter-Delay Interference}}$$

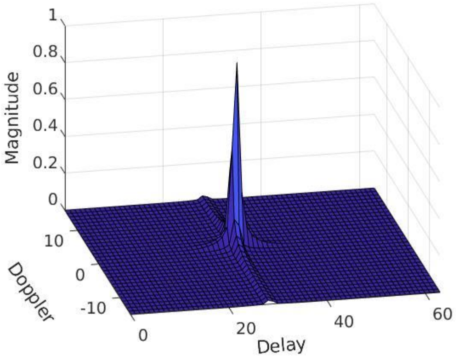
$$h_i e^{-j2\pi\tau_i\upsilon_i} x[(k-\beta_i+r)_N, (l-\alpha_i+q)_M]$$

Challenges

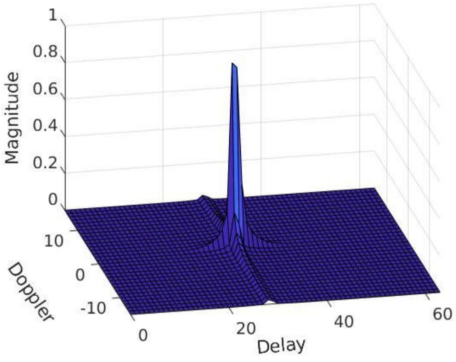
- Precisely estimating multipath parameters
  - Peak position only gives integer taps
  - Peak position gets shifted if multiple paths merge
- Number of underlying paths is unknown
  - Can’t be directly determined
  - Different number of overlapping paths show similar peak



1 Path



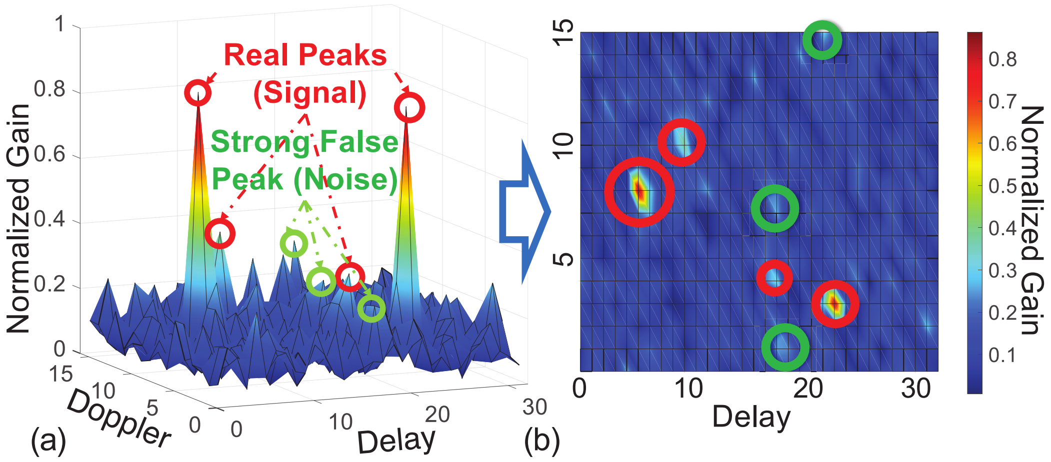
2 Paths



3 Paths

Challenges

- Precisely estimating multipath parameters
- Number of underlying paths is unknown
- Differentiating between noise peaks and real peaks
    - Thresholding does not work at low SNR



Challenges

- How to estimate multipath parameters?
  - Formulate non-linear optimization problem
- How to estimate number of overlapping paths?
  - Iteratively increase number of paths
- How to differentiating real signal from noise?
  - Neural Network classifier

Multipath Parameter Estimation

- Optimization problem

$$\underset{(\tau_i,\upsilon_i,h_i)\in\mathbb{P}}{\arg\min} \sum_{k=k_{\min}}^{k_{\max}} \sum_{l=l_{\min}}^{l_{\max}} |y_{\text{meas}}[k,l] - y[k,l]|$$

- Jointly estimate delay/Doppler/attenuation for P channels, to minimize the difference between measured and estimated channel

$$y[k,l] = \sum_{i=1}^{P}\sum_{q=0}^{M-1}\sum_{r=1}^{N-1}\left(\frac{e^{j2\pi(-q-a_i)}-1}{Me^{j\frac{2\pi}{M}(-q-a_i)}-M}\right)\left(\frac{e^{-j2\pi(-r-b_i)}-1}{Me^{-j\frac{2\pi}{N}(-r-b_i)}-N}\right) h_i e^{-j2\pi\tau_i\upsilon_i} x[(k-\beta_i+r)_N,(l-\alpha_i+q)_M]$$

