Translation Resilient Opportunistic WiFi Sensing

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Track 2: Biometrics, Human Analysis and Behavior Understanding, T2.4, 14th January 2021, 12:30 PM (CET)

25th International Conference on Pattern Recognition (ICPR2020)
MiCo Milano Congress Center, ITALY 10 - 15 January 2021

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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 $\rightarrow$ 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
CSI Extraction

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:

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

where $h_{pq}$ is a complex number representing the amplitude and phase between each antenna pair.
Example of CSI signal representation

- No activity
- Sit
- Stand
- Sit
- Stand
- No activity
- Walk
- No activity
- Sit
- Stand
- Sit
- Stand
- No activity
- Stand from floor
- Lie
- Stand from floor
- Lie
- Walk
- Sit
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

<table>
<thead>
<tr>
<th>Activity</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 walking</td>
<td>walking along positions 1-2-3, 4-5-6, 7-8-9, 1-4-7, 2-5-8 and 3-6-9</td>
</tr>
<tr>
<td>2 sitting</td>
<td>sitting on a chair at positions 2,4,5,6,8</td>
</tr>
<tr>
<td>3 standing</td>
<td>standing from a chair at positions 2,4,5,6,8</td>
</tr>
<tr>
<td>4 laying down</td>
<td>laying down on the floor at positions 2,4,5,6,8</td>
</tr>
<tr>
<td>5 standing from floor</td>
<td>standing from the floor at positions 2,4,5,6,8</td>
</tr>
<tr>
<td>6 picking up</td>
<td>picking up objects from the floor at positions 2,4,5,6,8</td>
</tr>
</tbody>
</table>
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

Spectrograms

Convolution + ReLU activation (64 filters, 2x2 kernel size)

Max-pooling (window size =2)

Fully-connected layers

Output layer

Walk
Sit
Stand
Lay down
Stand from floor
Pickup

(64 filters (32 filters + ReLU) + ReLU)

Softmax activation
Experimental Results – Activity Classification Accuracy

Classification Performance for Each Layout.

<table>
<thead>
<tr>
<th>Layout</th>
<th>Precision</th>
<th>Recall</th>
<th>F1-score</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>90.0%</td>
<td>89.5%</td>
<td>89.1%</td>
<td>90.8%</td>
</tr>
<tr>
<td>2</td>
<td>73.9%</td>
<td>74.4%</td>
<td>73.8%</td>
<td>75.7%</td>
</tr>
<tr>
<td>3</td>
<td>62.6%</td>
<td>61.9%</td>
<td>61.0%</td>
<td>61.5%</td>
</tr>
<tr>
<td>1, 2, 3</td>
<td>67.5%</td>
<td>66.3%</td>
<td>66.0%</td>
<td>67.3%</td>
</tr>
</tbody>
</table>

Layout 1

Normalized confusion matrix

Combined Layouts 1, 2, 3

Normalized confusion matrix
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.

![Bar Chart](image)
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