Translation Resilient Opportunistic WiFi Sensing

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Outline

- Motivations and Aims
- Key Insights for Human Activity Recognition
- Experiment Setup
- Experiment Results
- Summary and Conclusions

Introduction

- Wi-Fi has experienced rapid growth due to increasing number of wireless devices.
- Wi-Fi systems used for entertainment and accessing information.
- Multiple-Input Multiple-Output (MIMO) technology → high data rate.

Motivations

- Physical activity and behaviour patterns to monitor long-term chronic health conditions such as diabetes, dementia, etc.

- We are constantly surrounded by radio-frequency (RF) signals. But what if we could find another purpose for such radio systems?

Aims

- ➢ Passive sensing technology where we have a receiver-only radar network that detects the reflections of radio-frequency signals from people.

- ➢ Use of RF signals (e.g. Wi-Fi) as a medical radar system for automatic recognition of everyday activities to events which require urgent attention.

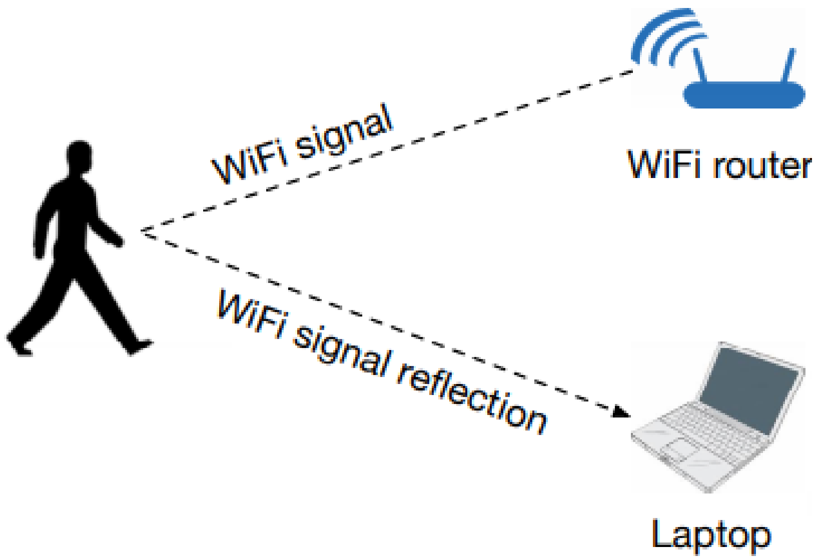
Human Activity Recognition

- Video camera
  - Sensitive to lighting conditions
  - Privacy concerns

- Wearable Sensors (e.g. accelerometers, gyroscopes, and proximity sensors)
  - Inconvenient – discomfort for users especially those with skin conditions

Human Activity Recognition

- What do we propose?
  - ➢ Wi-Fi signals for different sensing purposes.
  - ➢ Use commodity Wi-Fi devices (No additional infrastructure required)
  - ➢ Works in the dark
  - ➢ Privacy friendly



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CSI Extraction

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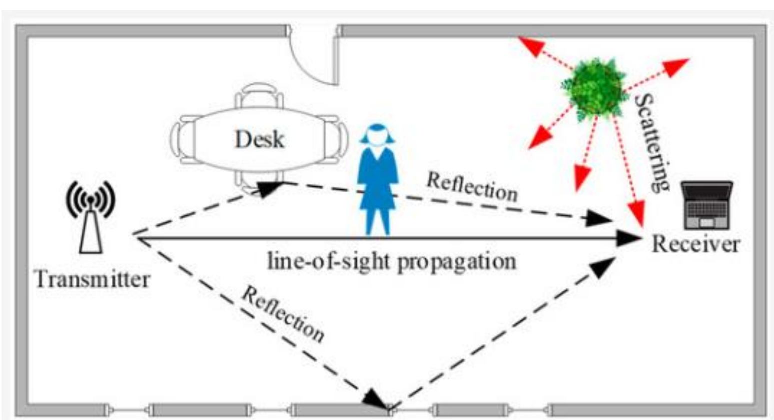
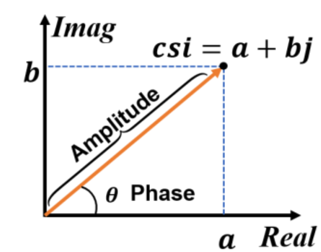


Wi-Fi standards (e.g. 802.11n/ac) based on Orthogonal Frequency Division Multiplexing (**OFDM**).