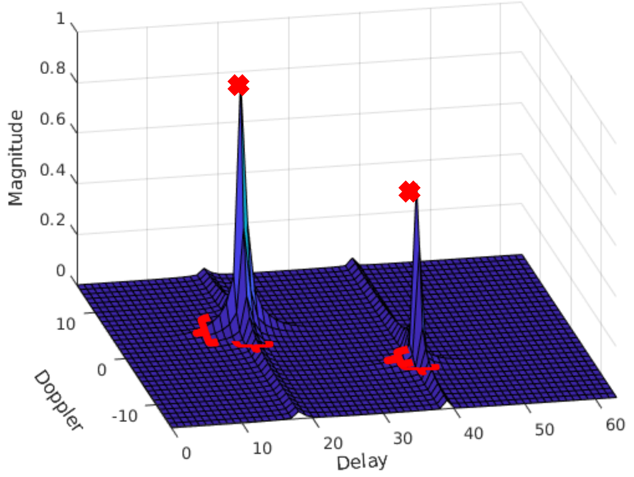
$$\mathbb{P} = \{(\tau_1,\upsilon_1,h_1),(\tau_2,\upsilon_2,h_2),...,(\tau_P,\upsilon_P,h_p)\}$$

$$\tau_i = (\alpha_i + a_i)\frac{1}{M\Delta f},\ \alpha_i\in\mathbb{Z},\ -1/2 < a_i < 1/2,$$

$$\upsilon_i = (\beta_i + b_i)\frac{1}{NT},\ \beta_i\in\mathbb{Z},\ -1/2 < b_i < 1/2.$$

Multipath Parameter Estimation

- Non-convex and constrained optimization function
  - Multiple local optimal solutions
- Solved using standard interior point method
  - Good Initialization (Peak detection)
  - Restrict search interval (Neighborhood of the peak)



Estimate Number of Paths

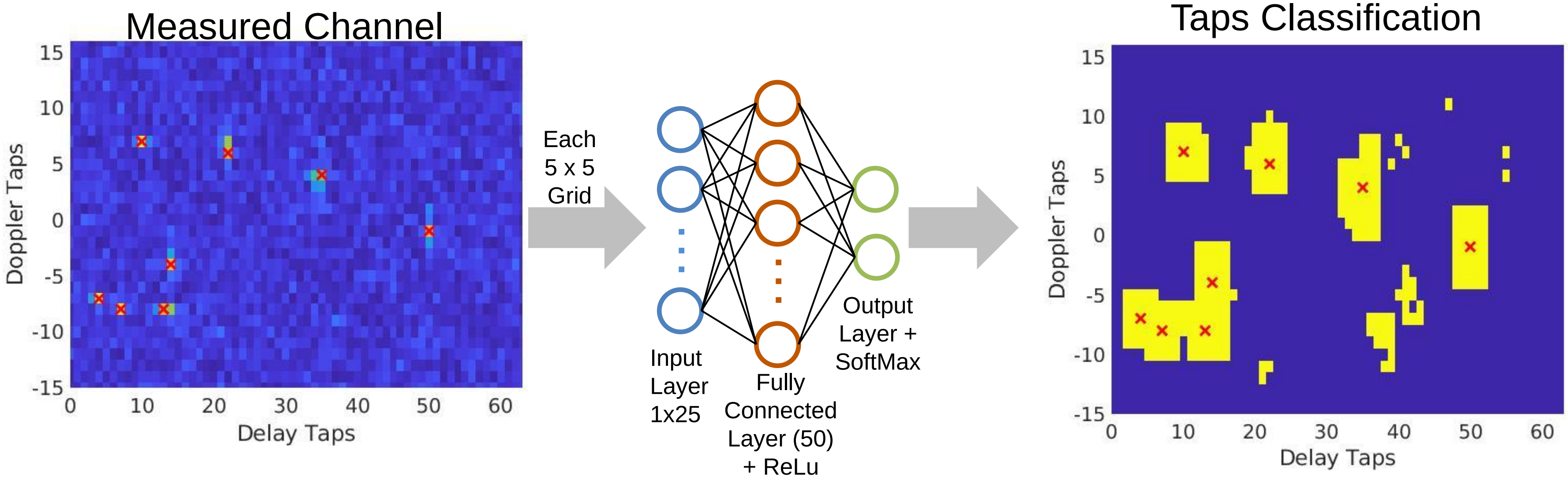
- Iteratively add more path until error is small

Algorithm 1: Delay-Doppler estimation pseudocode

$\mathbb{P} = \mathbb{P}_{\text{prev}}$;
compute channel y based on $\mathbb{P}$
if $|y - y_{\text{meas}}| > threshold_y$ **then**
    # Initialize based on peaks' positions;
    $\mathbb{P} = \{(\tau_1, \upsilon_1, h_1), (\tau_2, \upsilon_2, h_2), ..., (\tau_P, \upsilon_P, h_P)\}$;
end
$[\mathbb{P}, Err] = optimize(\mathbb{P})$;
while $Err > threshold_P$ **do**
    computed $(\tau_{\text{new}}, \upsilon_{\text{new}}, h_{\text{new}})$ using the peak in residual cluster $(y_{\text{meas}} - y_{\mathbb{P}})$
    $\mathbb{P} = \mathbb{P} \cup (\tau_{\text{new}}, \upsilon_{\text{new}}, h_{\text{new}})$;
    $[\mathbb{P}, Err] = optimize(\mathbb{P})$;
end

Noise Removal - Real Peak detection

- Neural Network classifier
  - Input: Vectorized 5x5 grid
  - Hidden layer: 50 neurons + ReLu activation
  - Output: SoftMax Layer (Classification of the center tap)
- Classifies each tap to contain real signal or noise

