Demo: Device-free Activity Monitoring Through Real-time Analysis on Prevalent WiFi Signals

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***Abstract*—In this demo, we present a device-free activity monitoring platform exploiting the prevalent WiFi signals to enable real-time activity recognition and user identification in indoor environments. It supports a broad array of real-world applications, such as senior assistance services, fitness tracking, and building surveillance. In particular, the proposed platform takes advantage of channel state information (CSI), which is sensitive to environmental changes introduced by human body movements. To enable immediate response of the platform, we design a real-time mechanism that continuously monitors the WiFi signals and promptly analyzes the CSI readings when the human activity is detected. For each detected activity, we extract representative features from CSI, and exploit a deep neural network (DNN) based scheme to accurately identify the activity type/user identity. Our experimental results demonstrate that the proposed platform could perform activity/user identification with high accuracy while offering low latency.**

***Index Terms*—Activity Monitoring, WiFi, Channel State Information**

I. Introduction

There exists a broad range of smart applications in indoor environments that could benefit from immediate recognition of the user's activity and identity. By monitoring a user's activity in real-time, it is possible to enable senior assistance services, fitness tracking, and building surveillance that require prompt response. Real-time activity monitoring could also facilitate emerging personalized services in smart environments, involving adjusting room temperature/lighting conditions and recommending TV contents.

Existing techniques for activity monitoring either rely on attaching wearable devices to the user's body or deploying dedicated sensors [1], [2] in the environment. These solutions require either inconvenient sensor attachment or significant infrastructure installation. In this paper, we design a platform that could facilitate device-free activity recognition/user identification through real-time sensing of human activities.

The prevalence of WiFi traffics generated by smart devices and appliances (laptop, smart refrigerator, smart microwave oven and smart printer), can be exploited to capture the environmental changes caused by the user's activities. Furthermore, even for the same activity, different users exhibit distinctive impacts of wireless channel due to their unique physiological (e.g., body shape, height) and behavioral characteristics. In particular, the fine-grained channel state information (CSI) [3] embedded in WiFi measurements could precisely describe the propagation of wireless signals between a pair of transmitting and receiving devices, making it possible to measure environmental changes introduced by human body movements. We are thus motivated to reuse the CSI of WiFi signals to monitor human activity and further enable real-time applications.

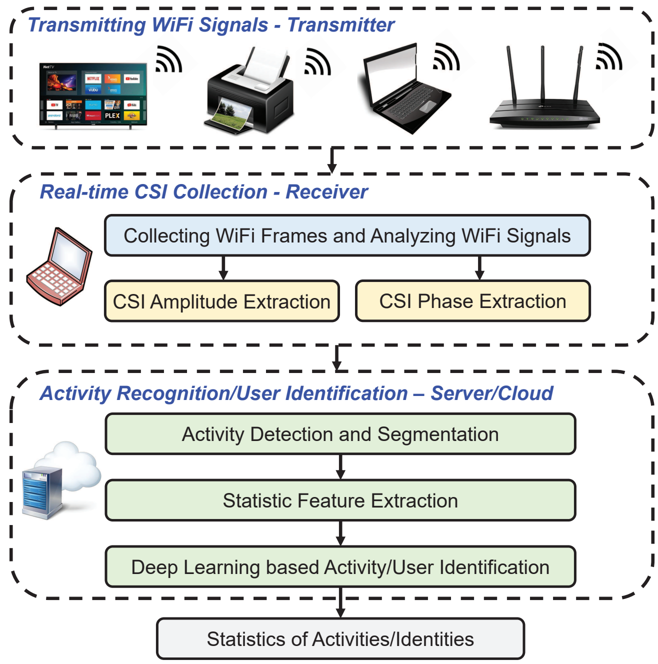

Fig. 1. The architecture of our platform.

II. System Design

The basic idea of our platform is to capture distinct WiFi fingerprints caused by human activities and unique physiological/behavioral characteristics of individual users. As illustrated in Figure 1, our platform exploits existing WiFi enabled devices (e.g., smart TV, printer) as transmitters and a laptop as the receiver for capturing the WiFi signals. After receiving the WiFi signals, the system performs *Real-time CSI Collection* to obtain a sequence of WiFi frames and extract embedded CSI measurements, including amplitude and phase information.

Next, we perform *Activity Detection and Segmentation* based on examining the CSI variation, which is sensitive to

Fig. 2. Demonstration setup.

the presence of human activities. The system then extract 6 statistic features to capture unique characteristics of each type of human activity or individual user. Given the extracted CSI features, a deep neural network (DNN) based model is developed to learn high-level abstractions for activity recognition and user identification.

Real Time CSI Collection. The fine-grained CSI describes how a wireless signal propagates between a pair of transmitting and receiving devices. It capture human motion in terms of wireless interferences, e.g., scattering, fading, and multipath. Without loss of generality, the CSI measurements of a WiFi frame could be defined as:

$$H_i = |H_i| e^{j \angle H_i}, \tag{1}$$

where $|H_i|$ and $\angle H_i$ denote the amplitude and phase response, respectively. By continuously capturing WiFi frames and extracting embedded CSI, our platform could provide real-time activity monitoring to facilitate activity recognition and user identification. In particular, the platform continuously monitors WiFi signals with a laptop and sends the raw WiFi frames to the server computer for CSI extraction.

Activity Recognition/User Identification. The human activities could lead to the variations in WiFi signals, resulting in changing CSI values. In this work, we first apply a 4-second sliding time window with a step size of $0.2 second$ on the time-series CSI amplitude and calculate variance of each window. The CSI segmentation process is initiated when the variance is over an empirical threshold. Then, our platform records CSI measurements of the window as a sequence of CSI clips and terminate the segmentation process when the activity is completed.

For each CSI clip, one set of features respect to each subcarrier is extracted. In particular, to capture both human activity/identity uniqueness, we extract 6 statistics features respected to CSI amplitude including mean, median, maximum, minimum, range, standard deviation. In total, 180 features are extracted from the 30 subcarrier groups. Given the extracted features, our platform performs activity recognition and human identification by building a DNN model based on convolutional neural network (CNN) with a SoftMax classifier. Our current activity recognition and human identification mechanisms are still based on offline processing and we will make them real-time in the future work.

III. Hardware and Demonstration Setup

We conduct the experiment in a 802.11n WiFi network with a WiFi router (TP-Link N750) and a laptop (i.e., Dell E6430). The laptop runs Ubuntu 14.04 LTS with 4.2 kernel and is equipped with 802.11n WiFi NIC (i.e., Intel 5300 NIC), which provides CSI measurements of 30 subcarrier groups [4]. The packet transmission rate is set to $100 pkts/s$. To enable real-time activity recognition and user identification, the received WiFi packets are sent to and processed with a server computer, Dell Precision 7910 with a powerful graphics card (i.e., NVIDIA Quadro GV100). To enable real-time process, we implement the data transmission process with C language and scoket API. The data segmentation and activity/user identification are based on offline processing with Python 3.7 and Tensorflow, an open-source library designed for deep learning. In the demonstration, as shown in Figure 2, we need two tables to hold the WiFi router and the laptop for CSI collection.

IV. Acknowledgment

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