WiFinger: Talk to Your Smart Devices with Finger-grained Gesture[3]

PhD Qualifiers Examination

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Overview

Introduction

WiFi Signals Can Sense People's Location and Activities

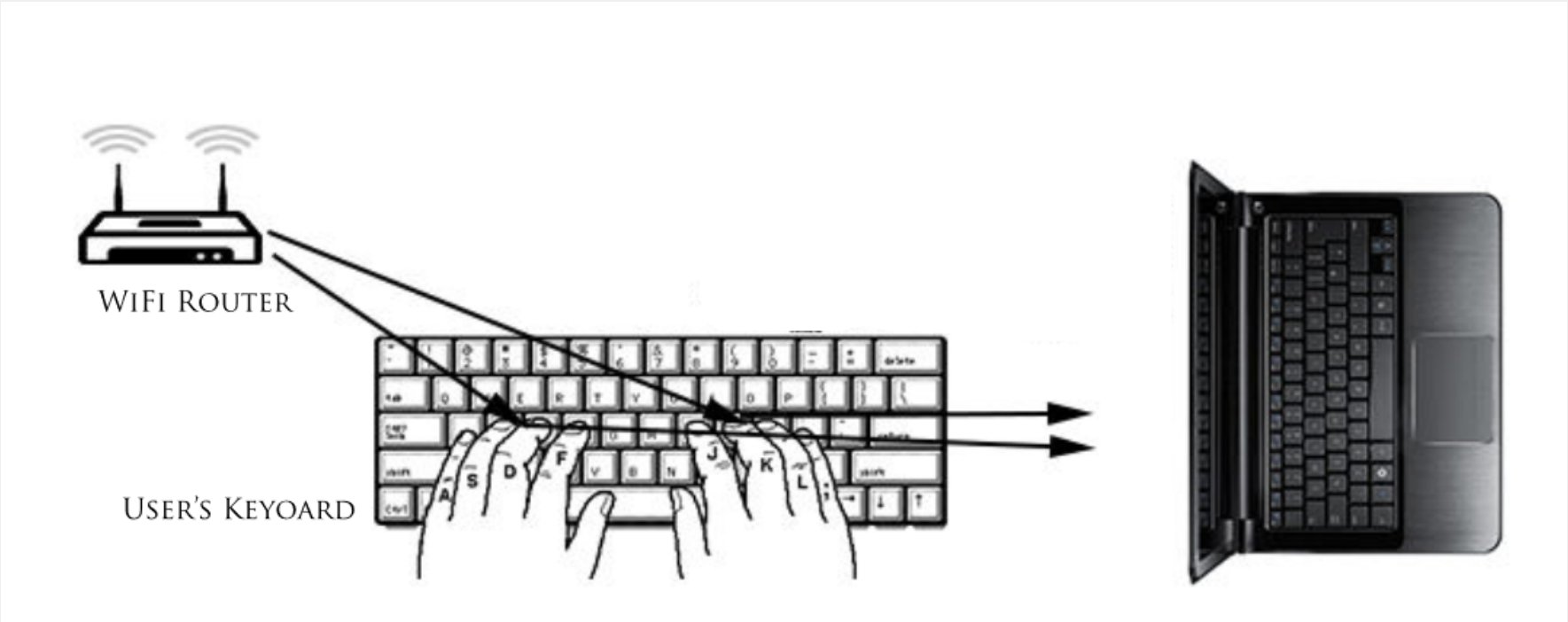


Figure: Detecting keyboard strokes using WiFi [1]