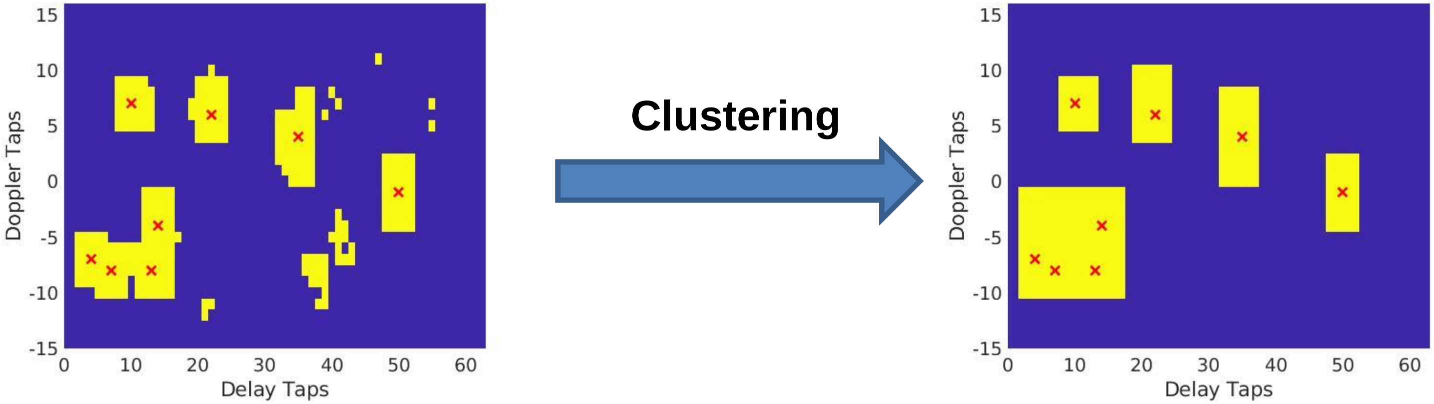


Noise Removal - Clustering Taps

- Nearby peaks interfere with each other
  - Should be optimized jointly
- Taps further away don’t interfere - Multiple smaller grids
  - More tractable
- Removes noise from false detection
  - Spurious taps detected to have a path

Taps Classification

Clusters



Channel Prediction

Estimate Mobility → Predict Mobility → Map Mobility To Channel

- Path alignment over time
  - Bipartite matching with edge cost = $\sqrt{\left(\frac{\tau_i - \tau_{i-1}}{\tau_{max}}\right)^2 + \left(\frac{v_i - v_{i-1}}{\tau_{max}}\right)^2}$
- Path prediction
  - Holt Winter
  - Exponential Weighted Moving Average (EWMA)
- Channel prediction
  - Use a simulated model (Maps paths to OFDM channel for each symbol)

Map Mobility to Channel

Estimate Mobility → Predict Mobility → Map Mobility To Channel

- Generate OTFS Channel with predicted Mobility

$$y[k,l] = \sum_{i=1}^{P}\sum_{q=0}^{M-1}\sum_{r=1}^{N-1}\left(\frac{e^{j2\pi(-q-a_i)}-1}{Me^{j\frac{2\pi}{M}(-q-a_i)}-M}\right)\left(\frac{e^{-j2\pi(-r-b_i)}-1}{Me^{-j\frac{2\pi}{N}(-r-b_i)}-N}\right) h_i e^{-j2\pi\tau_i v_i} x[(k-\beta_i+r)_N,(l-\alpha_i+q)_M]$$

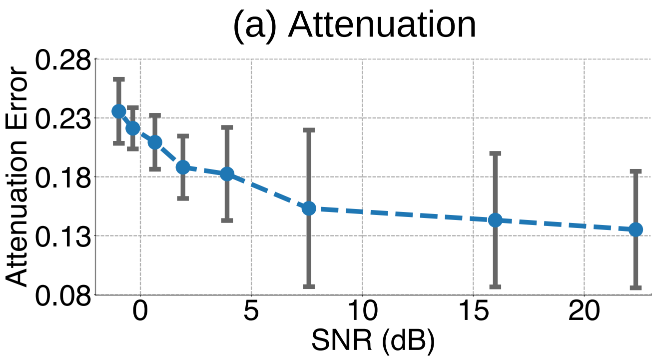
- Map it to OFDM channel via ISFFT

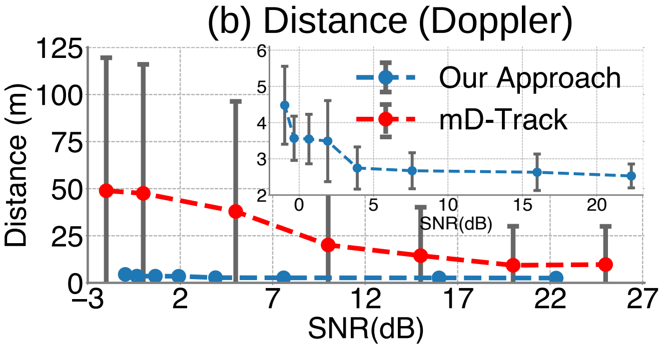
$$X[n,m] = \frac{1}{\sqrt{NM}}\sum_{k=0}^{N-1}\sum_{l=0}^{M-1} x[k,l]e^{j2\pi(\frac{nk}{N}-\frac{ml}{M})}$$

