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Wi-Motion : A Robust Human Activity Recognition Using WiFi Signals

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Outline

- Background
- Preliminary
- System Overview
- Data preprocessing method
- Classification algorithm
- Experiments
- Summary

Motivation

- **Existing techniques** for activity recognition have limitations
  - Cameras require enough lighting and breach human privacy
  - Low-cost radars (60 GHz) have limited operation range
  - Wearables are inconvenient since the users must always care the sensors
- Research **have tried to develop a WiFi-based** activity recognition system by analyzing the Chanel State Information (CSI).
- **BUT** not of the prior work has combined both the amplitude and phase information together
- Most of the works have utilized either:
  - The amplitude change in time domain
  - The phase shift in spatial and frequency domains of CSI values

Related work

- **Received Signal Strength Indicator (RSSI) – Based Approaches**
- It provides coarse grained information about channel variations
- Often affected by:
  - Multipath effects and noise
- **CSI – Based Approaches**
- It is a fine-grained value from the physical layer
- Provides a channel estimation of each subcarrier for each transmission link
- It describes the amplitude and phase on each subcarrier in the frequency domain

Contribution

- The **utilization** of both the **amplitude and phase information** in the **CSI** sequence

- An **activity extraction** method **combining a sliding window with a threshold-based image segmentation**

- After getting the results of each classifier, **Wi-Motion generates prediction results based on the output posterior probability of the two classifiers**

Human Activities

(a) Bend (b) Halve Squat (c) Step (d) Stretch Leg (e) Jump

Preliminary

- Different activities cause different multipath distortions in WiFi signals
- The receiver can receive more than one pulse and each of them may have different transmission delay
- Divide the multipaths into two groups:
  - Static p^s
    - The static paths (labeling by n) are not affected by the human activity and hence have constant delay λ_n and signal attenuation a_n
  - Dynamic p^d
    - Dynamic paths will experience a time-varying change if a person is moving