WiFi Signals Can Sense People's Location and Activities

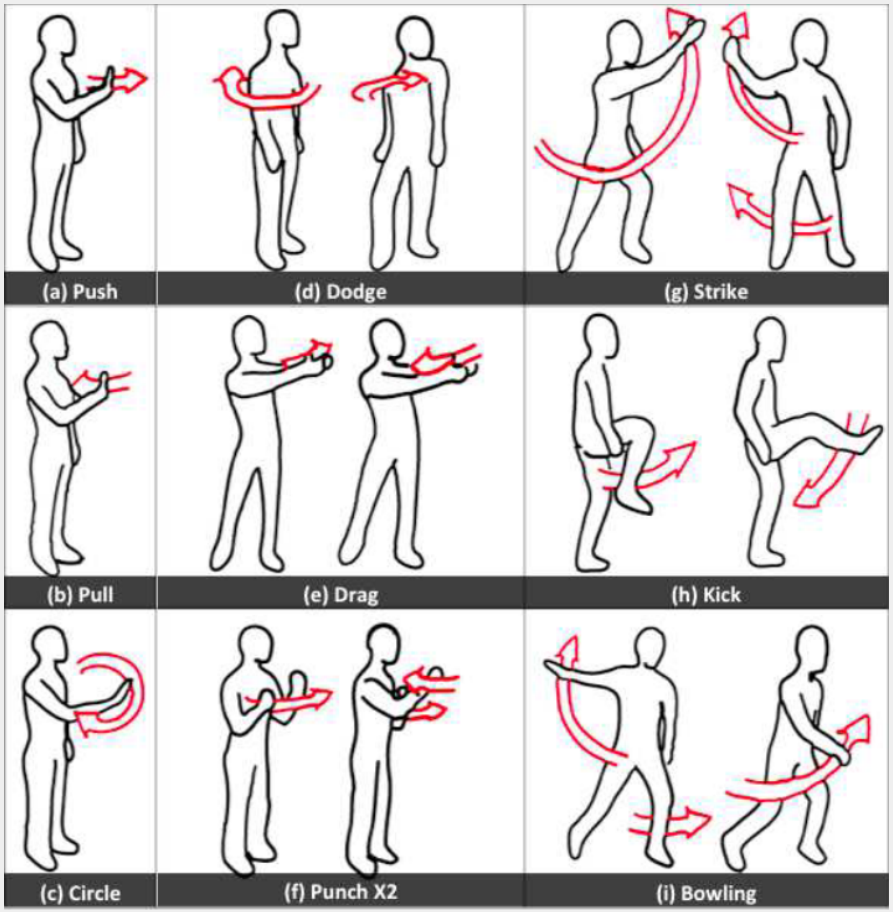


Figure: Detecting gestures using WiFi [4]

Objective

WiFinger is a wireless system that utilizes commercial WiFi devices to achieve human-computer interaction by recognizing people's finger-grained gestures.

Objective

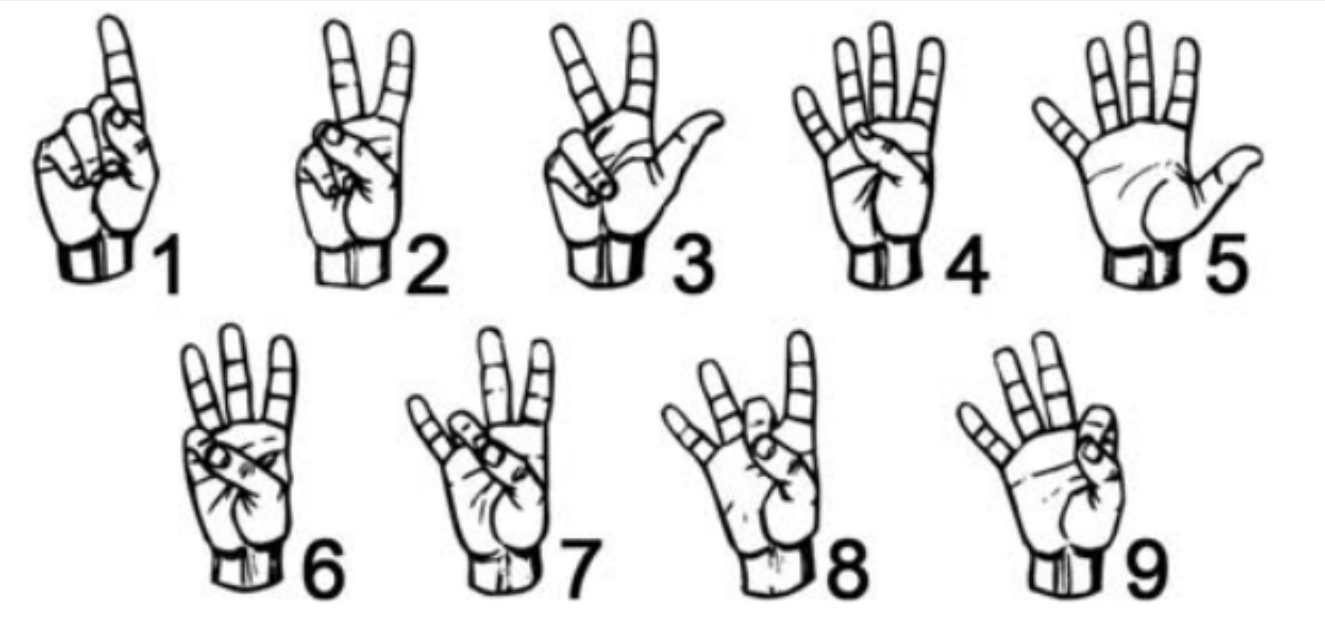


Figure: Parts of finger gestures that WiFinger [3] can detect and recognize

Related Work

Prior (and current) work on gesture detection can be categorized into two groups.