→provides Channel State Information (**CSI**) which gives information about the wireless channel characteristics between transmitter and receiver.

For a **MIMO-OFDM** system with p **transmit** antennas and q **receive** antennas, the CSI matrix, H_i of each subcarrier, i , is represented as follows:

$$H_i = \begin{bmatrix} h_{11} & h_{12} & h_{13} \ldots h_{1q} \\ h_{21} & h_{22} & h_{23} \ldots h_{2q} \\ \ldots & \ldots & \ldots & \ldots \\ h_{p1} & h_{p2} & h_{p3} \ldots h_{pq} \end{bmatrix}$$



where h_{pq} is a complex number representing the amplitude and phase between each antenna pair.

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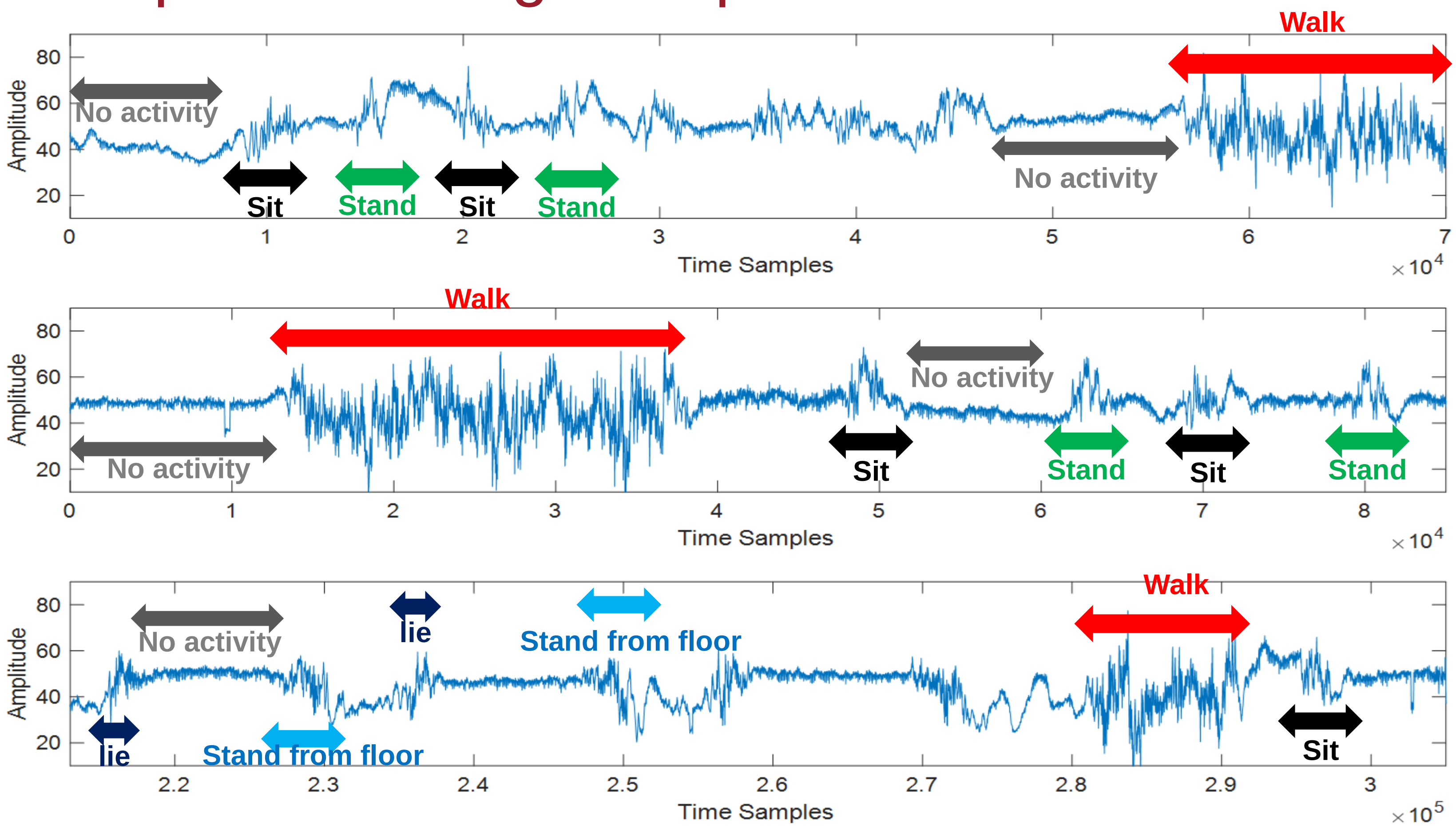
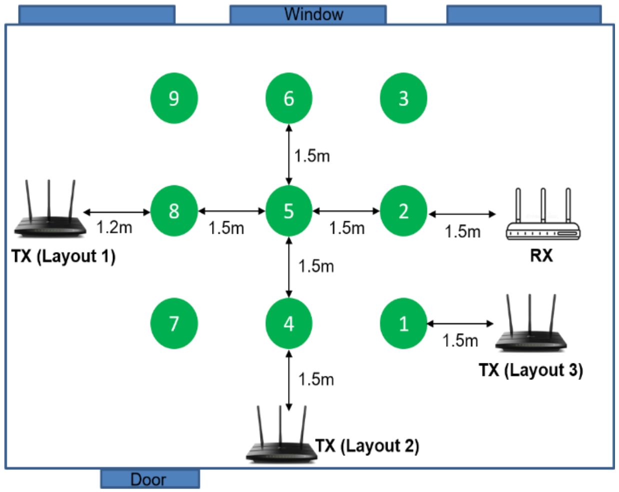
Example of CSI signal representation