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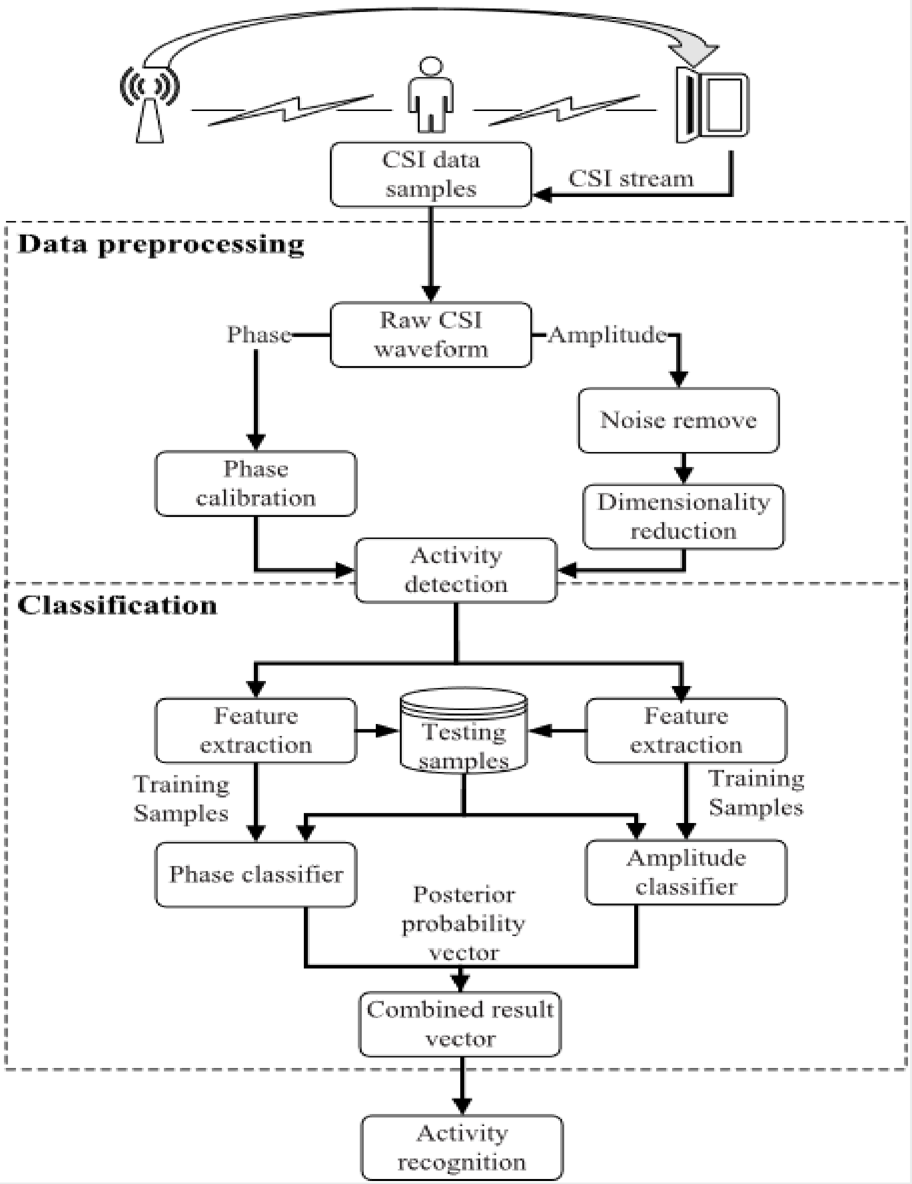
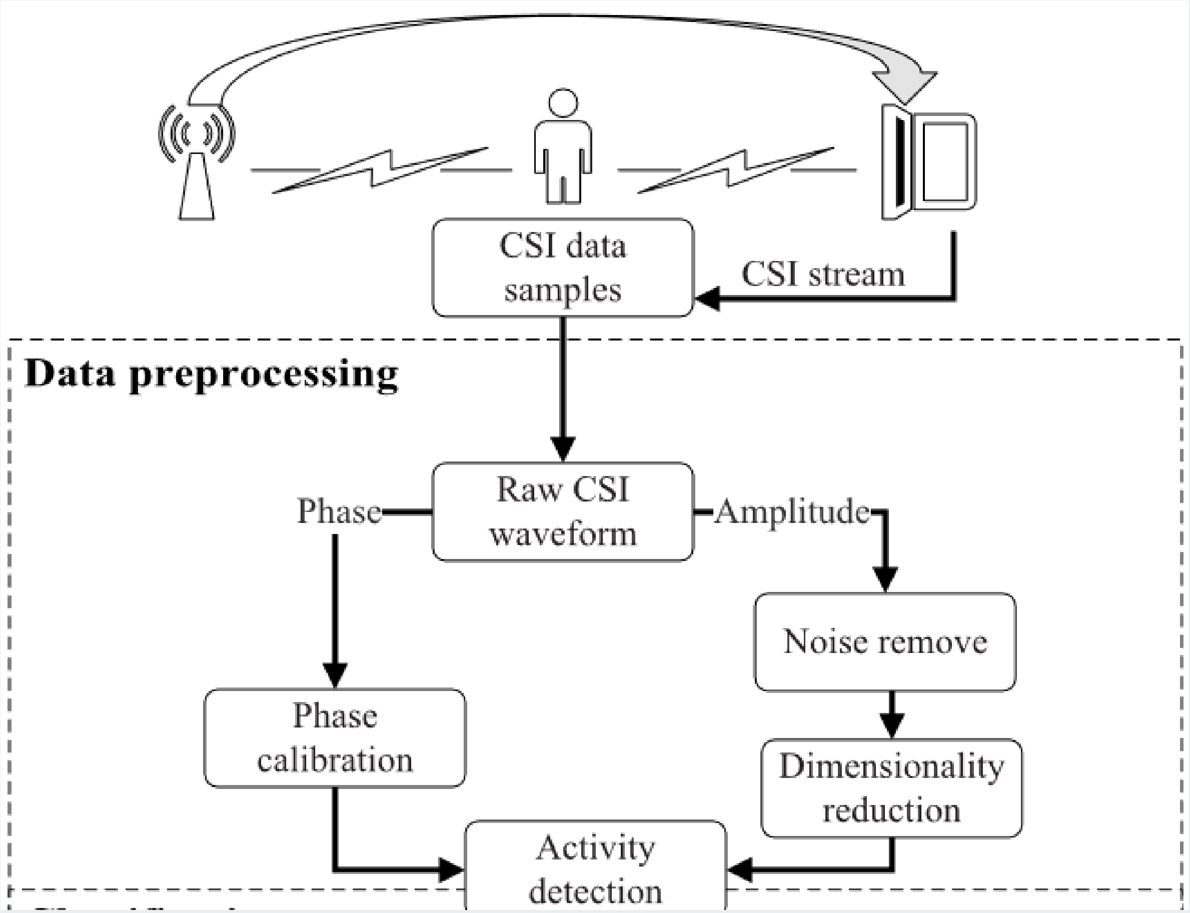
System overview