- Device based
  - Audio based
  - Vision based
  - Sensor based
- Device free - Wireless Signal

Received Signal Strength (RSS):
Universal Software Radio Peripheral captures RSS values from WiFi signals [6, 5]. RSS values are not suitable for recognizing fine-grained motions such as gestures in standard American Sign Language (ASL).

Channel State Information (CSI)

- CSI refers to known channel properties of a communication link. The channel between transmitter and receiver comprises of multiple subcarriers.
- is y is the received vector and x is the transmitted vector,

$$y = Hx + n$$

Channel State Information (CSI)

$$y = Hx + n$$

n is the noise vector. H is the channel frequency response. The dimension of H is N_c x N_t x N_r.

N_c: Number of sub carriers. N_t: Number of transmit antennas. N_r: Number of receive antennas.

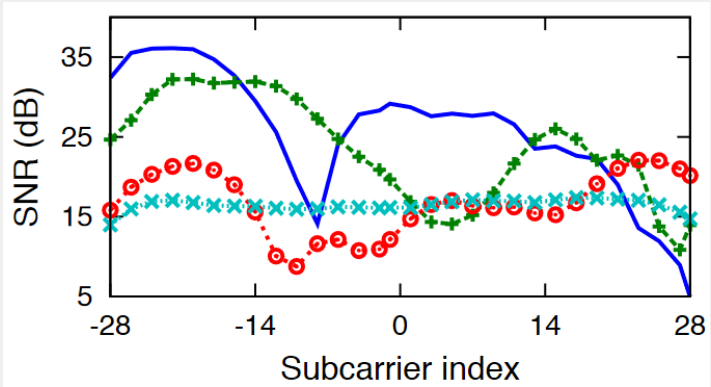


Figure: Subcarrier-level signal strength computed from channel stateinformation for four single-antenna 802.11n links [2].

