On Spatial Diversity in WiFi-Based Human Activity Recognition: A Deep Learning-Based Approach

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IEEE Internet of Things Journal, Vol. 6, No. 2, April 2019

2022.12.27.

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Outline

- Overview
- Background
- Observations
- Multiple-antenna Observation
- Area Determination
- System Implementation : WiSDAR
- Evaluation
- Conclusion

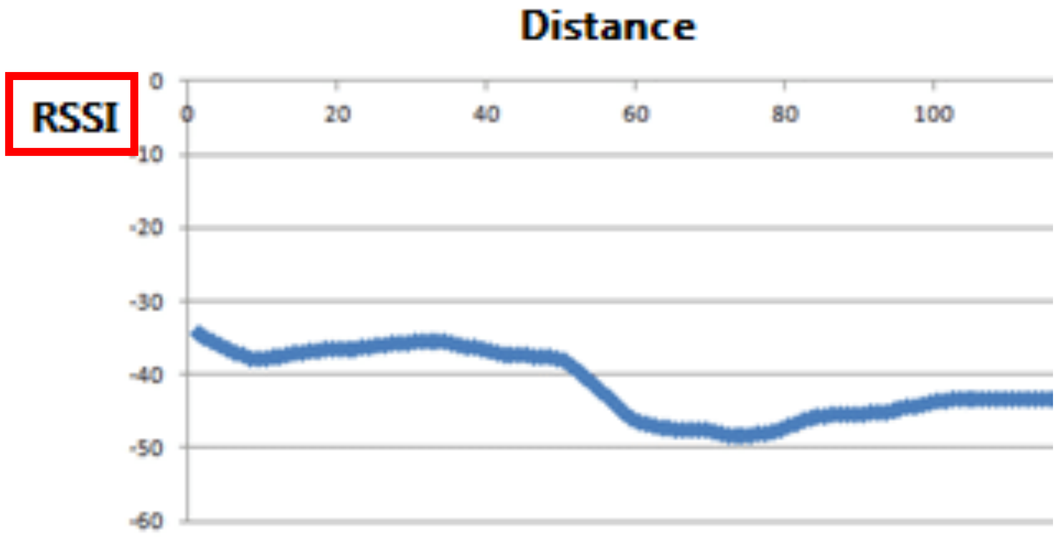
Overview

- **HAR(Human activity recognition)** has attracted great attention in both academia and industry
- WiFi-based HAR → Ubiquity, low cost, device-free, low dependence
  - Coarse-grained RSSI(Received Signal Strength Indicator)
  - Fine-grained **CSI(Channel State Information)**
- But, in a certain **IA(Ineffective Area)** → The accuracy of recognition **can decrease**

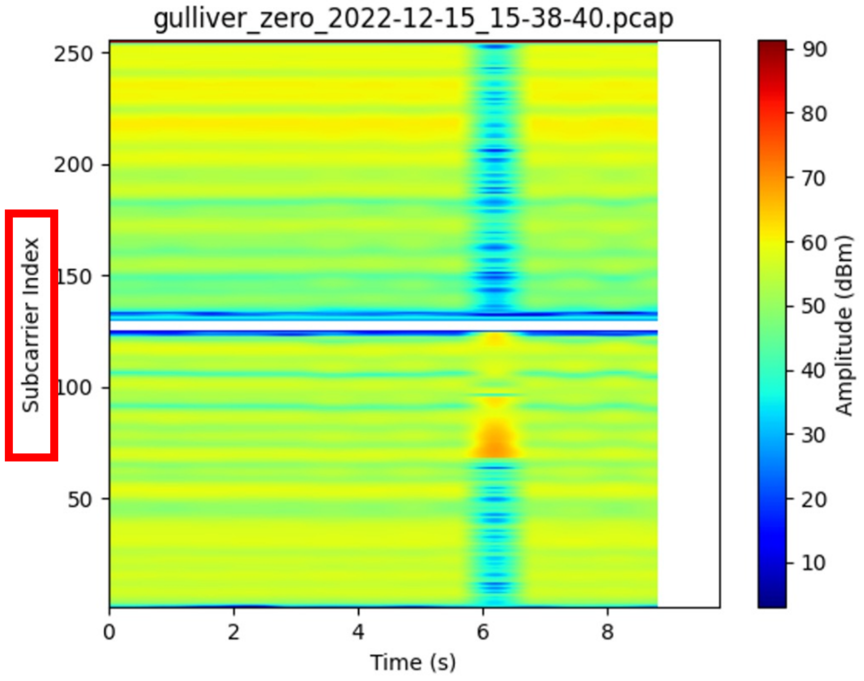
- In this paper :
  - Examine the spatial diversity in WiFi-based HAR
  - Develop a WiFi-based **spatial diversity-aware** device-free activity recognition (WiSDAR) system

Background (1) – CSI (Channel State Information)

- CFR* is the frequency response(magnitude, phase) of the channel
- CSI is commonly used to **characterize the CFR in WiFi systems**



https://www.bluetooth.com/blog/proximity-and-rssi/



* CFR : Channel Frequency Response

Background (2) – Reflection Model

- **Doppler effect**
  - **Relative movement** between transceivers and a reflector → **Change the frequency**

