Demo: A Training-Free Contactless Human Vitality Monitoring Platform Using Commodity Wi-Fi Devices

Yue Zhang
Peking University
Haidian, Beijing 100871, China
zy.zhangyue@pku.edu.cn

Jie Xiong
University of Massachusetts, Amherst
Amherst, MA 01003, USA
jxiong@cs.umass.edu

Xiang Li
Peking University
Haidian, Beijing 100871, China
lixiang13@pku.edu.cn

Daqing Zhang
Peking University
Haidian, Beijing 100871, China
dqzhang@sei.pku.edu.cn

Shengjie Li
Peking University
Haidian, Beijing 100871, China
lishengjie@pku.edu.cn

UbiComp/ISWC '18 Adjunct, October 8-12, 2018, Singapore, Singapore

ACM ISBN 978-1-4503-5966-5/18/10.
https://doi.org/10.1145/3267305.3267613

Abstract
Human vitality information is pivotal to many sensing applications. By vitality, we mean the status of a human target in a multi-room environment: whether he/she is still and which room he/she is located in. Continuous monitoring of human vitality helps us obtain important high-level contexts like one's emotions, living habits, and physical conditions. Unlike the most existing solutions that require human efforts in offline training or calibration, in this demo, we present WiVit, a training-free contactless Wi-Fi based sensing platform that can capture human vitality information in 7*24 hours. In typical indoor environments, WiVit can achieve 98% accuracy of vitality detection and nearly 100% accuracy of area detection.

Author Keywords
Wi-Fi; Channel State Information(CSI); Training-Free; Contactless; Human Vitality

ACM Classification Keywords
H.5.m [Information interfaces and presentation (e.g., HCI)]: Miscellaneous

Introduction
Contactless sensing has attracted a lot of attentions in recent years. Compared with other contactless sensing technologies like camera [6, 1] and ultrasound [5, 11], Wi-Fi

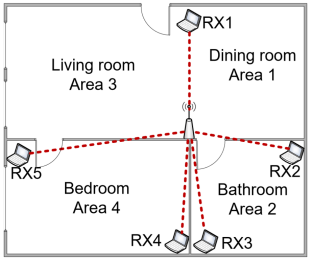

Figure 1: An example of WiVit platform deployment.

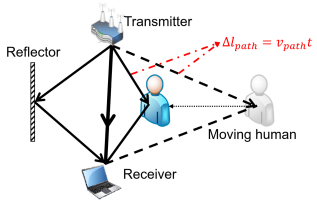

Figure 2: The human reflected path length will change when the human target is moving.

based technologies have their congenital advantages in its ubiquity, privacy protection and larger area coverage. Among the various Wi-Fi based contactless human sensing applications developed in recent years [4, 10, 3, 8, 9], human vitality information plays an important role in most of these applications.

Unlike the most existing solutions that require human efforts in offline training or calibration [3, 7], in this demo, we present WiVit, a contactless Wi-Fi based human vitality monitoring platform that can work without any human intervention. WiVit utilizes the access point and the Wi-Fi enabled devices in a typical home environment to form transceiver pairs, and further utilizes these transceiver pairs to divide a large sensing area into smaller sub-areas. These transceiver pairs serve as the sensing boundaries between two adjacent sub-areas. Figure 1 shows an example of WiVit platform deployment in a typical indoor environment. By making use of the phase change caused by human movement in CSI in each receiver, WiVit can accurately detect human movement and estimate the area a person is located in. Based on our extensive experiments in three typical indoor environments, the accuracy of vitality detection is higher than 98% and the area detection accuracy is close to 100%.

Platform Overview

WiVit is a contactless and non-intrusive human vitality monitoring platform. It only leverages CSI samples available at commodity Wi-Fi devices and does not require any human intervention. Following is a brief description of the key steps of WiVit platform:

(1) The first step is to detect whether the target is still or non-still with Wi-Fi CSI readings. If the target is non-still, WiVit will record the path changing speed spectrum and calculate the changing speed of the human-reflected path.

(2) When the target is non-still, WiVit calculates the approximate human speed and determine whether the target is walking or just performing in-place activities. WiVit then detects which area the target is located in based on the estimated path changing speed.

(3) WiVit records human target's current activeness status(still or non-still), area status, approximate human speed and the path changing speed spectrum on each receiver as the target's current vitality information. Based on these vitality information, we can build more Wi-Fi based contactless indoor human sensing applications on the platform, such as activity recognition.

Key Ideas

WiVit platform is built based on two key ideas:

(i) The signal at the receiver is the superposition of signals from all paths. Among the signals received, there is one that we care about most: the one that is directly reflected by human body, which we call the human-reflected path signal. Human movements cause changes in the length of this path, as shown in Figure 2, and thus cause phase changes in CSI. By capturing this CSI changes, we can detect human activeness, then estimate the changing speed of this path and further, calculate the human movement speed.

(ii) For each pair of transceivers, when the human target is moving, the human-reflected path changing speed is not only related to the target's moving speed, but also to the target's position. So with multiple transceiver pairs, we can accurately estimate which area the target is located in.

By combining these two key ideas, WiVit could achieve good performance.

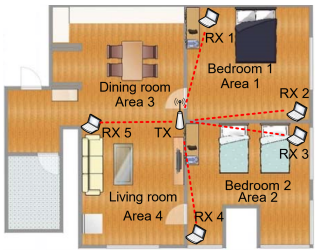

Figure 3: An example of WiVit platform deployment.