Approach

Overview

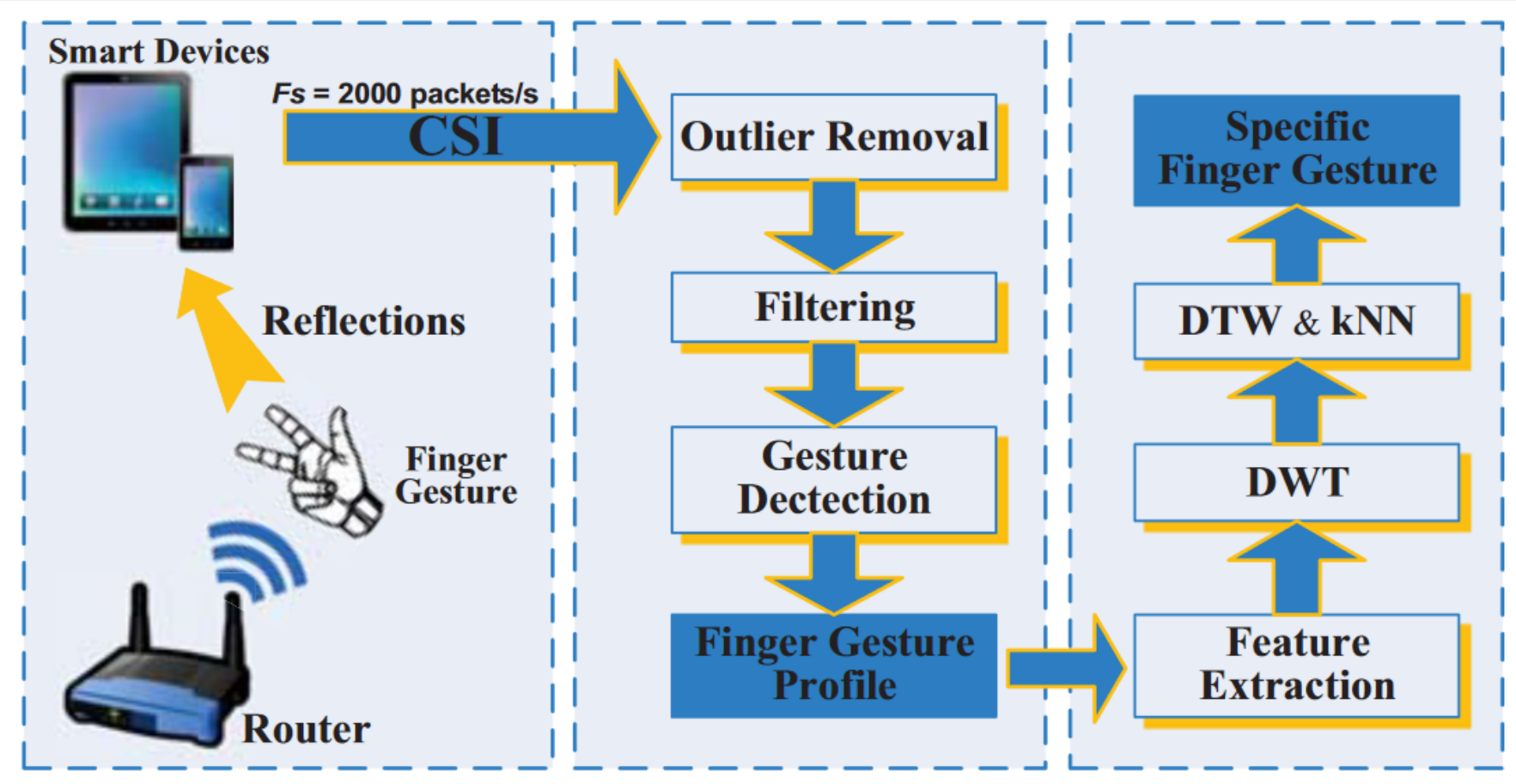


Figure: Framework of WiFinger

Signal Preprocessing

Signal changes caused by finger motions lie at the low end of the frequency spectrum while noise induced by hardware imperfections has a relatively high frequency.

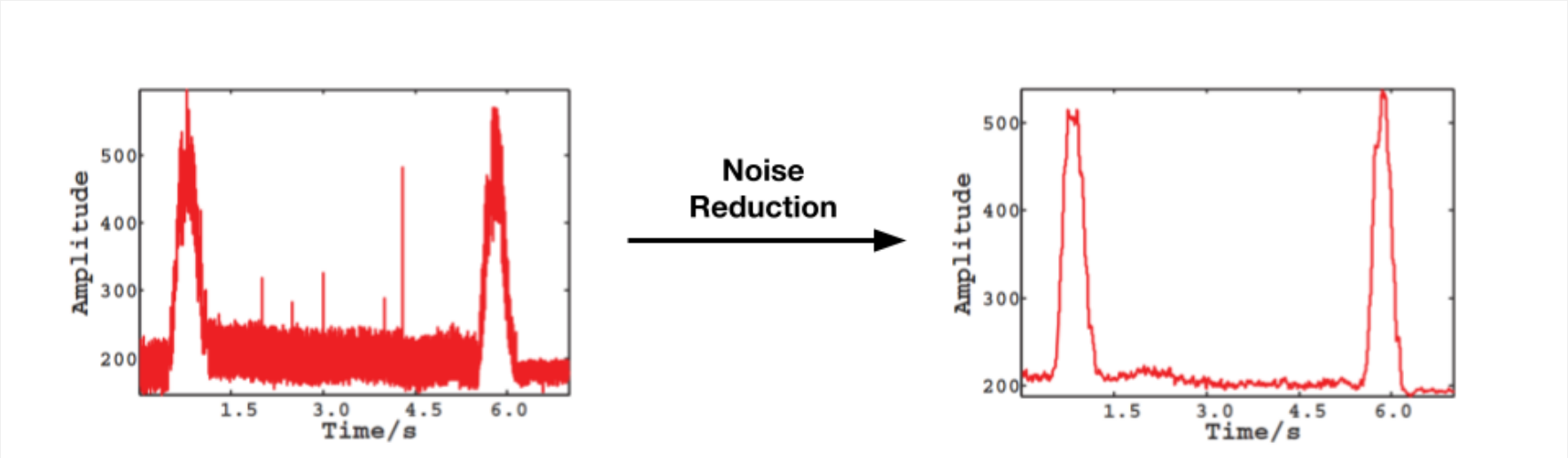
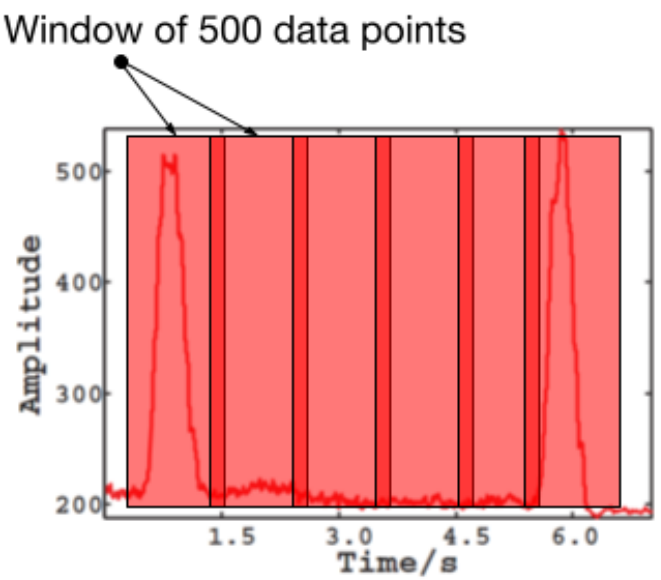