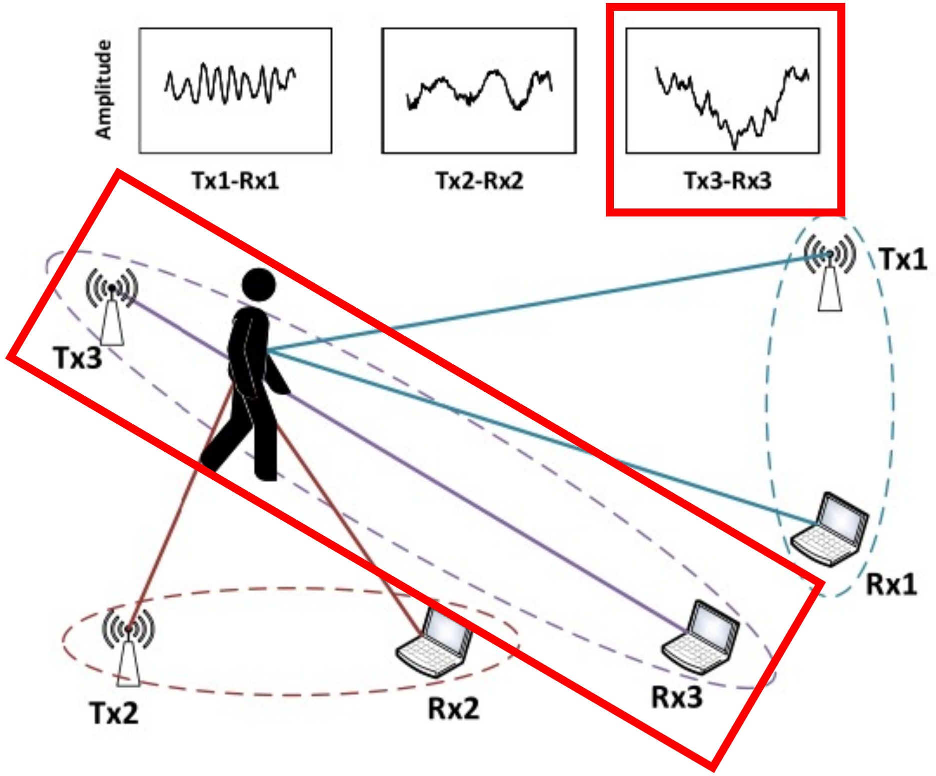
- Total CFR $H(f,t)$

$$e^{-j2\pi\underline{\Delta f}t}\left(H_s(f) + \sum_{k\in P_d}\alpha_k(t)e^{j2\pi\int_{-\infty}^{t}\underline{f_{D_k}(u)du}}\right)$$

