# Moving object classification with a sub-6 GHz massive MIMO array using real data

B. R. Manoj†, G. Tian*, S. Gunnarsson*, F. Tufvesson*, and E. G. Larsson†

† Department of Electrical Engineering (ISY), Linköping University, Linköping, Sweden
* Department of Electrical and Information Technology, Lund University, Lund, Sweden

IEEE ICASSP
Virtual conference
June, 2021

# Introduction

- Wireless-based activity sensing is evolving rapidly due to the interest in many applications such as intrusion detection, patient care, smart home, etc.
- Traditional human activity recognition systems
  - Achieved using cameras or motion sensors
  - Imposes inconvenience in wearing sensors and cameras require good lighting
- State-of-the-art: shown benefits of utilizing wireless signals with only WiFi devices for activity sensing
  - Non line-of-sight (NLOS)/line-of-sight (LOS) identification
  - Human presence detection
  - Classification of human activities

# Introduction

- Received signal strength (RSS): limited accuracy
- Channel state information (CSI): reveals the multipath features of the channel at the granularity of the OFDM subcarriers
- Machine learning (ML)-based approaches: widely used in numerous applications due to their ability to learn the statistical patterns from the CSI
- Limitations of WiFi-based activity sensing
    - Performance is limited since the devices typically are equipped with two or three antennas
    - Difficulties in exploiting statistical patterns in the spatial domain and degraded accuracy especially in NLOS conditions

# Problem statement and contributions

- Objective is to show the potential of using massive MIMO for wireless sensing applications with machine-learning algorithms
- We use real data from a massive MIMO system to exploit the advantages of the spatial domain
- Proposed algorithms to extract features from the amplitude and phase information of the measured massive MIMO data
- Efficiently classify moving objects in LOS and NLOS scenarios by using ML models

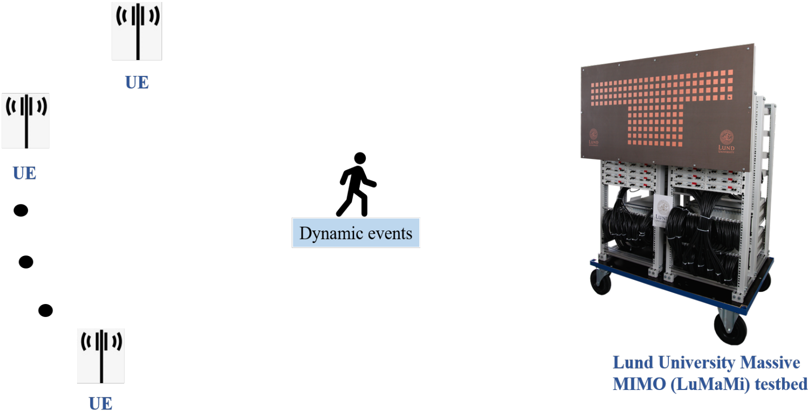



Figure: Measurement setup for activity sensing

# System model

- Uplink narrow band massive MIMO OFDM system with multiple UEs
- Received signal matrix $\mathbf{Y}_f \in \mathbb{C}^{M \times N}$

$$\mathbf{Y}_f = \mathbf{H}_f \odot \mathbf{\Gamma}_f + \mathbf{N}_f$$

- Subcarrier $f \in [1, F]$, radio-frequency (RF)-chain $m \in [1, M]$, snapshot $n \in [1, N]$, and $\mathbf{H}_f \in \mathbb{C}^{M \times N}$ is the complex-valued channel matrix
- Difficult to precisely model $\mathbf{H}_f$ due to unknown positions of the UEs and the environment as well as unknown Doppler shifts caused by unpredictable speeds and directions of different moving objects

# System model

- Frequency response of the RF chains $\mathbf{\Gamma}_f \in \mathbb{C}^{M \times N}$, each element is defined as

$$\mathbf{\Gamma}_f(m,n) = d_m e^{j(\alpha_m - n\,\epsilon_{m,f})}$$

- $d_m$ = amplitude scaling, $\alpha_m$ = initial phase offset, $\epsilon_{m,f}$ = carrier frequency offset
- $\mathbf{N}_f \in \mathbb{C}^{M \times N}$ = noise for the $f$-th subcarrier
- $\mathcal{Y} \in \mathbb{C}^{F \times M \times N}$ = received data for a total of $F$ subcarriers