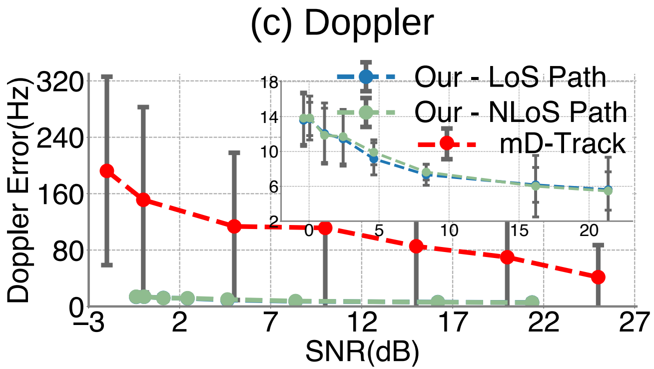
Evaluation

- Multipath Traces
  - Wireless Insite – Ray tracing simulator used by industry
    - Reflection, Diffraction and Penetration
    - 3D reconstructed real environment (Metropolitan City & University Campus)
    - Real base station locations
    - Up to 2000 Hz Doppler
- Mobility Traces
  - GPS location + IMU readings while driving
- USRP testbed
  - N210 USRP
  - Emulated Multipath Channel
  - Real Noise and Interference

Multipath Parameter Estimation

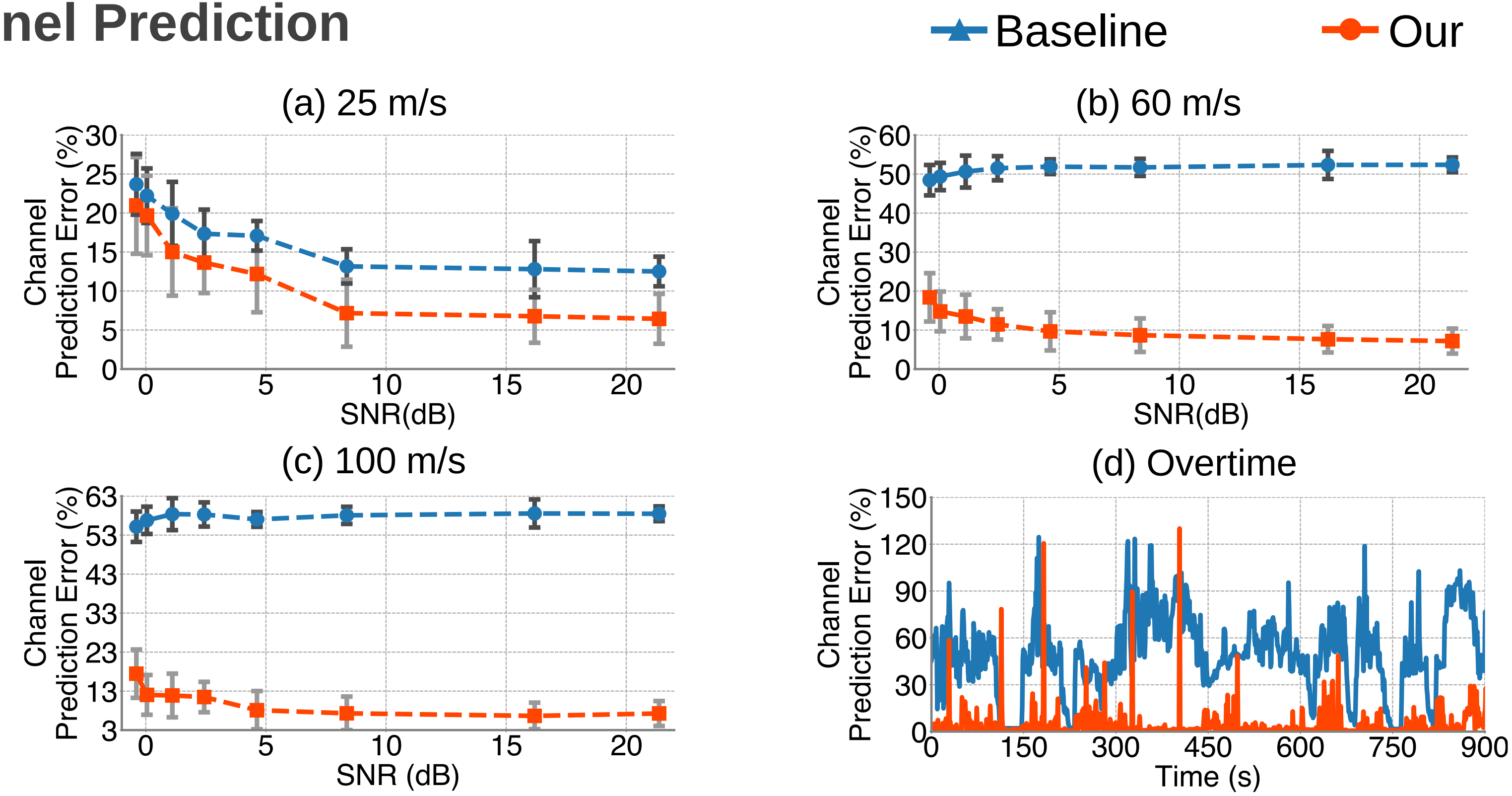






Our optimization framework can estimate multipath parameters with high accuracy even under low SNR