CFO : Carrier Frequency Offset

$$f_D = -(1/\lambda)(d/dt)\underline{d(t)}$$

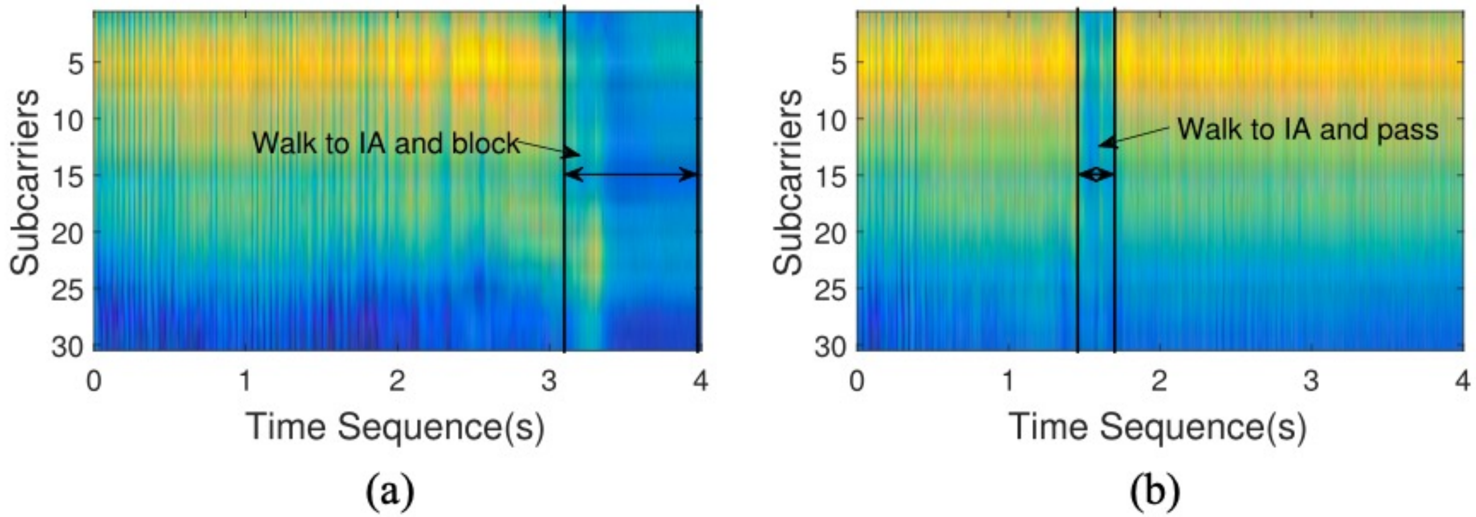
The change of reflected path length

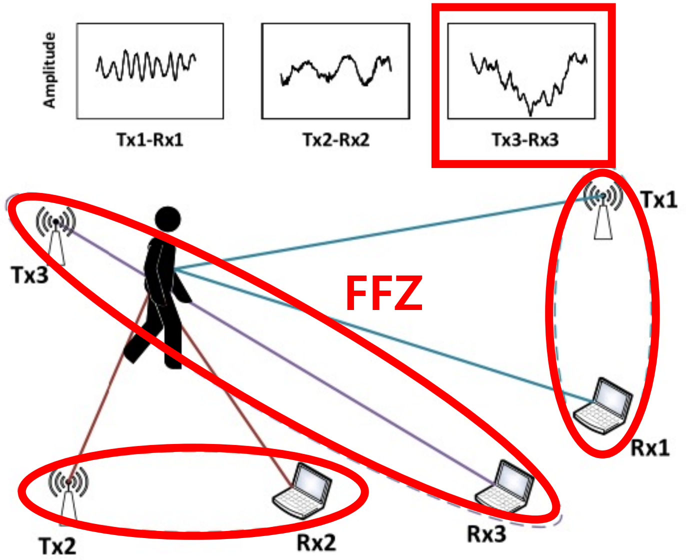


Observations (1) : Target in the IA

- The CFR power can be largely **attenuated** when **the target is located in a certain area(the IA)** of a transceiver pair → Affecting the HAR accuracy