Figure: Noise reduction using low pass filter

Gesture Detection

Preprocessing

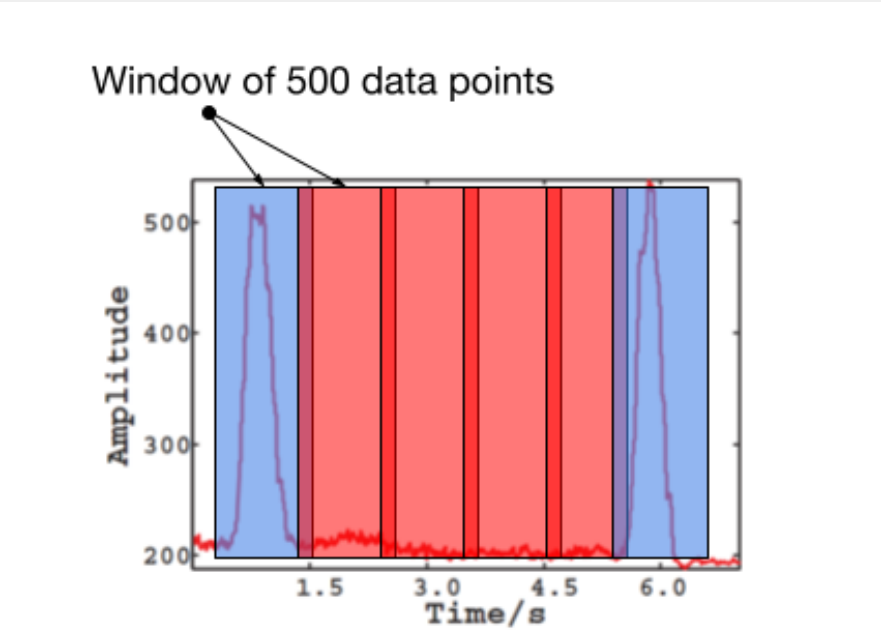
- The CSI stream is cut into bins using a sliding window
- The window size is 500.
- Each bin is a matrix of size 30 x 500 = **M**



Gesture Detection

Correlation Estimation

- WiFinger calculates the correaltion matrix as $\mathbf{M}^T$ x $\mathbf{M}$
- The value of the second eigenvector of the above matrix indicates the presence and absence of a *sign*