Channel Prediction



Our channel prediction performs up to 10x better than LTE channel prediction

Conclusion

- Existing channel prediction schemes easily fail under high mobility
- Use delay-Doppler representation for channel estimation and prediction
- Proposed approach achieves appealing estimation performance
  - Delay error < 1%, Doppler error < 0.4% (SNR > 10dB).
  - Delay error < 4%, Doppler error < 2% (SNR ≈ -4 dB).
  - 10x better than existing approach.
- Delay-doppler channel representation may benefit other applications
  - Cross-band channel estimation
  - Motion sensing

Acknowledgement

This work is supported in part by NSF Grant CNS-2008824 and CNS-2107037. Yuanjie Li acknowledges the support from the National Natural Science Foundation of China (62132009). We thank anonymous reviewers for their insightful comments.

Ethical Concern

The experiment in LTE/5G bands was conducted under the United States Federal Communication Committee experimental license (File number 0111-FX-CN-2021). The vehicular experiment was conducted on a highway frontage road in Austin, TX, USA, within its speed limit of 96 km/h (60 mph). The personnel involved in the experiment are fully insured and paid. No personally identifiable information (PII) was collected during the exploration. This work does not raise any ethical concern.

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Thank You!

Questions?

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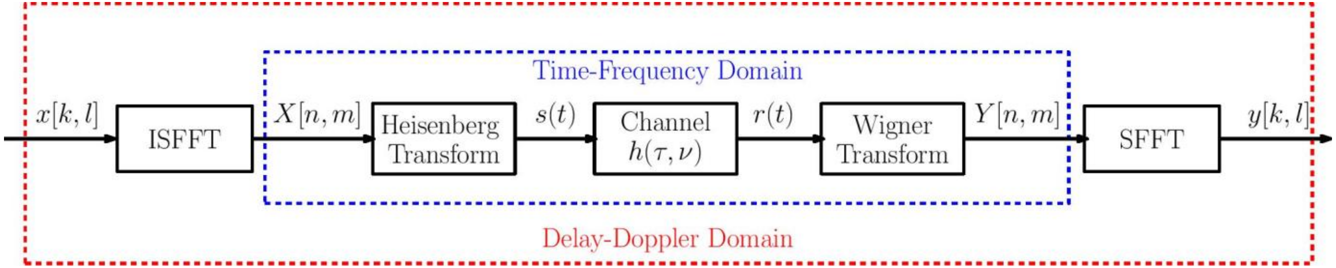
UCLA

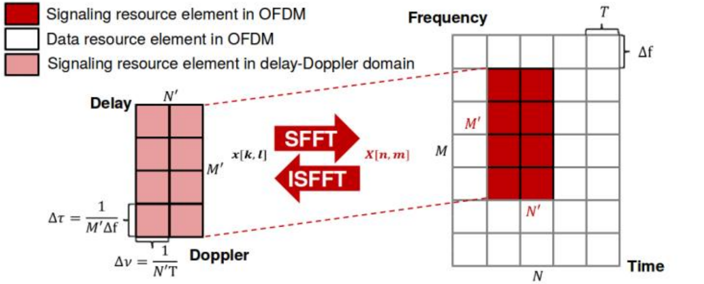
Corrigenda

- We the authors are deeply sorry for discovering several typos in the camera-ready version and would like to make a correction. For your reference, the typos that have been corrected are listed below.
  - On page 3, All the "i" as the superscript of equation (3) should be removed.
  - On page 4, in the 4th paragraph, the "convolutional neural network (CNN)" should be changed to "neural network (NN)".
  - On page 7, the 3rdn sentence in the 2nd paragraph should be modified to "We pick a 2.6 × 1.8 km2 satellite city for our measurement and simulation, which includes campus, downtown urban canyon, suburban, and pure highway."
  - On page 9, 6th paragraph, we would like to add “TX transmits signal at 2.2 GHz” after the 3rd sentence.
  - The third author Lili Qiu would like to add her dual affiliation "Microsoft Research Asia" in the author information.
  - We provide the corrected version of the paper here.

Appendix - Channel Estimation in OTFS

- OTFS is compatible with LTE Modulation
  - Precoding/Decoding blocks on N consecutive OFDM symbols

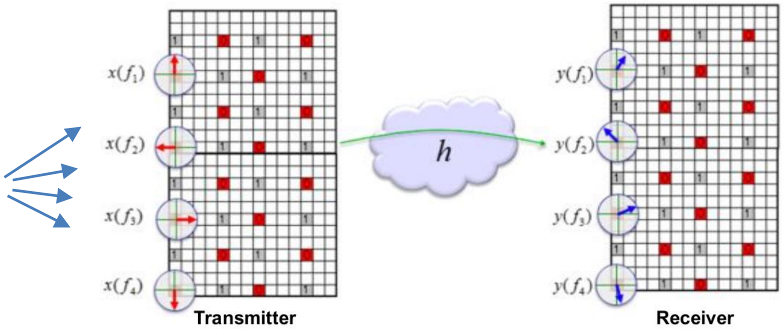




Delay-Doppler domain
Time-frequency domain (OFDM)