- **The FFZ*** outlines an IA(Ineffective Area) for HAR

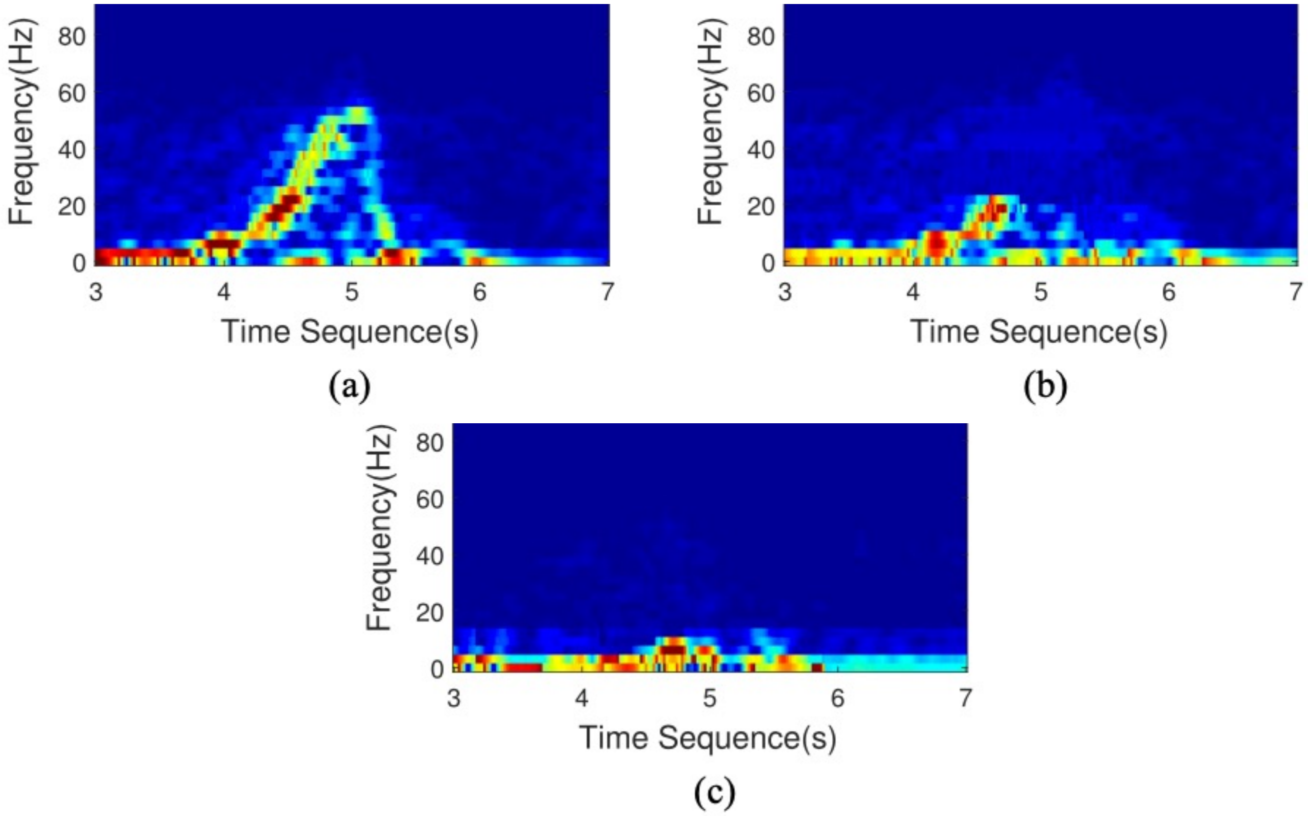


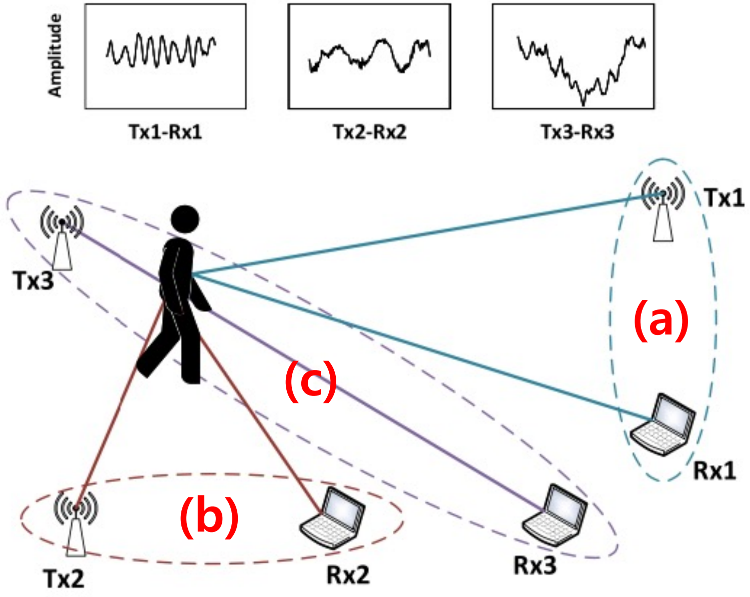


* FFZ : First Fresnel Zone

Observations (2) : Location of Transceivers

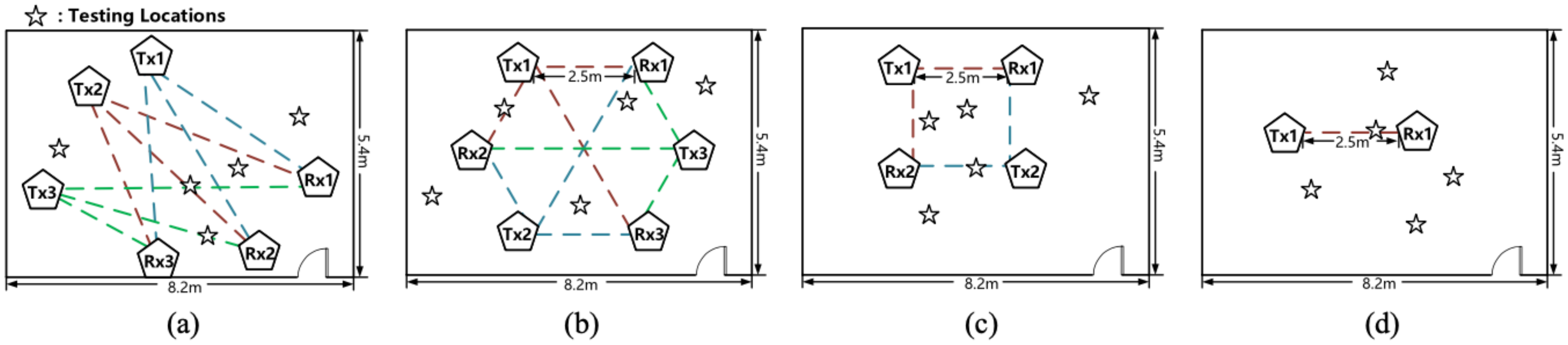
- **<u>For the same activity</u>**, a pair of transceivers can observe different CFR power characteristics **<u>when they are placed at different locations and orientations</u>**





Multiple-antenna Observation

- SA(Separated Antenna)
  - Utilizing the MIMO feature and multiple extended antennas of existing WiFi devices
  - Obtaining <u>**more diverse features**</u> from multiple spatial dimensions for deep learning



- WiSDAR separates the WiFi antennas by extended cables
  - <u>**Only one pair of physical WiFi devices with no extra NICs or APs**</u>

Area Determination (1)

- To select **ineffective pairs** and **filter out** the corresponding **dirty features** → **Minimizing the IAs** and increasing the performance

- IA selection criteria
  - When the target is in the IA,
  - 1) The amplitude of most subcarriers will have **an obvious drop**
  - 2) The amplitude drop **lasts for a relatively long duration**

  ⇒ Large amplitude drops with long durations = IA

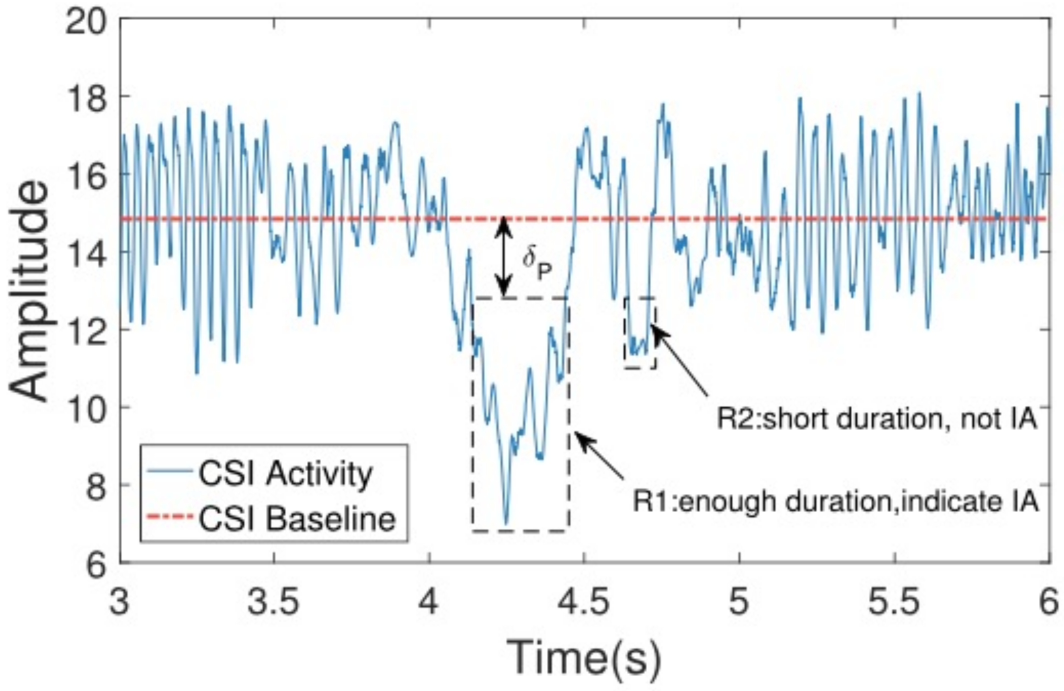
Area Determination (2)