Experiment Setup

- Evaluate the activity recognition performance in different physical geometry using Wi-Fi CSI → 5 participants performed 6 activities each.
- 9 testing positions separated by 1.5 m (office space 8 m x 6 m)
- 3 layouts



Parameters:
2.4 GHz band
20 MHz bandwidth
1 transmit antenna and 3 receiving antennas
1 kHz packet rate
Omni-directional antennas

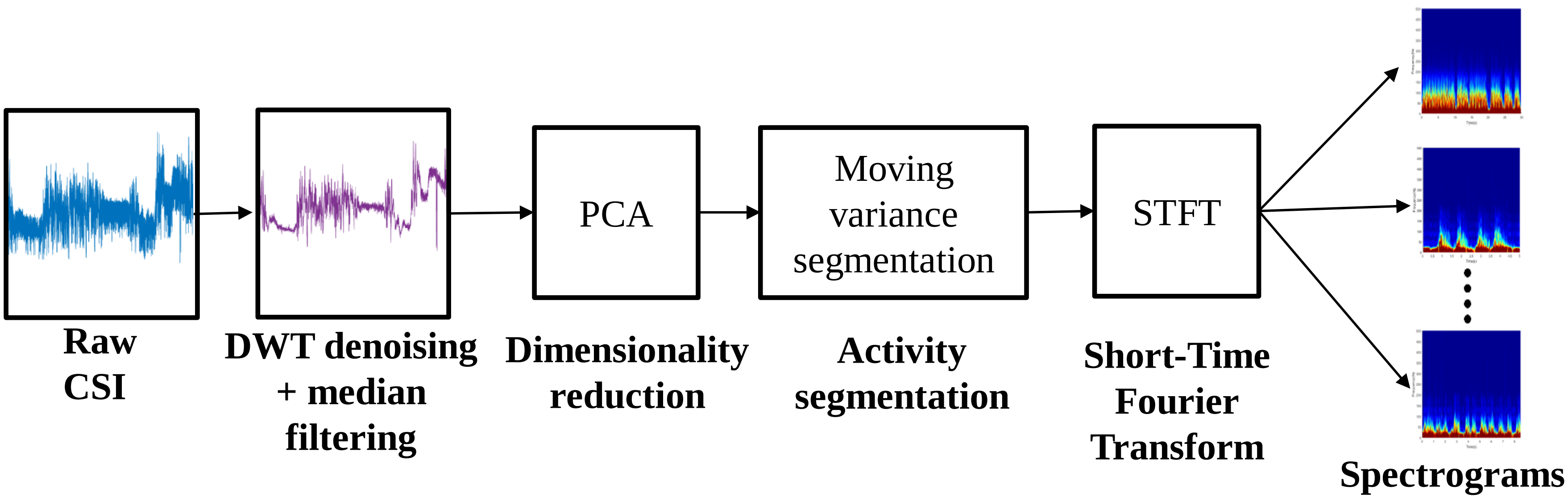
Experiment Setup

	Activity	Description
1	walking	walking along positions 1-2-3, 4-5-6, 7-8-9, 1-4-7, 2-5-8 and 3-6-9
2	sitting	sitting on a chair at positions 2,4,5,6,8
3	standing	standing from a chair at positions 2,4,5,6,8
4	laying down	laying down on the floor at positions 2,4,5,6,8
5	standing from floor	standing from the floor at positions 2,4,5,6,8
6	picking up	picking up objects from the floor at positions 2,4,5,6,8