# Feature extraction

- Challenging to apply traditional detection and estimation theory since we do not have a physically accurate signal model
- Motivated to exploit the statistical features that can be efficiently used by ML models
- ML models can operate with raw I/Q samples: requires a huge data set for training the models
- We therefore, exploit features from a real data set to reduce the dimensionality, which significantly reduces the training data set

# Data pre-processing

- Linear interpolation: to overcome sampling jitter during measurements
- Wavelet-based denoising method: to eliminate random noise present in the data

# Amplitude-based feature

**Input:** $|\mathcal{Z}| \in \mathbb{R}^{F\times M\times N}$ and $T_w$, **Output:** Amplitude feature, $\mathcal{A}$

**for** $n = 1$ to $N$ **do**

Define $\mathbf{B}_n \in \mathbb{R}^{F\times M}$, as the matrix obtained from $|\mathcal{Z}|$ at time $n$:

$\mathbf{B}_n = [\mathbf{b}_n(1), \ldots, \mathbf{b}_n(F)]^{\mathrm{T}}$, $\mathbf{b}_n(f) \in \mathbb{R}^{M}$, $f \in [1, F]$.

**end**

Define $\mathbf{D} \in \mathbb{R}^{FM\times N}$, as the matrix obtained from vectorizing the matrices $\mathbf{B}_n$, $n \in [1, N]$:

$\mathbf{D} = [\mathrm{vec}(\mathbf{B}_1), \mathrm{vec}(\mathbf{B}_2), \ldots, \mathrm{vec}(\mathbf{B}_N)]$.

**for** $j = 1$ to $N/T_w$ **do**

$\mathbf{E} = [\mathbf{D}(1), \mathbf{D}(2), \ldots, \mathbf{D}(T_w)]$, $\mathbf{E} \in \mathbb{R}^{FM\times T_w}$, $\mathbf{D}(i) \in \mathbb{R}^{FM\times 1}$, $i \in [1, T_w]$.

Determine the inner product: $\mathbf{S} = \mathbf{E}^{\mathrm{T}}\mathbf{E}$, $\mathbf{S} \in \mathbb{R}^{T_w\times T_w}$.

Perform eigenvalue decomposition: $\mathbf{S} = \mathbf{U}\boldsymbol{\Sigma}\mathbf{U}^{\mathrm{T}}$.

$\mathbf{g}_j$ = Sort the eigenvalues in the descending order. Discard the first eigenvalue and store the rest.

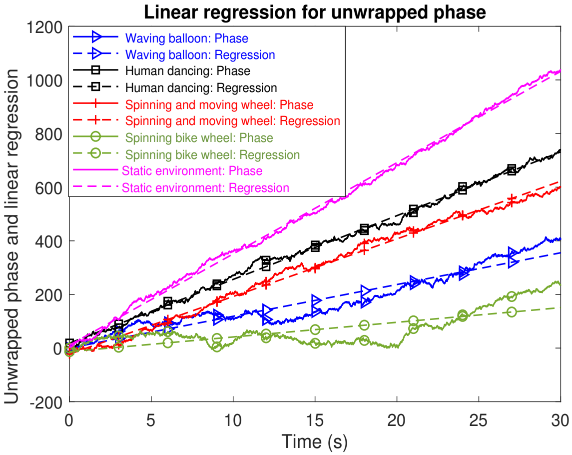
Slide $T_w$ in $\mathbf{D}$ and repeat the calculations of $\mathbf{S}$ and $\boldsymbol{\Sigma}$.