- Area determination scheme

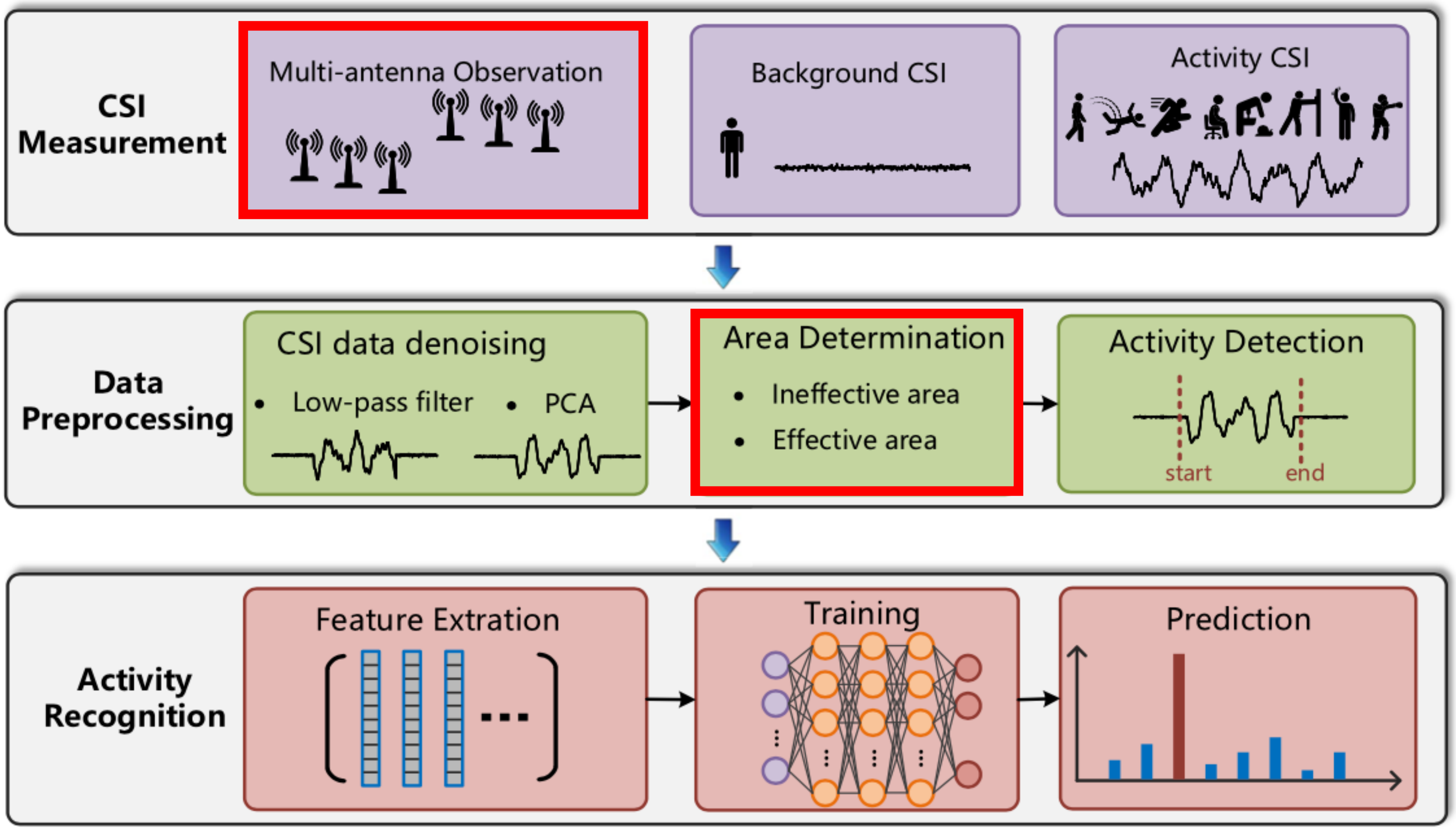
$$\forall t_i \in [t_p, t_q], s.t.$$

$$\underbrace{\bar{C}_b}_{\text{Baseline Avg}} - C_a(t_i) \geq \delta_P \rightarrow \text{Power Threshold}$$