- Two stages
  - Data processing
  - Classification

- Wi-Motion enables commercial WiFi devices to identify user's activities using CSI measuremen

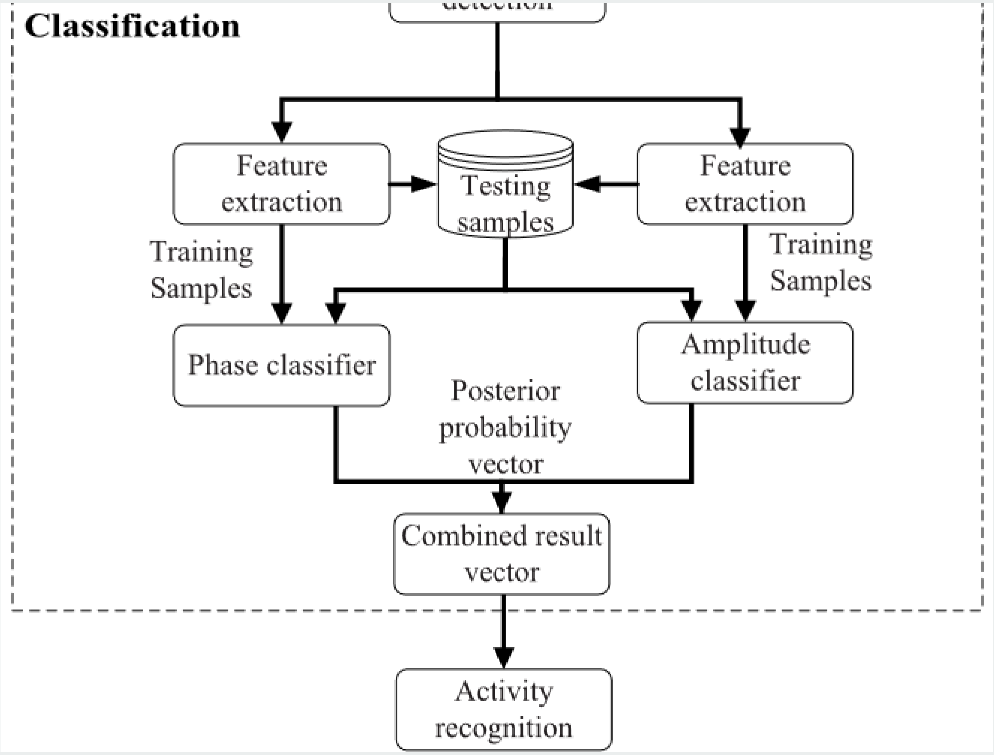


Data processing



Classification

- Useful features which can represent the relationship between the time-series of CSI and human activities are extract, as a basis for classification



Noise Removal

The raw amplitude sequence of the first subcarrier at time **t** is denoted by **{**$\hat{a}_{1,1}$ **,…,** $\hat{a}_{t,1}$**}**

- The raw amplitude measurement obtained from raw CSI sequence is usually not reliable enough to be used for feature extraction
  - The noise, originates from environmental changes, radio signal interference
- They utilize low-pass filtering to remove high-frequency noise and further introduce **weighted moving average (WMA)** method to process the raw amplitude waveform.

m → being a window size and the largest weighting factor

$$\tilde{\alpha}_{t,1} = \frac{(m \times \hat{\alpha}_{t,1} + \ldots + 1 \times \hat{\alpha}_{t-m-1,1})}{m + (m-1) + \ldots + 1}$$

$\tilde{a}$ → filter output

- The most recent amplitude is assigned the highest weight.
- In this paper, they empirically set **m=10**