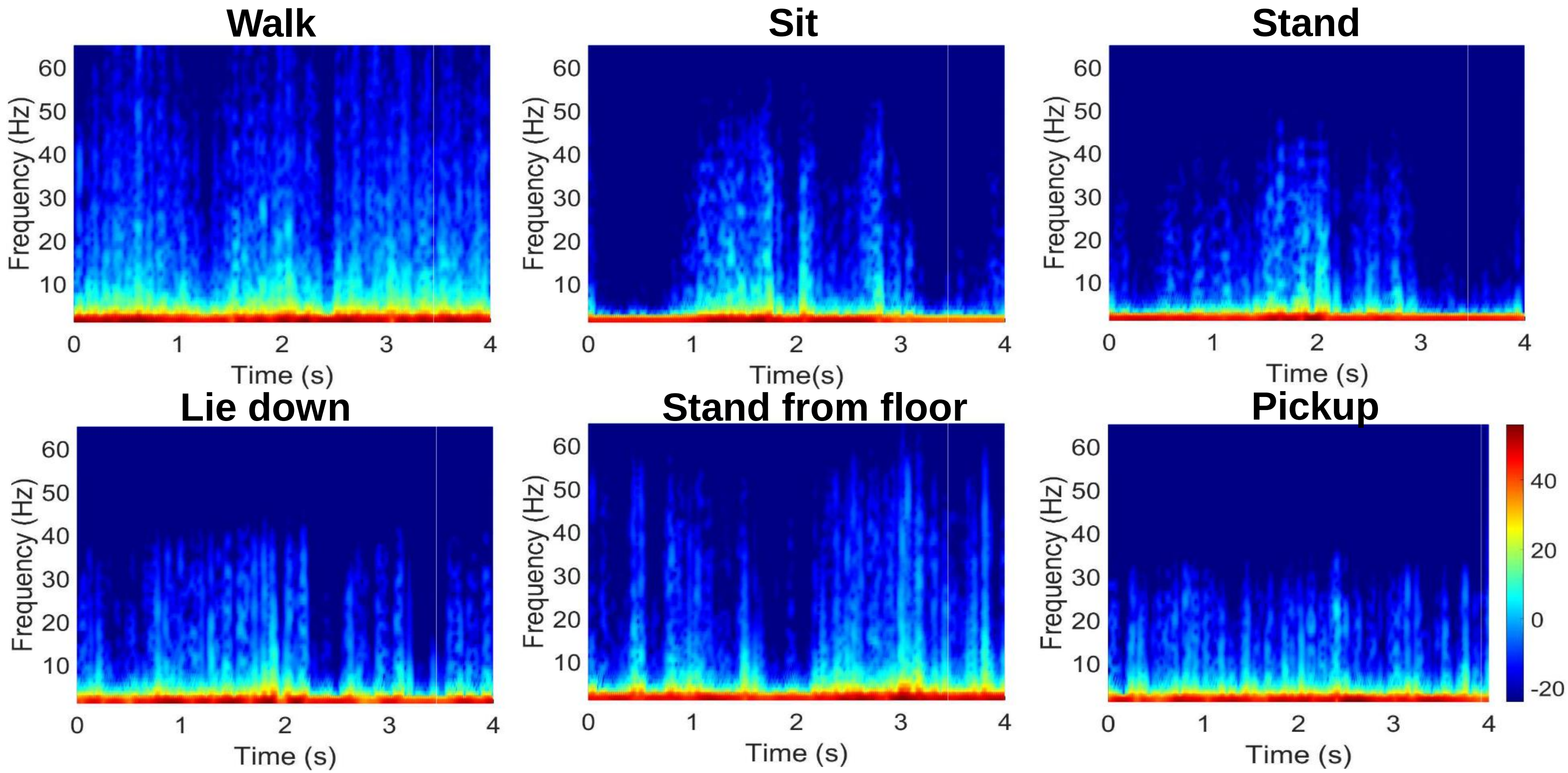
Activity Description

Main Signal Processing Steps

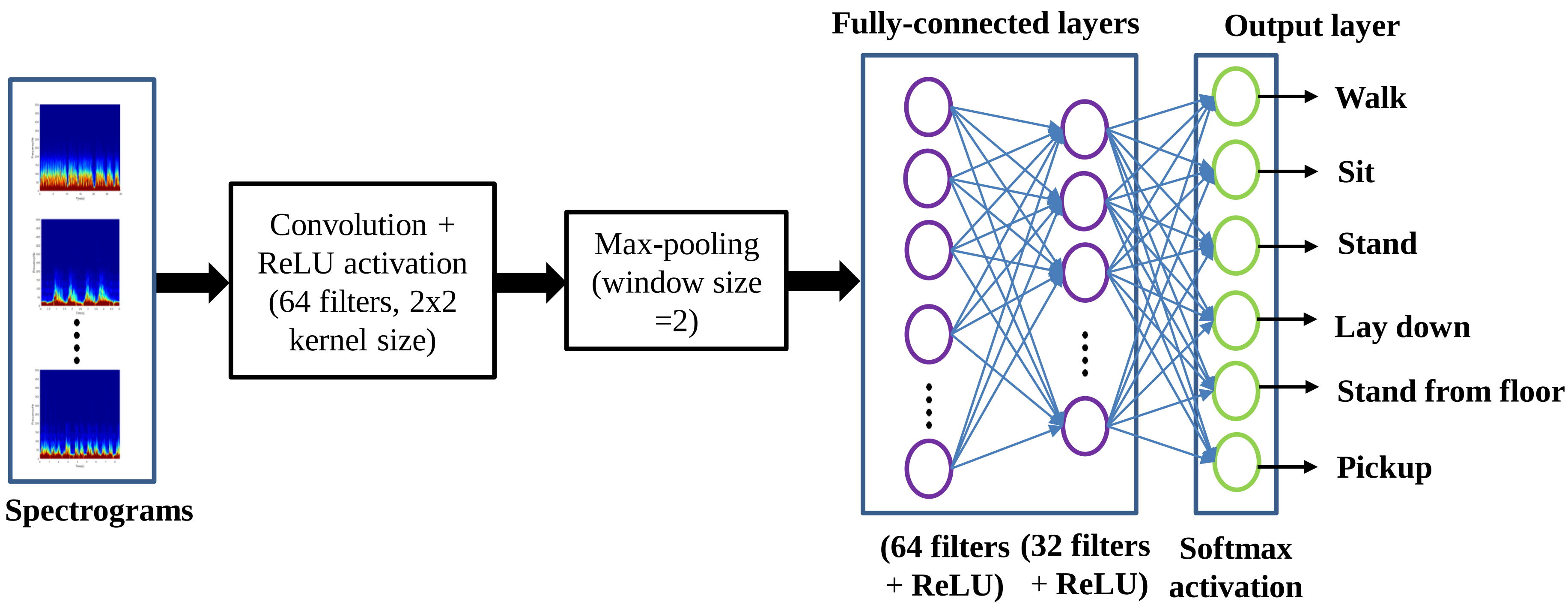
- Raw CSI very noisy in nature.
- Discrete Wavelet Transform (DWT) to filter out in-band noise.
- Principal Component Analysis (PCA) for dimensionality reduction.
- Moving variance segmentation to identify starting and ending points of an activity.
- Short Time Fourier Transform (STFT) for time-frequency analysis of each activity.