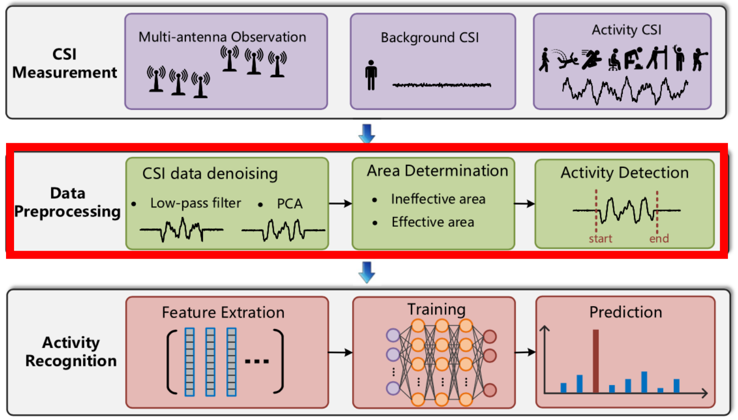
$$\text{and } t_q - t_p \geq \underbrace{\delta_T}_{\text{Time Threshold}}$$



System Implementation : WiSDAR (1)



System Implementation : WiSDAR (2)

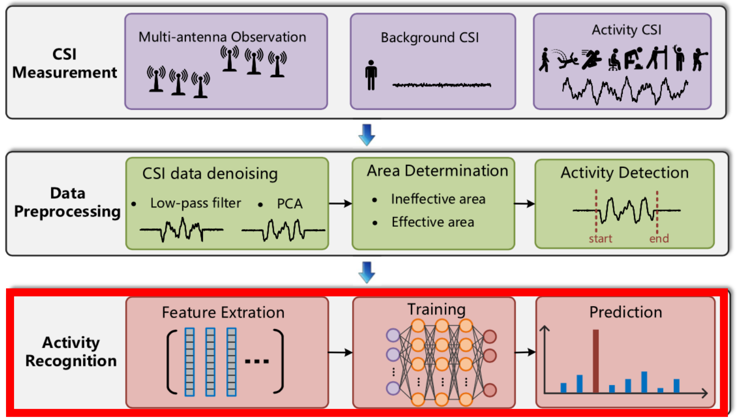


- CSI data denoising
  - Low-pass filter
  - PCA(Principal Component Analysis)

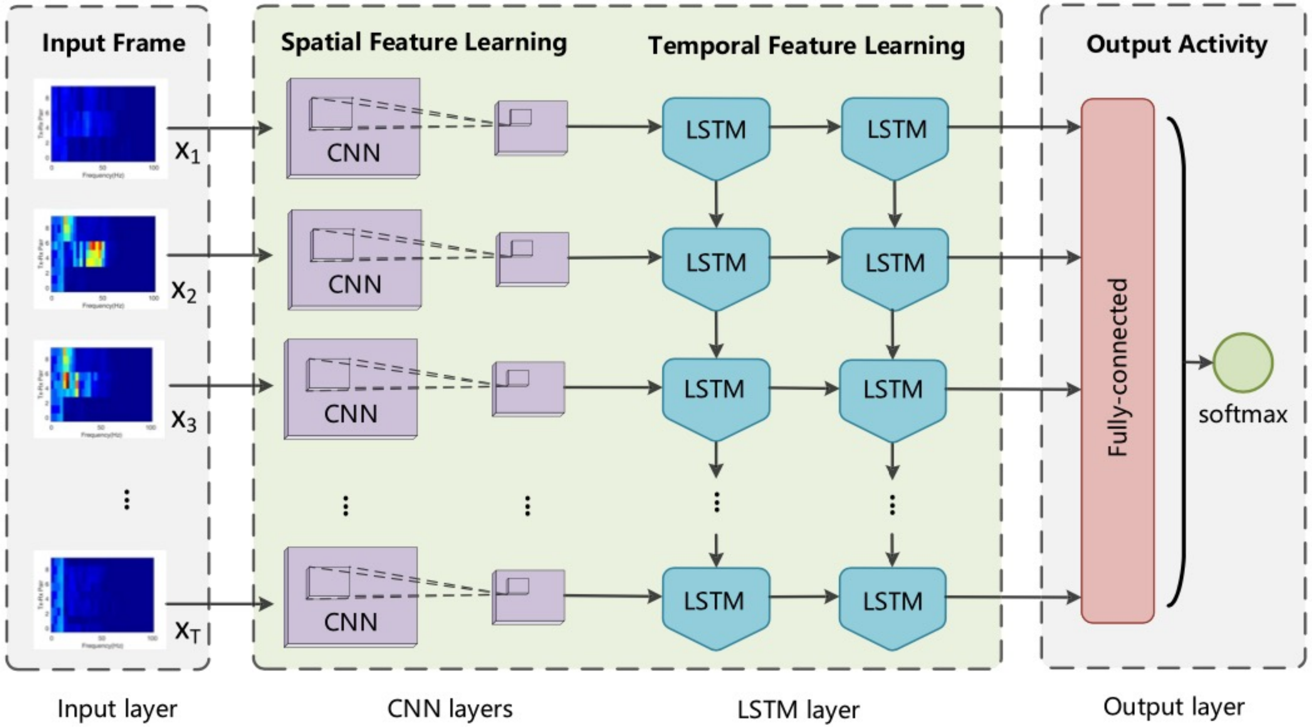
- **Area determination**

- Activity detection
  - Currently no activity → $P_t > \theta_P$ → During the θ_L, no other peak values larger than θ_P → **t=Start point**
  - Currently in activity → $P_t > \theta_P$ → During the θ_L, no other peak values larger than θ_P → **t=End point**

System Implementation : WiSDAR (3)



- Feature extraction
  - Frequency component with STFT*
- Training
  - CNN : For spatial features
  - LSTM : For temporal features