Dimensionality Reduction

- CSI information from different subcarriers will experience different changes
  - **Each subcarrier has different sensitivity to human activities**
- **Variance** of the **CSI** sequence is used as an **indicator** of the sensitivity of the subcarrier
- Principal Component Analysis (PCA) algorithm **reduces** the **dimensions** of the CSI sequence and **eliminates redundant information** remaining in the data sequence

Feature Extraction

- Discrete Wavelet Transform (DWT) analyses signals on multiple frequency scales
- **Amplitude Feature**
- Perform DWT on the extracted amplitude waveform (based on the first-order Daubechies wavelet)
- **Phase Feature**
- **It sorts the subcarriers** according to the **variance of phase sequence** in each subcarrier
- **Selects the top 20** (empirical value) **subcarriers** for PCA process
  - The obtained 1st component is chosen for constructing the classifier

Classifier Training

- The **choice of kernel function** plays a **key role** in the performance of classical SVM
- The **feature vectors** of different human activities **may not share** the **same length → not suitable** for traditional SVM algorithm (which requires the dimension of the feature vector to be consistent)
- **Leverages** Dynamic Time Wrapping (**DTW**) to **calculate** the **distance** among the feature vectors
- DTW is resilient to signal distortion or shift
- It **compares** two time-dependent series (which can be discrete signals)
- **DTW distance** is used to **construct** a new kernel function

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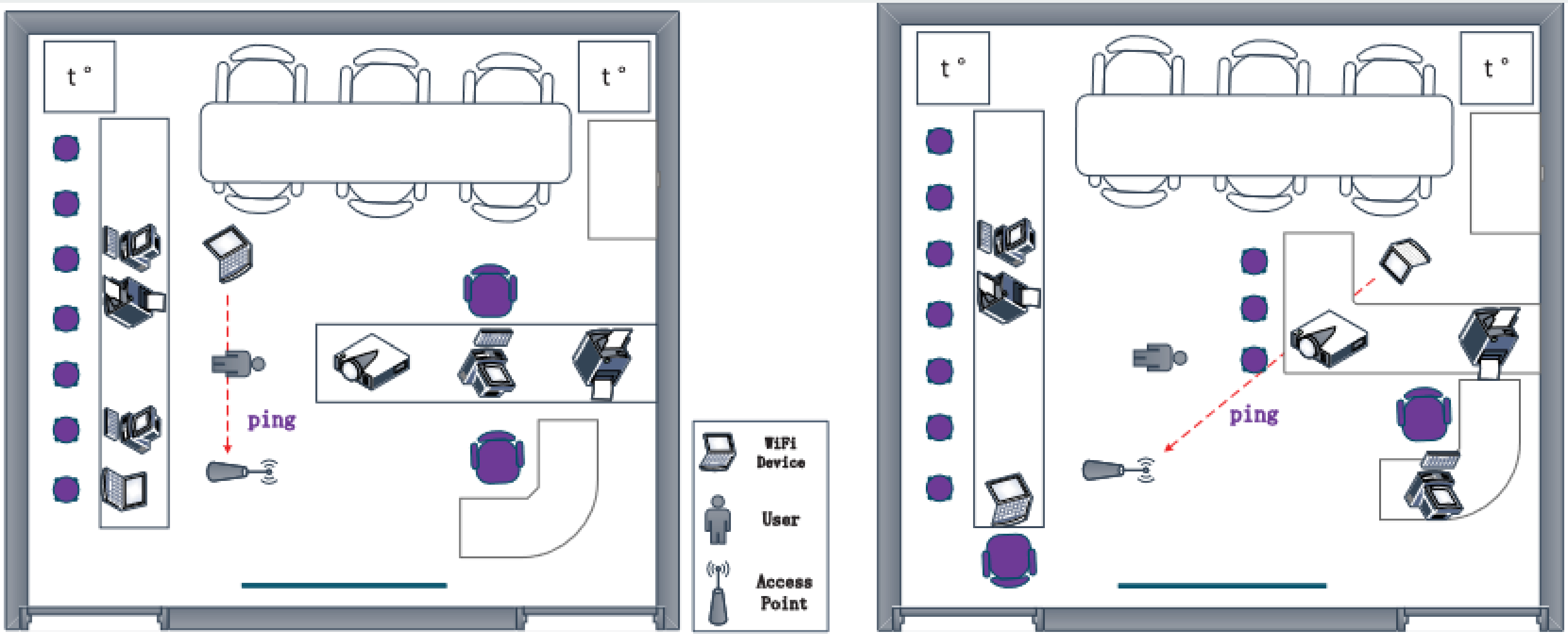
Experiment