Example of Layout 2 spectrograms



Experimental Results – 2D CNN for Activity Classification

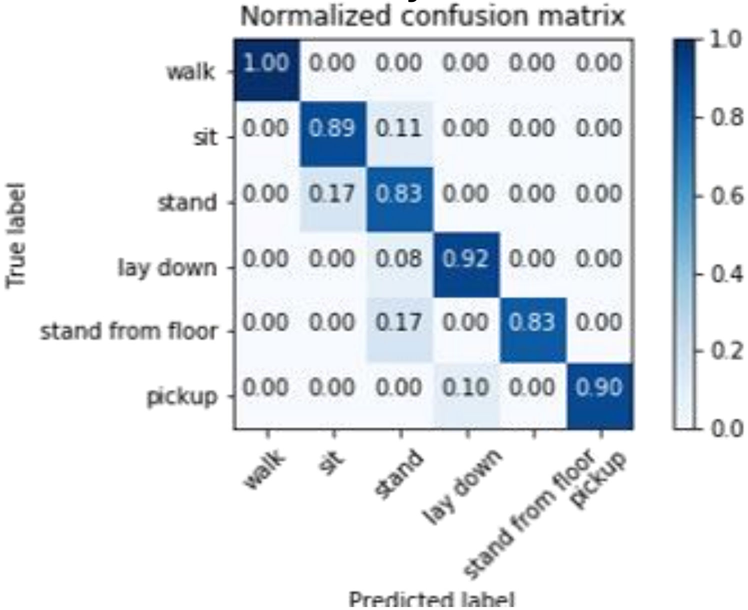


Experimental Results –Activity Classification Accuracy

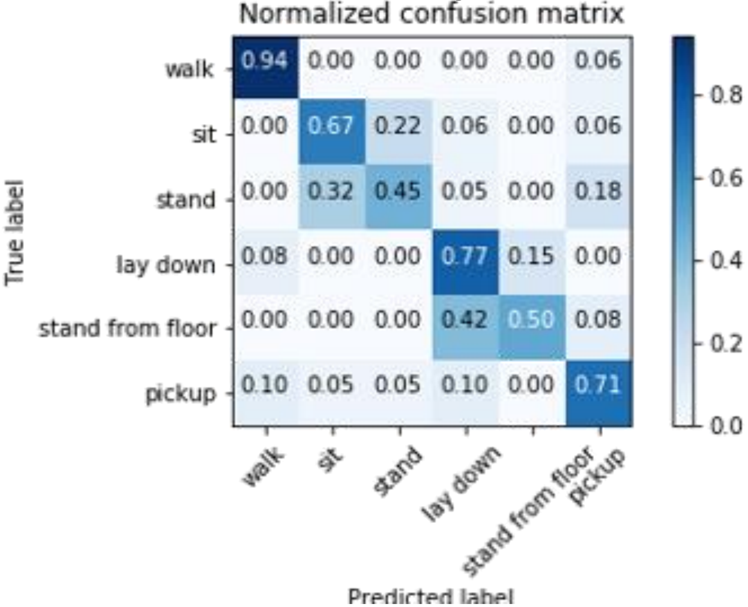
CLASSIFICATION PERFORMANCE FOR EACH LAYOUT.

Layout	Precision	Recall	F1-score	Accuracy
1	90.0%	89.5%	89.1%	90.8%
2	73.9%	74.4%	73.8%	75.7%
3	62.6%	61.9%	61.0%	61.5%
1, 2, 3	67.5%	66.3%	66.0%	67.3%