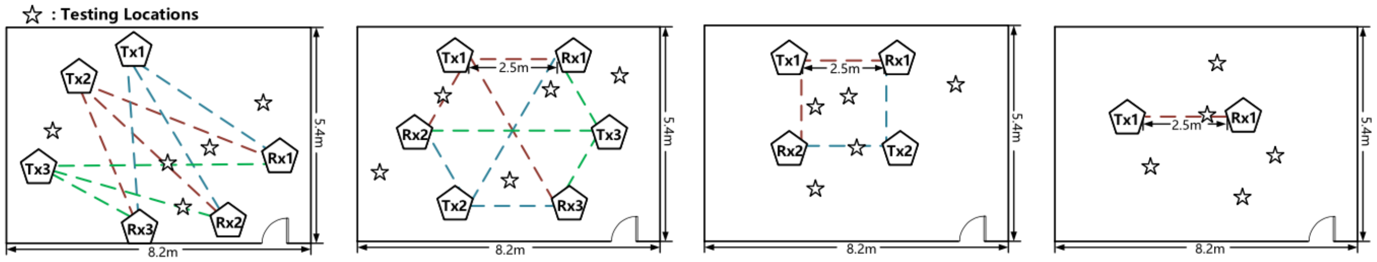


* STFT : Short Time Fourier Transform

Evaluation (1)

- Overall setup
  - COTS hardware : Dell Latitude D820 laptops with an Intel 5300 WiFi
  - Colleting CSI values : CSI tool, 5GHz WiFi channels with 20MHz bandwidth
  - Testing with 6 volunteers(different gender, height, weight, age) in hexagon topology

- Dataset
  - 5760 training samples for 8 activities and data augmentation
  - Different antenna topologies

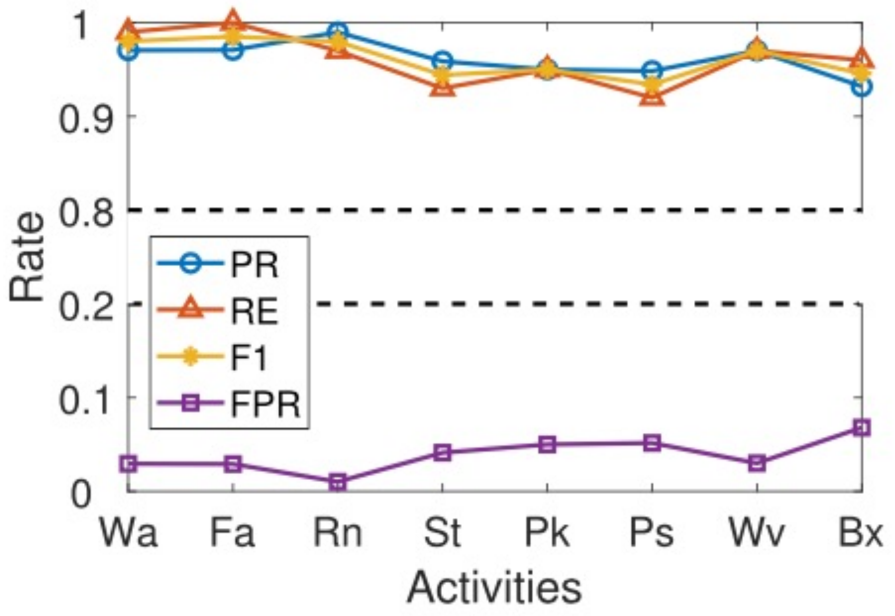


(a) (b) (c) (d)

Evaluation (2)

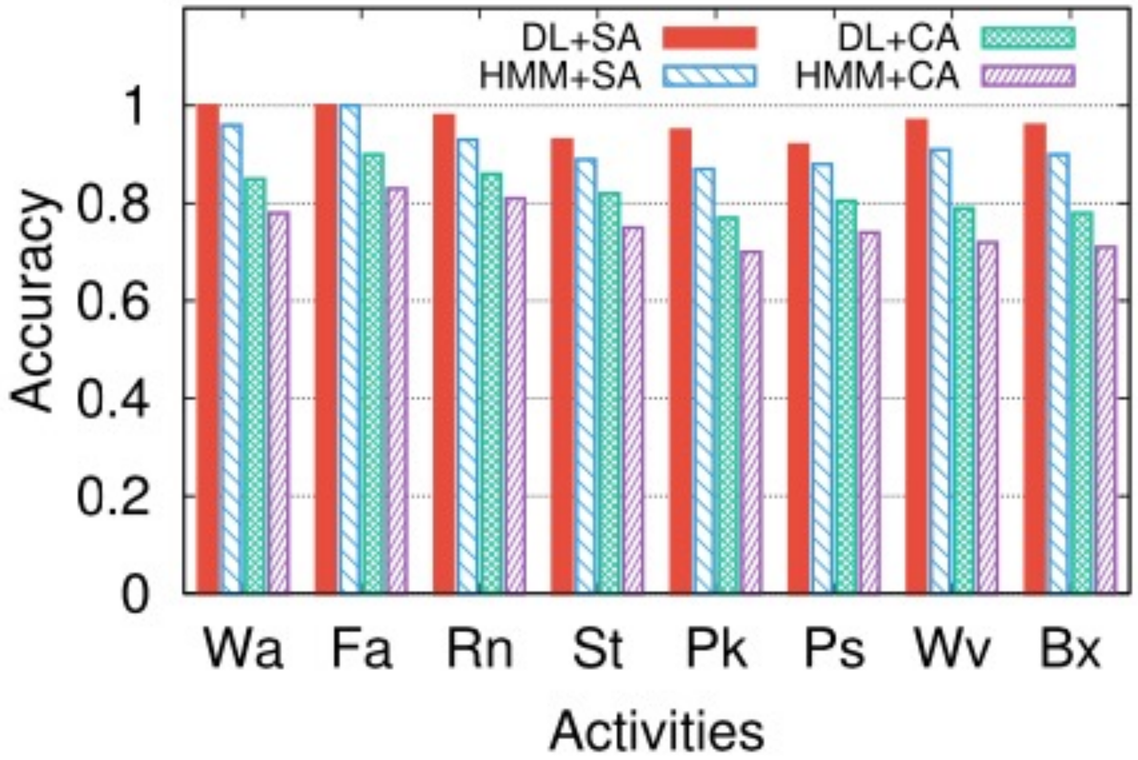
- Overall performance (activity recognition)