LOS environment → line-of-sight environment
NLOS environment → not line-of-sight environment

- 6 testers, 5 human activities



(a) Environment A of data collection (LOS).   (b) Environment B of data collection (NLOS).

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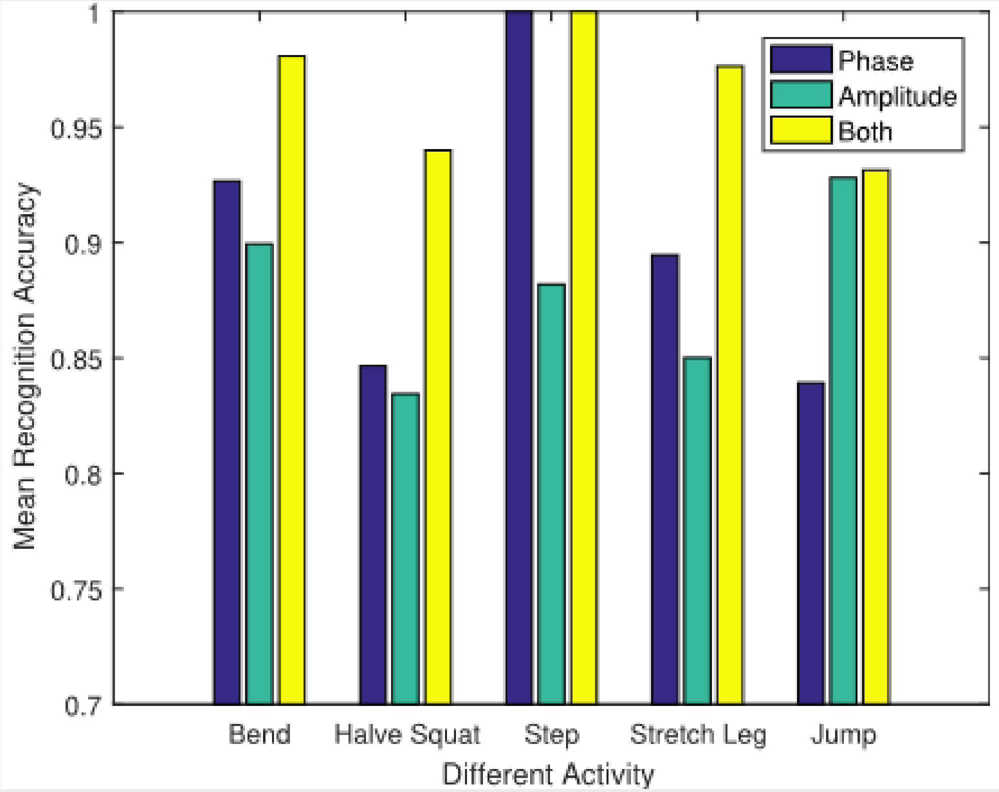
Results (1)