Feature Extraction

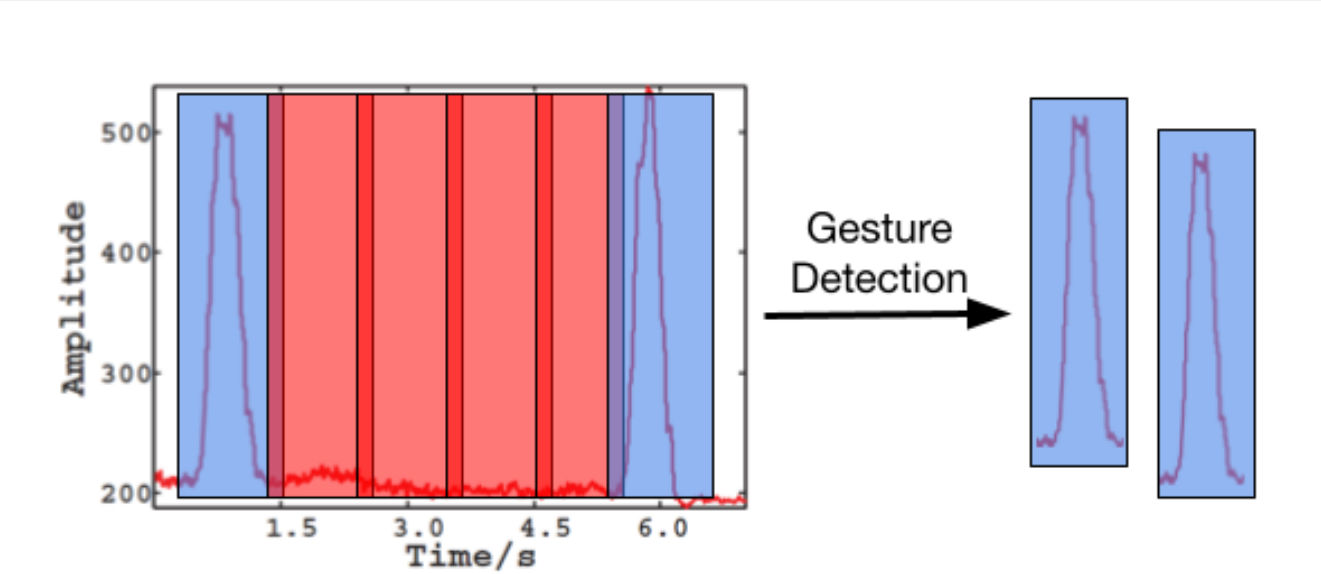


Figure: Gesture Profile Extraction

The profile of a particular sign can be mathematically represented as $\mathbf{P_i} = [H_{t_i^s} \ldots H_{t_i^e}]$

Feature Extraction

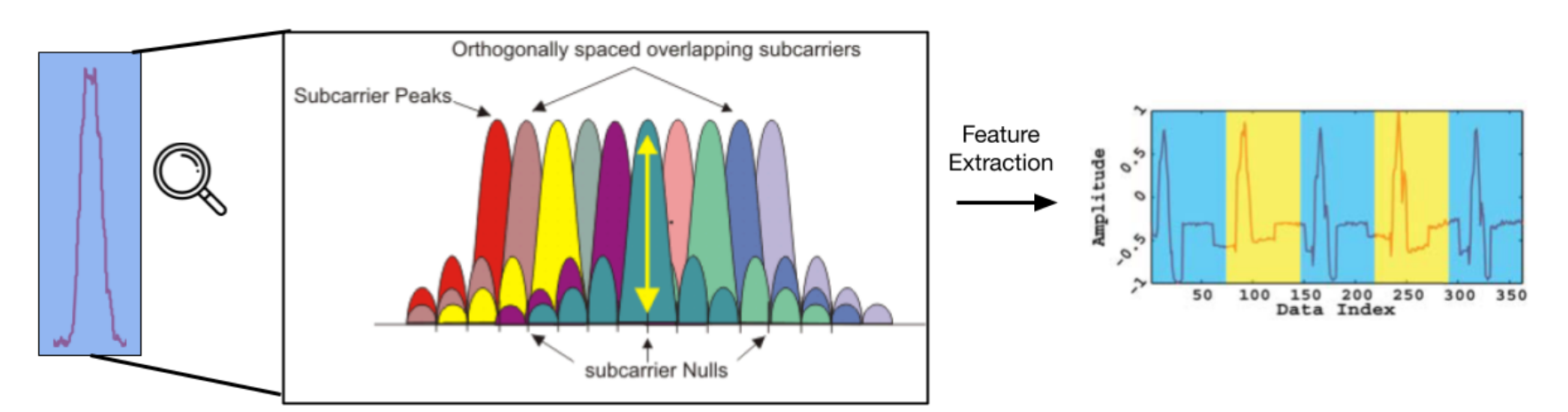


Figure: Gesture Profile Extraction

WiFinger combines 30 subcarriers by averaging every 6 subcarriers and then concatenated them to form a synthetic waveform.

Feature Extraction

WiFinger compresses the feature vectors by utilizing **Discrete Wavelet Transform** (DWT).

- Reduces computational cost compared to Fast Fourier Transform (FFT).
- Preserves both time and frequency domain information.

Classification

- WiFinger utilizes kNN classifier to recognize different finger gestures.
- Feature vector of gestures might not share the same length.

Dynamic Time Wrapping

Dynamic Time Wrapping (DTW) provides intuitive distance between two waveform and can be resilient to signal distortion and shift.