**end**

$\mathbf{G} = [\mathbf{g}_1, \mathbf{g}_2, \ldots, \mathbf{g}_{N/T_w}]^{\mathrm{T}}$

$\mathcal{A} = \mathbb{E}[\mathbf{G}]$, where $\mathbb{E}[\cdot]$ is the expectation operator

# Phase-based feature



# Phase-based feature

- For a static scenario, only minor phase changes are expected due to measurement noise
- For dynamic events, the phase of $\mathbf{H}_f$ changes more rapidly across the snapshots due to Doppler shifts
- The phase of $\mathbf{\Gamma}_f(m, n)$ increases or decreases linearly with snapshots due to the CFO across the subcarriers
- We perform linear regression on the unwrapped phase of $\mathcal{Y}$ for each $f$ and $m$ across all snapshots

# Phase-based feature

- $\hat{\mathcal{Y}}$: unwrapped phase of $\mathcal{Y}$
- $\boldsymbol{\xi} = [1, 2, ..., N]^{\mathrm{T}} \in \mathbb{R}^N$: indexes of the snapshots
- $\mathbf{1}_N \in \mathbb{R}^N$: unit vector
- $\boldsymbol{\Psi} \in \mathbb{R}^{N \times 2}$ as $\boldsymbol{\Psi} = [\mathbf{1}_N, \boldsymbol{\xi}]$

**Input:** Unwrapped phase $\hat{\mathcal{Y}} \in \mathbb{R}^{F \times M \times N}$, **Output:** Phase feature, $\mathcal{P}$

**for** $m = 1$ to $M$ **do**

  **for** $f = 1$ to $F$ **do**

    Linear regression for each $f$ and $m$: $\boldsymbol{\beta}_{f,m} = (\boldsymbol{\Psi}^{\mathrm{T}} \boldsymbol{\Psi})^{-1} \boldsymbol{\Psi}^{\mathrm{T}} \hat{\mathbf{y}}_{f,m}$ .

    Define $\boldsymbol{\eta}_{f,m} \in \mathbb{R}^N$ as the deviation between $\hat{\mathbf{y}}_{f,m}$ and the regression line:

    $\boldsymbol{\eta}_{f,m} = \hat{\mathbf{y}}_{f,m} - \boldsymbol{\beta}_{f,m}(2) \cdot \boldsymbol{\xi} - \boldsymbol{\beta}_{f,m}(1) \cdot \mathbf{1}_N$

    Define $q_{f,m}$ as the variance of $\boldsymbol{\eta}_{f,m}$: $q_{f,m} = \mathrm{var}(\boldsymbol{\eta}_{f,m})$

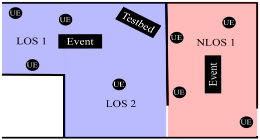
  **end**

**end**

Define $\mathbf{Q} \in \mathbb{R}^{F \times M}$, where the $f$-th row and $m$-th column of $\mathbf{Q}$ is $q_{f,m}$ .
Calculate the pairwise column correlation of $\mathbf{Q}$: $\tilde{\mathbf{S}} \in \mathbb{R}^{M \times M}$.
Perform eigenvalue decomposition: $\tilde{\mathbf{S}} = \tilde{\mathbf{U}}\tilde{\boldsymbol{\Sigma}}\tilde{\mathbf{U}}^{\mathrm{T}}$.
Sort the eigenvalues in the descending order and discard the first eigenvalue. The rest are stored in $\mathcal{P}$ as the phase-based features.

# Massive MIMO measurements

- Measurement campaign: indoor laboratory environment at Lund University, to capture samples under both LOS and NLOS scenarios




- Dynamic events: waving an aluminium foil balloon, spinning a bike wheel, spinning and moving a bike wheel, and human dancing
- Samples were also collected in static environments
- For each of the static and dynamic events, 18 experiments were conducted, resulting in a total of 90 experiments

# Massive MIMO measurements

- BS: Lund University massive MIMO testbed (LuMaMi)
- Software-defined radio-based testbed that operates in OFDM-mode with 100 antennas connected to 100 transceiver chains at a carrier frequency of 3.7 GHz with 20 MHz of bandwidth
- Antenna elements are separated half a wavelength apart and arranged in four rows of 25 elements each
- UEs consist of an USRP with two transceiver chains and are equipped with either one or two dipole antennas
- Each measurement and active UE transceiver chain: 100 frequency points and 3000 snapshots over 30 seconds were collected, this constituting one experiment

# Machine learning models

- Classifier model

$$f(\mathbf{x};\boldsymbol{\theta}) : \mathbf{x} \in \mathcal{X} \to \mathbb{R}^2$$