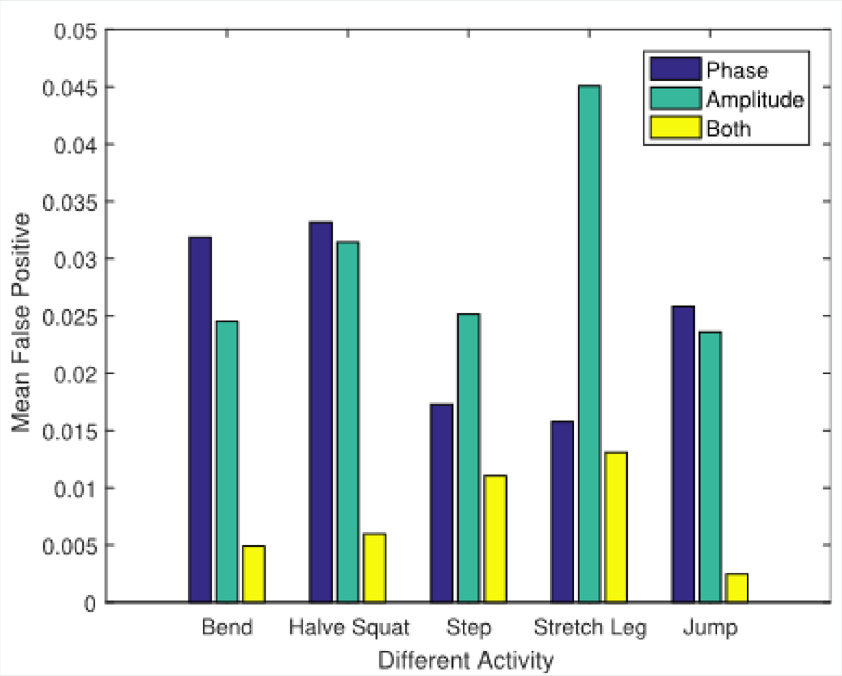
- Accuracy:
  - Halve squat: 94.7%
  - Step: 100%
  - Stretch leg: 97.8%

- More accurate estimation by combining output posterior probability of two classifiers

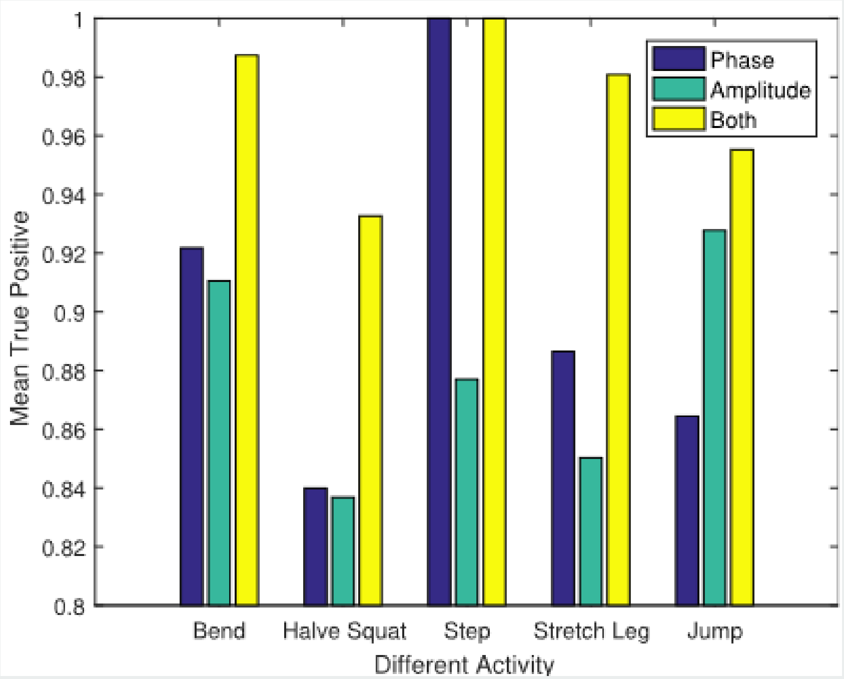


Results (2)