Layout 1



Combined Layouts 1,2,3



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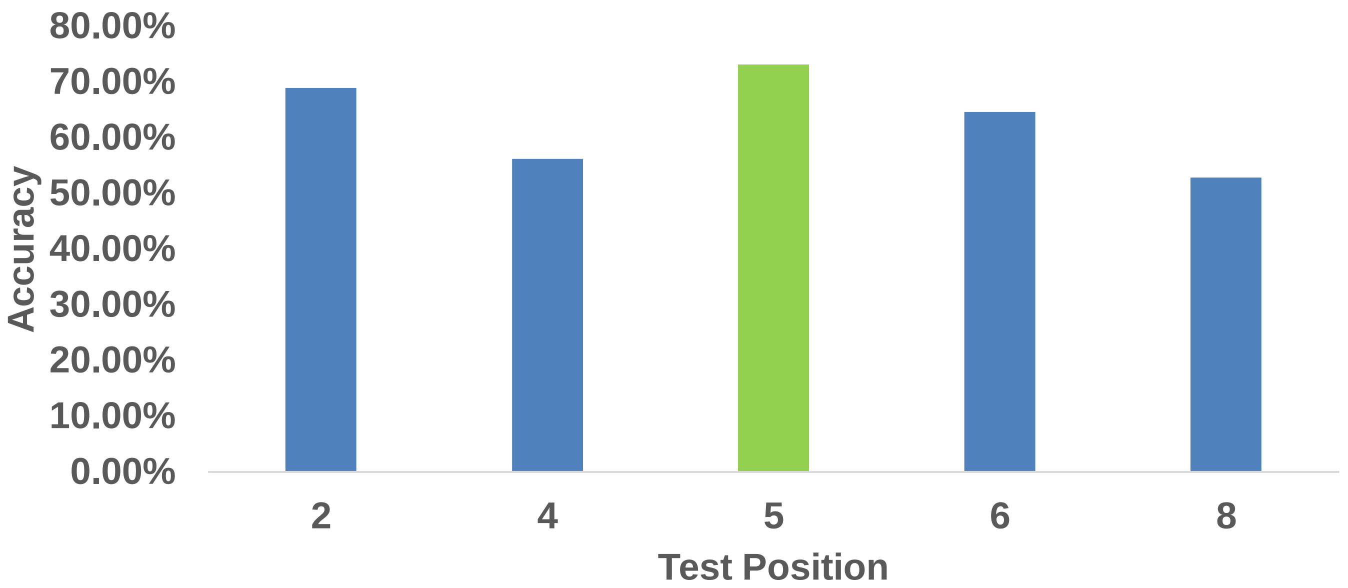
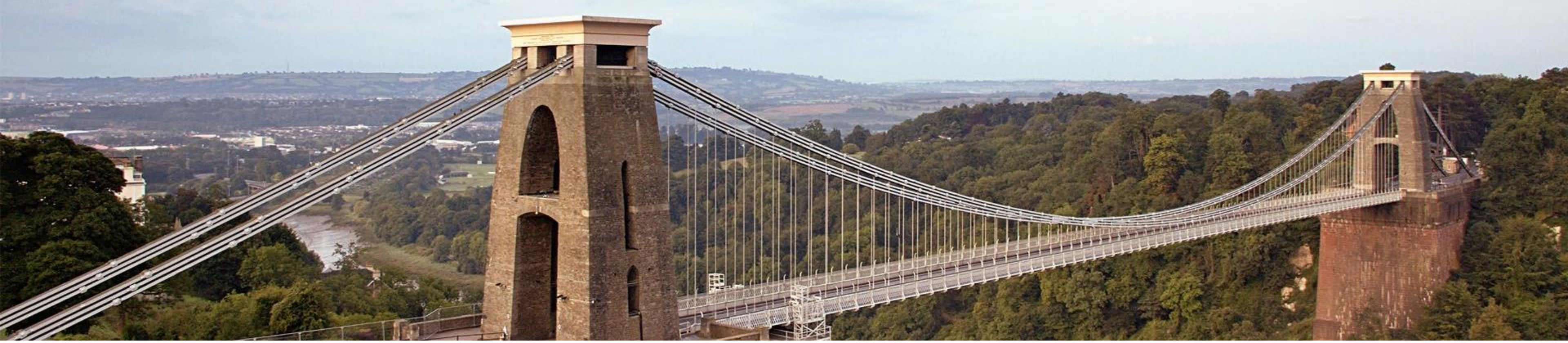
Experimental Results – Position Test Accuracy

- Data from all layouts considered.
- Data is tested for a specific position and trained for all other positions.
- Walking activity excluded.



Summary and Conclusions

- Use of commodity WiFi devices (No additional wireless infrastructure required) for activity recognition in different physical layouts, covering both Line-of-Sight (LoS) and non LoS scenarios.
- Participants performed the activities in a random fashion or different orientations with respect to the transmitter/ receiver (not controlled experiment). This is more representative of the real-world scenario.
- Identify the layout and coverage sensitivities. Results provide a benchmark for the expected accuracy in different physical transmitter-receiver geometry at different positions.
- Best activity classification accuracy (~91%) in LoS setup (Layout 1).
- Centre position achieved the highest accuracy (~73%) in the position test (all layouts combined).
- Activity detection performance is dependent not only on the locations of the TX and RX but also on the positioning of the person performing the activity.



Thank You

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