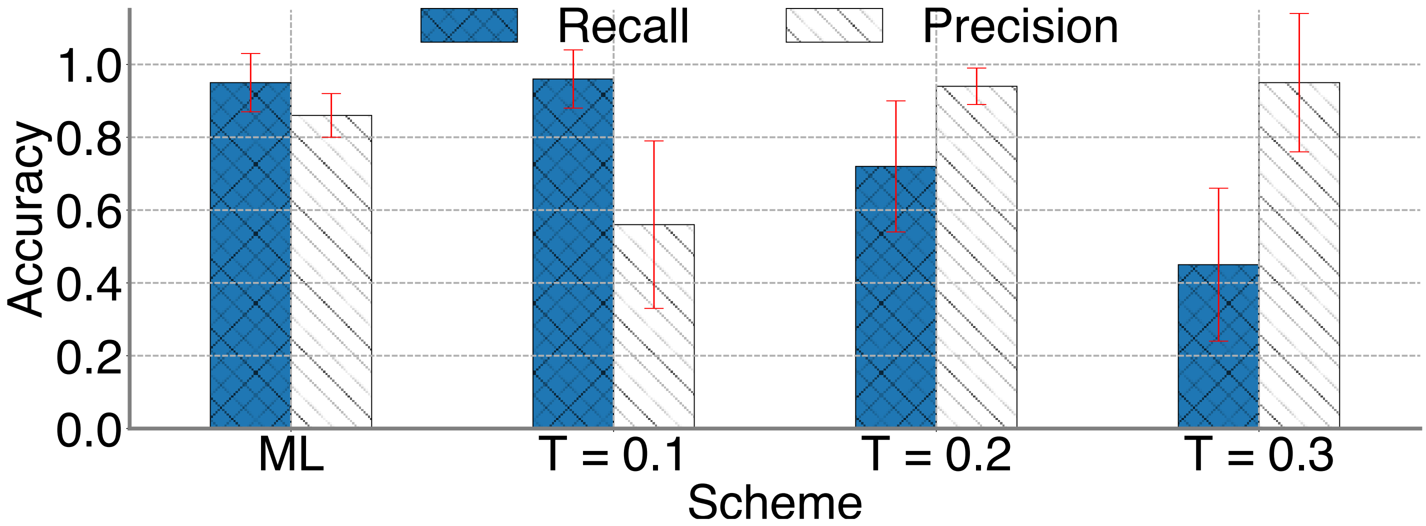
Appendix - Channel Estimation and Predication in LTE

- Estimation
  - Embed known signals at predefined slots
  - Estimate channel based on received signal
- Prediction
  - Predict channel for other slots by interpolation



$$y(f_1) = \boxed{h(f_1)} \cdot x(f_1)$$
$$y(f_2) = \boxed{h(f_2)} \cdot x(f_2)$$
$$y(f_3) = \boxed{h(f_3)} \cdot x(f_3)$$
$$y(f_4) = \boxed{h(f_4)} \cdot x(f_4)$$

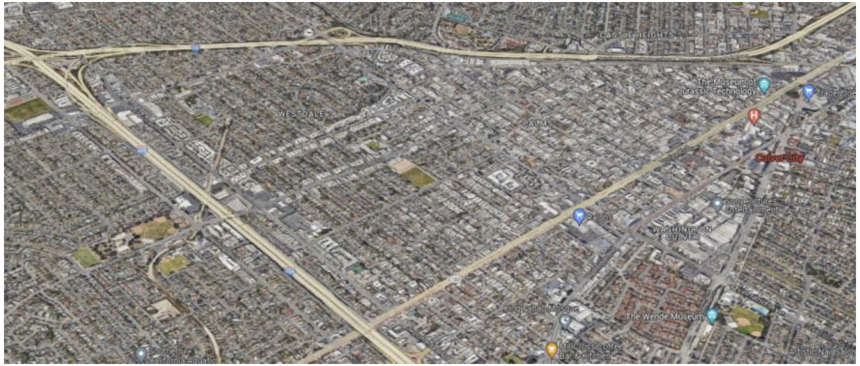
Appendix - Peak Detection



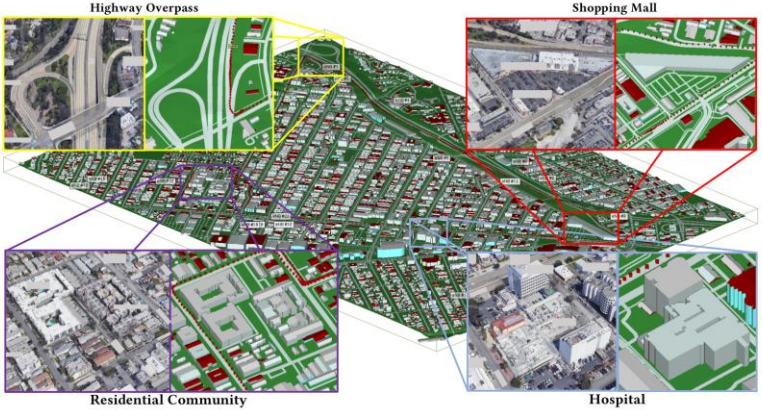
Classifier can differentiate noise from actual signal with high precision and recall