- False positives of different activities



True positives of different activities



- **Accuracy:**
  - **FP** : can be improved to about 0.75% & **TP** : 97.1%

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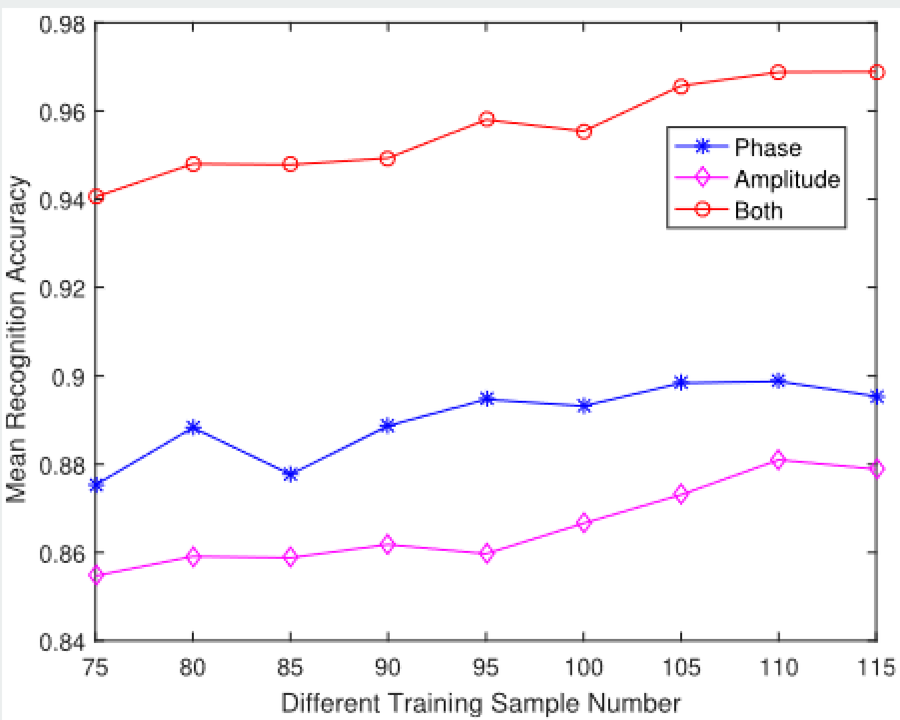
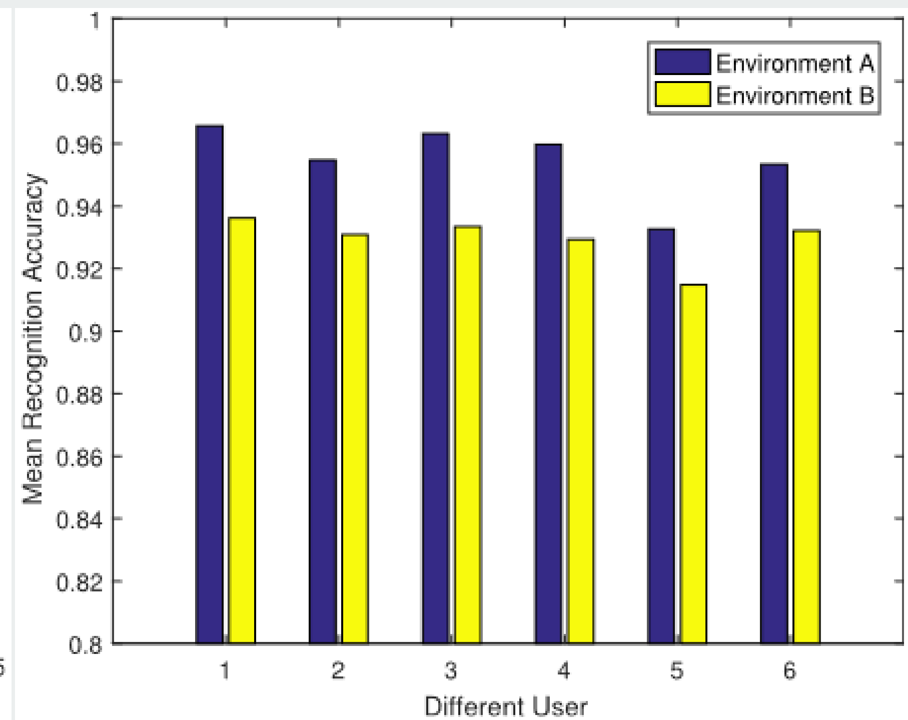
Results (3)