- Input $\mathbf{x} = [\mathcal{A}, \mathcal{P}]$ is a combination of the amplitude and phase-based features
- Classical supervised ML: Implemented using the SVM model by utilizing the package *sklearn* with the kernel type *linear*
- Feedforward neural network

Table: NN architecture with trainable parameters of $3,576$

| | Size | Parameters | Activation function |
|---|---|---|---|
| Input: $[\mathcal{A}, \mathcal{P}]$ | 12 | - | - |
| Layer 1 (Dense) | 64 | 832 | elu |
| Layer 2 (Dense) | 32 | 2080 | elu |
| Layer 3 (Dense) | 16 | 528 | elu |
| Layer 4 (Dense) | 8 | 136 | elu |
| Layer 5 (Dense) | 2 | 18 | softmax |

# Results

- Measurement events
  - $v_1$: static, $v_2$: human dancing, $v_3$: spinning bike wheel, $v_4$: waving of an aluminium foil balloon, and $v_5$: spinning and moving bike wheel
- Classification problems

Table: Classification of different moving objects

| Cases | Classifications | Labels |
|---|---|---|
| 1 | Between $\{v_2, v_3, v_4, v_5\}$ and $\{v_1\}$ | $\{v_2, v_3, v_4, v_5\} \rightarrow$ '1'<br>$\{v_1\} \rightarrow$ '0' |
| 2 | Between $\{v_2\}$ and $\{v_3\}$ | $\{v_2\} \rightarrow$ '1'<br>$\{v_3\} \rightarrow$ '0' |
| 3 | Between $\{v_2\}$ and $\{v_3, v_4, v_5\}$ | $\{v_2\} \rightarrow$ '1'<br>$\{v_3, v_4, v_5\} \rightarrow$ '0' |

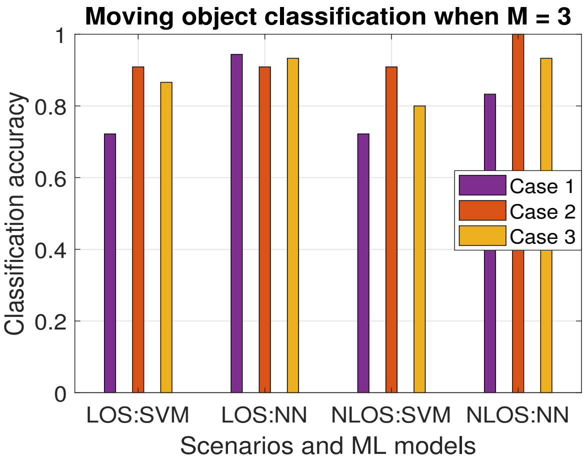



Figure: Classification accuracy of Case 1–3 in LOS and NLOS scenarios

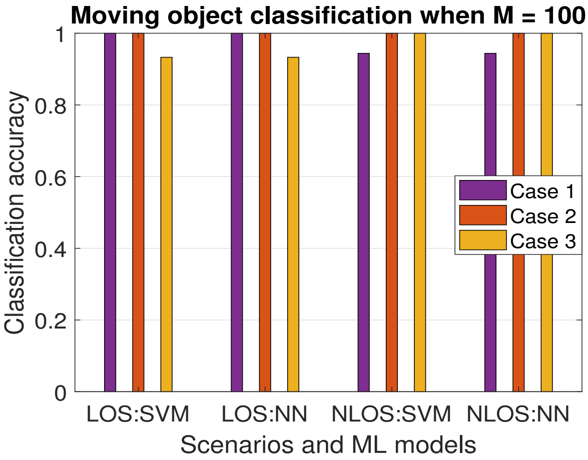



Figure: Classification accuracy of Case 1–3 in LOS and NLOS scenarios

# Conclusions

- Presented ML algorithms for the classification of human and non-human activities using wireless signals received at a massive MIMO base station
- Tested the methods on data obtained from a measurement campaign conducted indoors, using the 100-antenna LuMaMi massive MIMO testbed operating at 3.7 GHz carrier frequency
- Classification performance when using all $M = 100$ antennas at the base station was significantly better compared to when using only $M = 3$ antennas
- Due to the spatial resolution capabilities, massive MIMO technology has the potential to significantly enhance the accuracy in wireless sensing applications

# Thank you