Appendix – USRP Emulation

Google Map

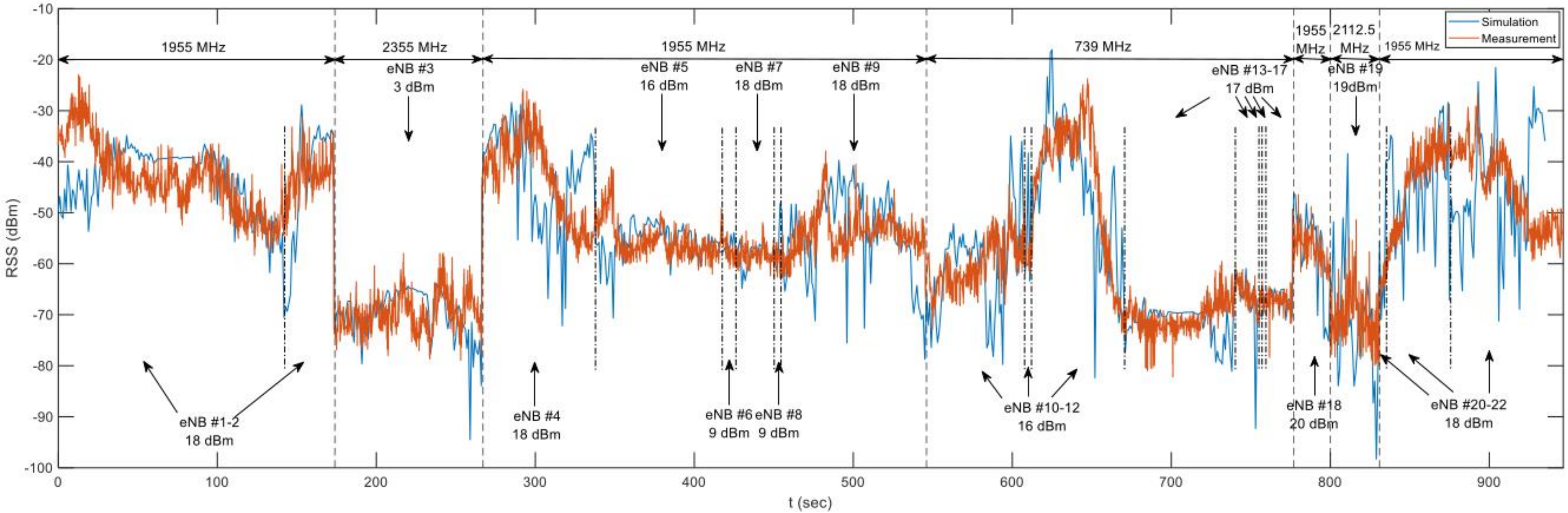


OpenStreetMap + Blender + Wireless Insite
3D Reconstructed



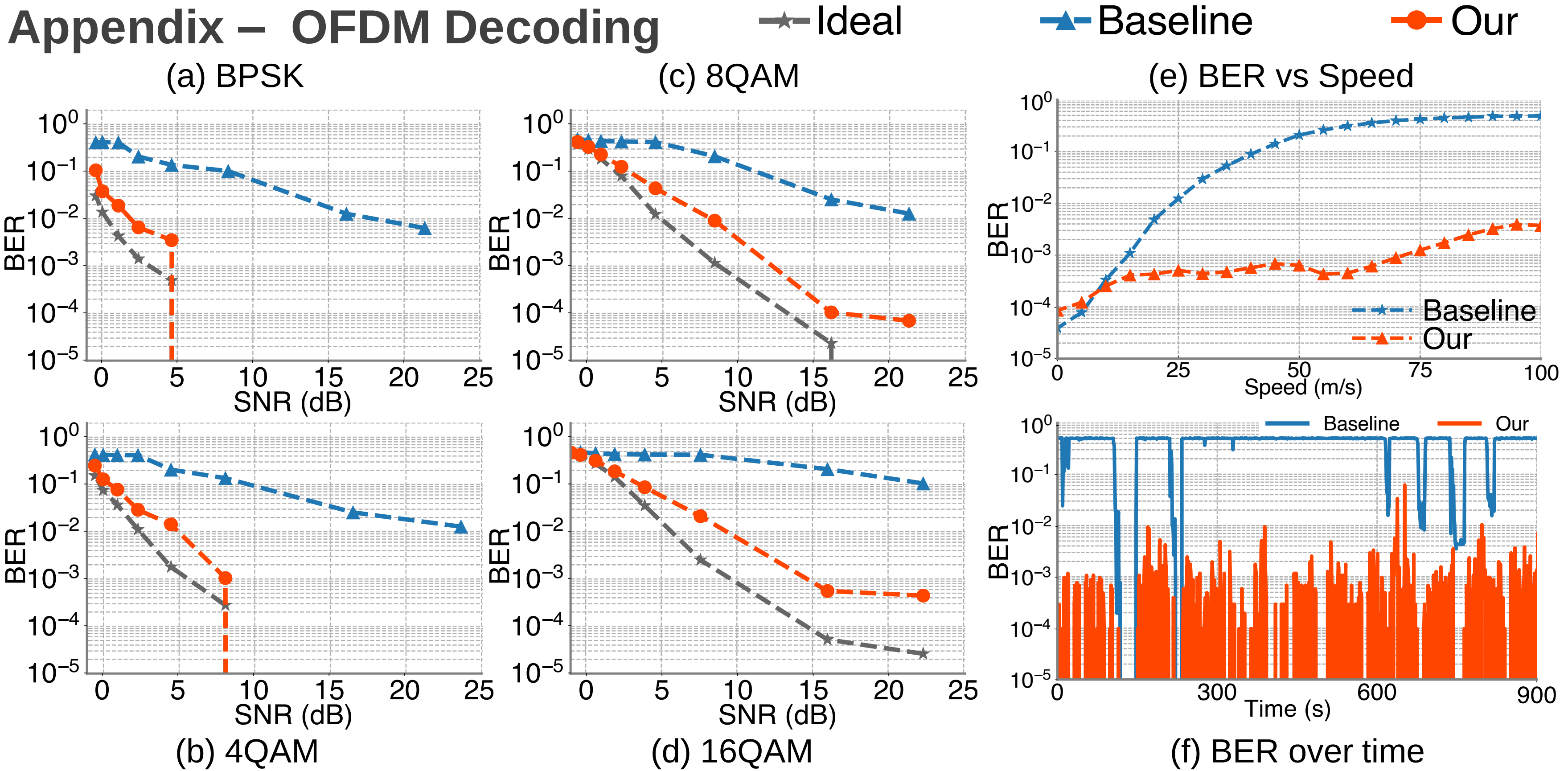
Location: A 2.6 × 1.8 km^2 Satellite City in Los Angeles, California, USA
GPS Bounding Box: Longitude: -118.434348 to -118.389582 Latitude: 34.011263 to 34.033075