- Different number of training samples

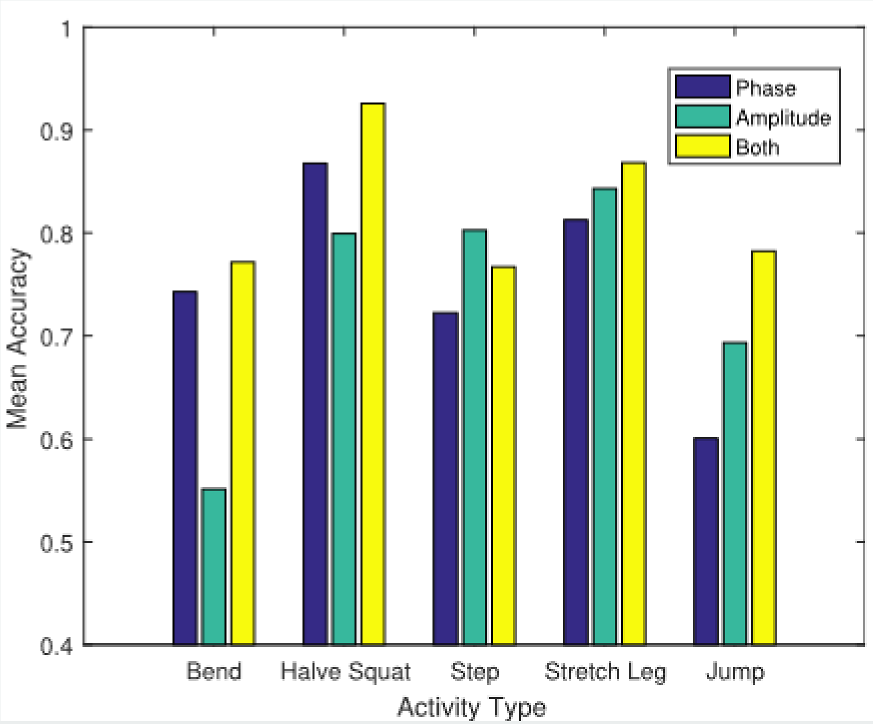


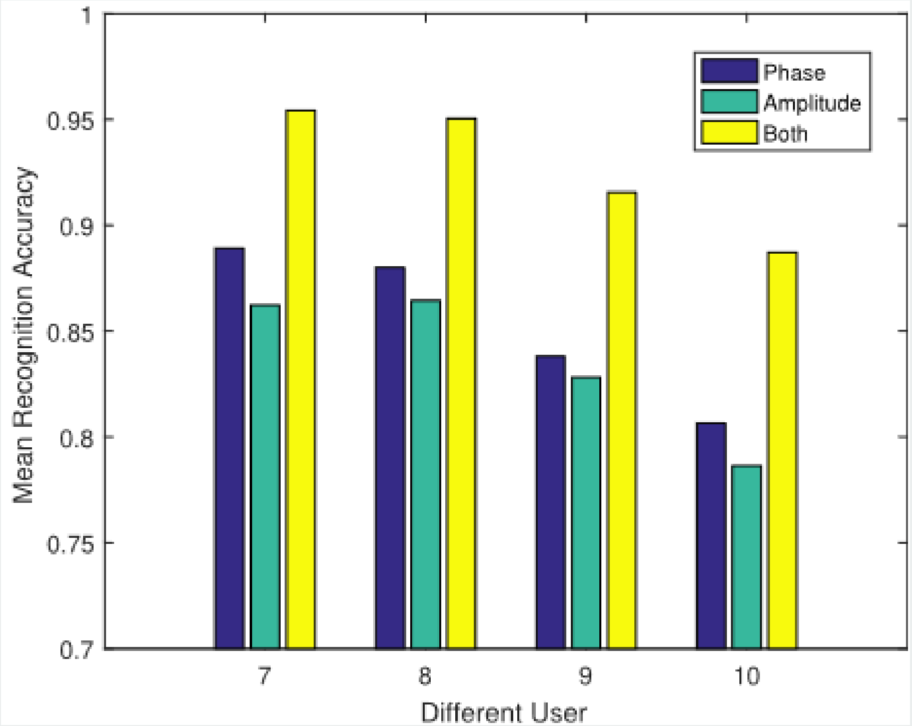
Different environments



Results (4)

- Performance for two users   Performance for users with different age





Limitations

Both the receiver and the laptop are inside the same room with the tester

Most experiments were conducted with only one person each time

- Under both LOS and NLOS environment

Considering the experiments that had more than one person, the accuracy of the system was (significantly) less, ≈ 68%

Summary

- **A WiFi-based indoor activity recognition system**
- Both **amplitude** and **phase** information are being adopted
  - To construct classifiers for extra recognition performance

- The **recognition accuracy** is 96.6% in the LOS environment
- The **accuracy drops**
  - In the NLOS environment (92%)
  - As more people exist in the same room

Thank you!

Questions?