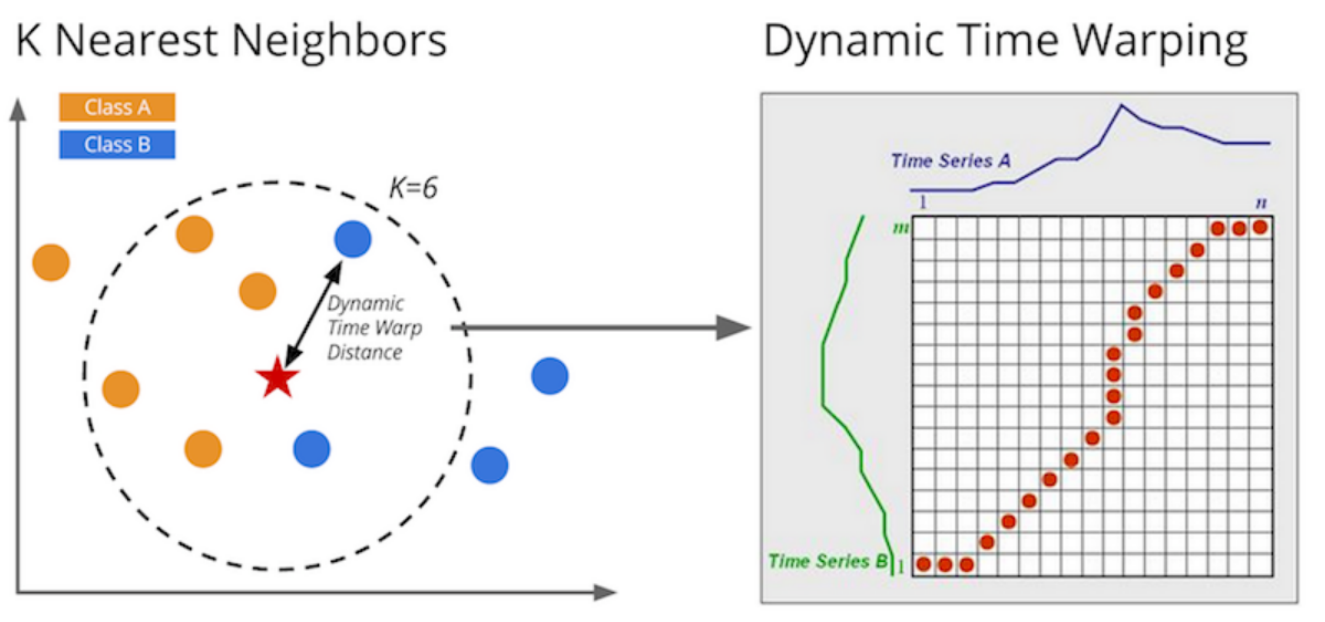


Figure: kNN and kNN with DTW[1]