Appendix – USRP Emulation



Wireless Insite Simulated RSS matches closely with MobileInsight measurements

Appendix – OFDM Decoding



Significantly low BER compared to LTE channel prediction

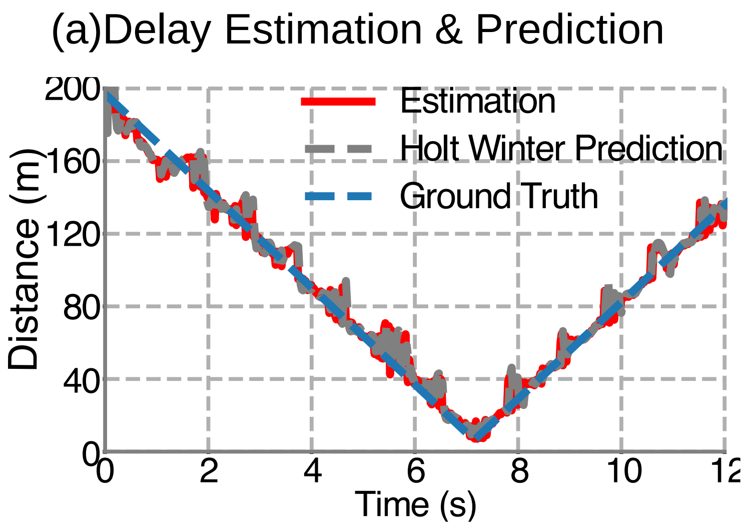
Appendix - USRP Mobile Experiment

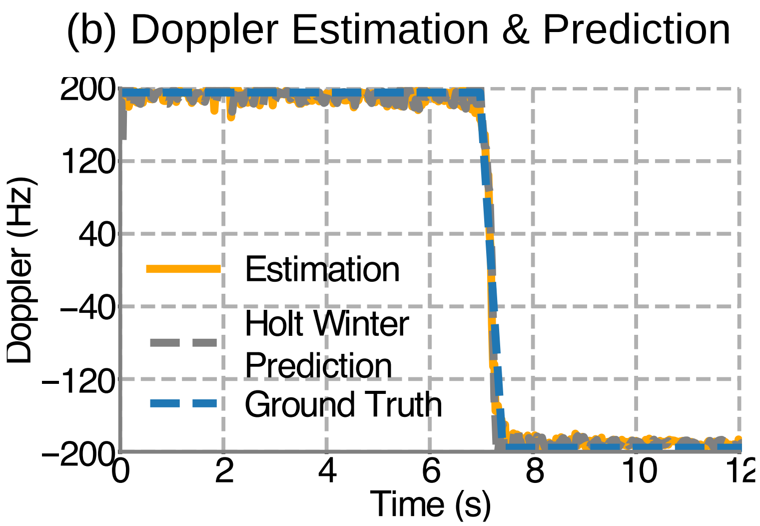
- Static TX
  - Ettus N210 with SBX-40 Daughterboard
  - 100 mW transmit power
  - Clock driven by 10 MHz 1PPS GPS Disciplined Oscillator
  - Linux laptop with GNU radio 3.7
- Moving RX
  - A sedan with Ettus N210 on its top
  - Travel at 96 km/h (60 mph, 26.67 m/s)
  - Moving towards TX then passes it

Location: Texas State Highway – 1 Frontage Road near 2301 South Mopac Expressway, Austin TX, UCA

- ❖ The experiment in LTE/5G bands was conducted under the United States Federal Communication Committee experimental license (File Number 0111-FX-CN-2021).
- ❖ The vehicular experiment was conducted on a highway frontage road in Austin, TX, USA, within its speed limit of 96 km/h (60 mph).

Appendix – USRP Mobile Experiment





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