Actual Label	Predicted Label							
	Wa	Fa	Rn	St	Pk	Ps	Wv	Bx
Wa	1	0	0	0	0	0	0	0
Fa	0	1	0	0	0	0	0	0
Rn	0.03	0	0.97	0	0	0	0	0
St	0	0.02	0	0.93	0.05	0	0	0
Pk	0	0.01	0	0.04	0.95	0	0	0
Ps	0	0	0	0	0	0.92	0.02	0.06
Wv	0	0	0	0	0	0.02	0.97	0.01
Bx	0	0	0	0	0	0.03	0.01	0.96



Evaluation (3)

- Performance by recognition methods
  - **DL : Deep Learning**
  - HMM : Hidden Markov Model
  - **SA : Separated Antenna**
  - CA : Combined Antenna



Evaluation (4)

- Performance with/without target area determination

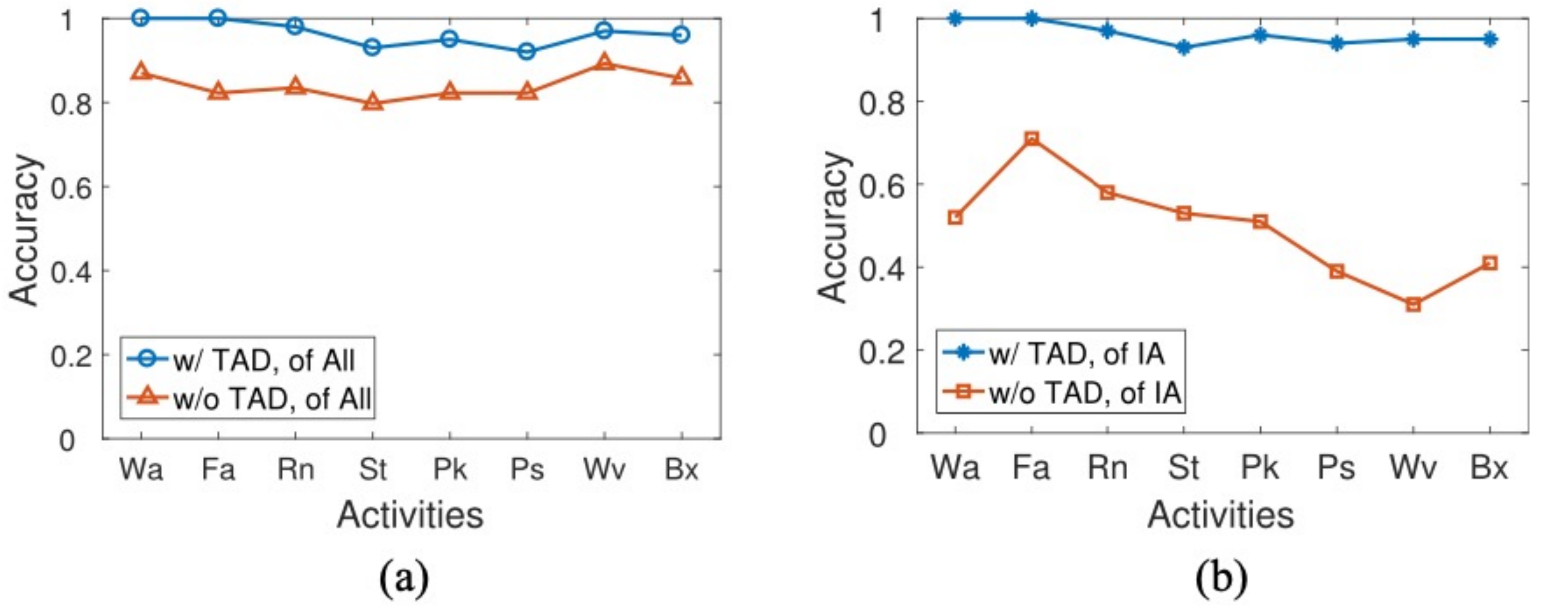


Fig. 20. Accuracy when with or without target area determination mechanism. (a) Accuracy relevant to all activities. (b) Accuracy relevant to activities in IA.

Conclusion

- WiFi-based HAR methods, especially using the CSI, have many benefits for HAR
- But, there are IA(Ineffective Area) and IA usually drops the HAR performance
- **Target area determination** and **SA(Separated Antenna)** methods helped overcome the effect of the IA
- High performance in the COTS environments

- However,
    - Similar values are also detected in frequency domain features
    - SA with cable → Not practical