[1]https://github.com/markdregan/K-Nearest-Neighbors-with-Dynamic-Time-Warping

Evaluation and Result

Implementation

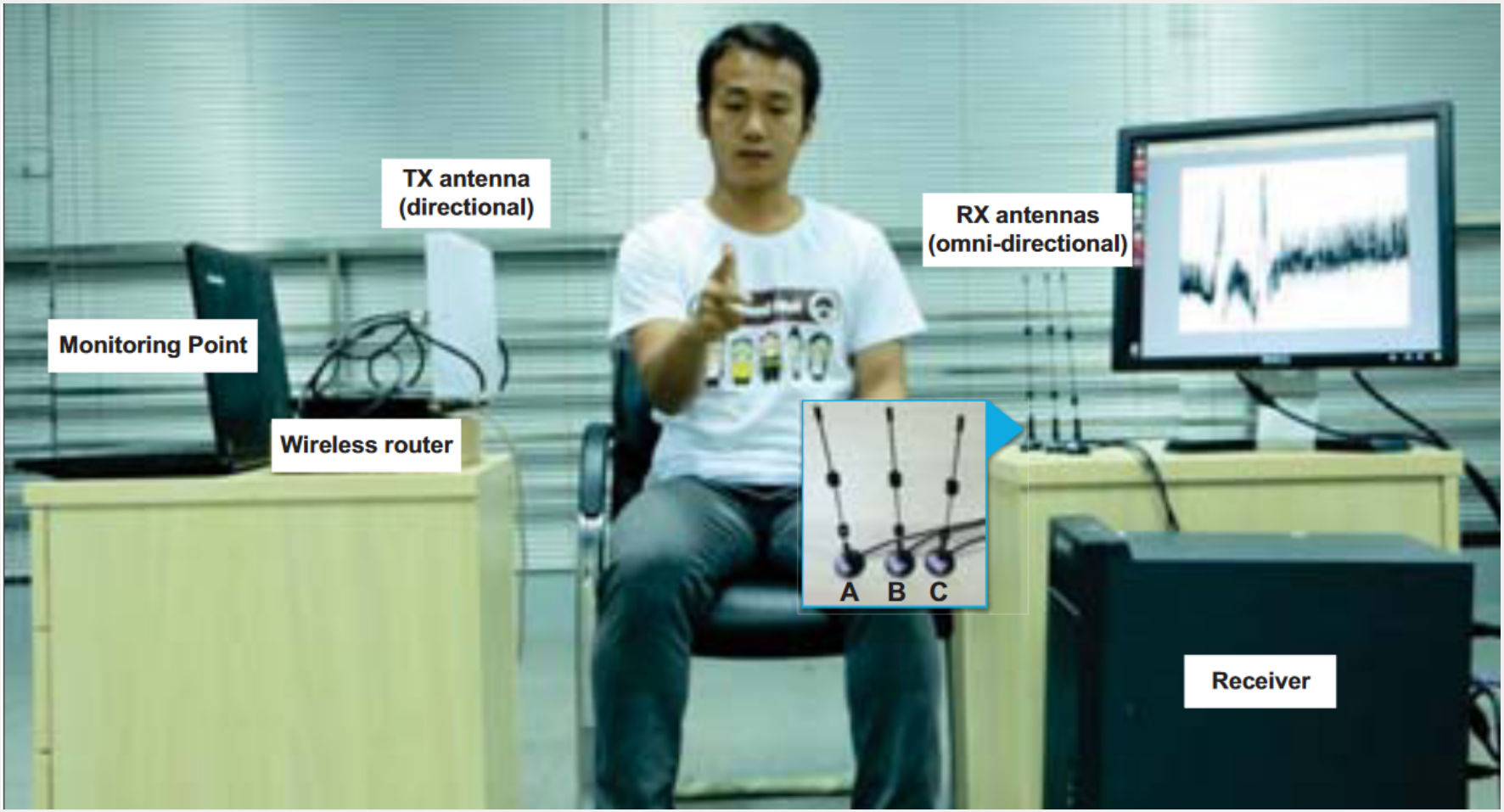


Figure: The experimental setup of WiFinger

Evaluation

- 10 users volunteered for the study.
- 9 users performed each gestures 35 times. One user performed each gesture 70 times.

Result

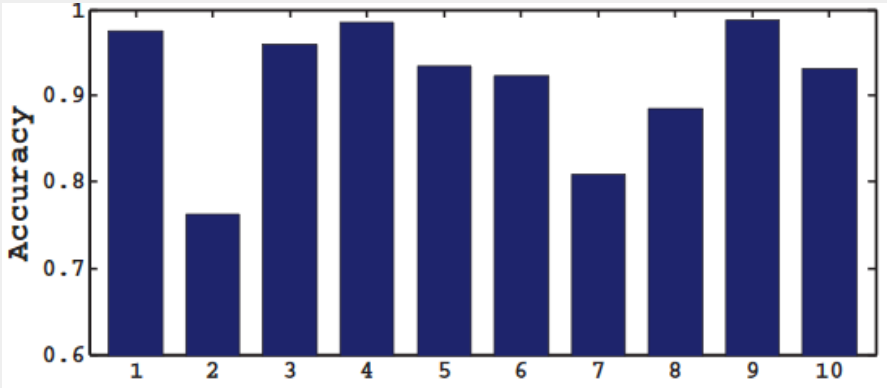


Figure: Finger gesture extraction accuracy per gesture for users 1-10

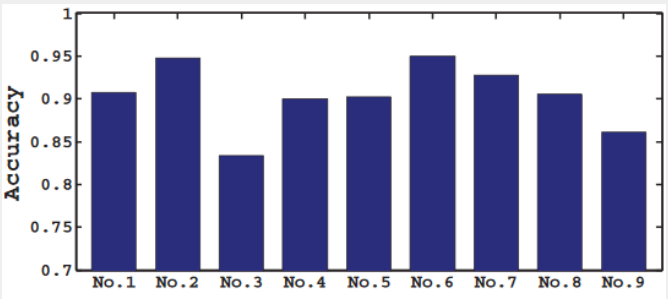


Figure: Recognition accuracy per gesture for users 1-10

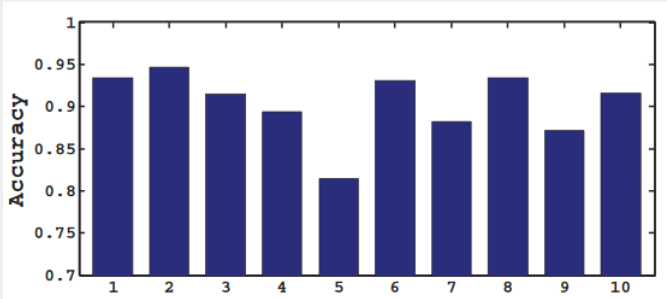


Figure: Finger gesture recognition accuracy per user

Limitations and Summary

Limitations

- Requires line of sigh between transmitter and receiver.
- Presence of human body motion, moving objects and the orientation of transceiver impacts the accuracy.
- An environment full of objects (like chair, table etc) reduces the accuracy due to multipath reflections.
- Cannot be used with crowded WiFi bandwidth. For example, 2.5 GHz band is crowded compared to 5 GHz band.
- User demographics are not mentioned.

Summary

- WiFinger exploits the ubiquitous WiFi signals to sense ginger-grained gestures.
- The novelty of the system is the ability to extract fine-grained information from the CSI.
- WiFinger achieves an average recognition accuracy of 90.4% per user.

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