Environment Setup

We conduct WiVit demonstration in a real-life multi-room smart home environment. The smart home environment has four rooms: 1 dining room, 1 living room and 2 bedrooms. One transmitter and five receivers are placed in this environment to form five transceiver pairs. These transceiver pairs form different straight lines which function as the boundaries of the four sensing areas. Figure 3 shows the layout of the smart home environment and the positions of these transceivers. It is worth mentioning that the four sensing areas, which are divided by five transceiver pairs, each corresponds to an individual room.

The transmitter and receivers are miniPCs equipped with cheap off-the-shelf Intel 5300 Wi-Fi cards, and each receiver is attached with two antennas. CSI tool [2] is installed on each miniPC to collect the CSI samples at the rate of 200Hz. WiVit works on 5.56GHz band and uses a 20MHz channel.

Demonstration Process

During demonstration, a participant could do any activity in four areas freely, such as walking, sleeping, exercising, sweeping the floor and watching TV, etc. Or he/she could just keep still. While the participant is conducting activities, WiVit will track his/her status, and capture the human vitality information, including when the participant is still, which area the participant is located in and how fast the participant is moving. Meanwhile, WiVit will display the captured information in the user interface in real time.

WiVit's user interface, as shown in Figure 4, is composed of 2 major parts:(i) the ground truth information is captured by cameras, and is displayed at the bottom of the interface. (ii) the human vitality information, including area-level location, activeness status and human speed, is displayed at the top

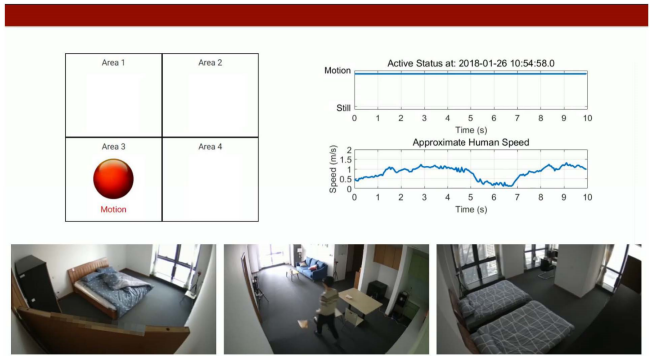

Figure 4: Graphical user interface of WiVit platform

of the interface. If the participant enters a certain area, say area 3, a circle will appear in this area to highlight his/her presence, and the color of the circle indicates his/her status: blue for still and red for non-still.

Summary

In this demo, we present a training-free contactless human vitality sensing platform called WiVit. It is hosted on cheap commodity Wi-Fi devices to accurately capture human vitality information in 7*24 hours without any human effort in offline training or calibration, moving one step further towards real life adoptions.

Acknowledgements

We thank all the volunteers who participate in this work and the support of the NSFC Grant No. 61572048.

REFERENCES

1. Mohamed Eldib, Francis Deboeverie, Wilfried Philips, and Hamid Aghajan. 2016. Behavior Analysis for Elderly Care Using A Network of Low- Resolution Visual Sensors. J. Electron. Imaging 25, 4 (Mar. 2016),

17.

2. Daniel Halperin, Wenjun Hu, Anmol Sheth, and David Wetherall. 2011. Tool Release: Gathering 802.11N Traces with Channel State Information. SIGCOMM Comput. Commun. Rev. 41,1 (Jan. 2011), 53–53.

3. Shengjie Li, Xiang Li, Kai Niu, Hao Wang, Yue Zhang, and Daqing Zhang. 2017. AR-Alarm: An Adaptive and Robust Intrusion Detection System Leveraging CSI from Commodity Wi-Fi. In *International Conference on Smart Homes and Health Telematic (ICOST '17)*. Springer International Publishing, 211–223.

4. Xiang Li, Shengjie Li, Daqing Zhang, Jie Xiong, Yasha Wang, and Hong Mei. 2016. Dynamic-MUSIC: Accurate Device-free Indoor Localization. In *Proceedings of the 2016 ACM International Joint Conference on Pervasive and Ubiquitous Computing (UbiComp '16)*. ACM, New York, NY, USA, 196–207.

5. Wenguang Mao, Jian He, and Lili Qiu. 2016. CAT: High-precision Acoustic Motion Tracking. In *Proceedings of the 22nd Annual International Conference on Mobile Computing and Networking (MobiCom '16)*. ACM, New York, NY, USA, 69–81.

6. Katsunori Ohnishi, Atsushi Kanehira, Asako Kanezaki, and Tatsuya Harada. 2016. Recognizing Activities of Daily Living With a Wrist-Mounted Camera. In *The IEEE Conference on Computer Vision and Pattern Recognition (CVPR '16)*. 3103–3111.

7. Kun Qian, Chenshu Wu, Zheng Yang, Yunhao Liu, and Zimu Zhou. 2014. PADS: Passive detection of moving targets with dynamic speed using PHY layer information. In *2014 20th IEEE International Conference on Parallel and Distributed Systems (ICPADS)*. 1–8.

8. Hao Wang, Daqing Zhang, Junyi Ma, Yasha Wang, Yuxiang Wang, Dan Wu, Tao Gu, , and Bing Xie. 2016. Human Respiration Detection with Commodity Wifi Devices: Do User Location and Body Orientation Matter?. In *Proceedings of the 2016 ACM International Joint Conference on Pervasive and Ubiquitous Computing (UbiComp '16)*. ACM, New York, NY, USA, 25–36.

9. Hao Wang, Daqing Zhang, Yasha Wang, Junyi Ma, Yuxiang Wang, and Shengjie Li. 2017. RT-Fall: A Real-Time and Contactless Fall Detection System with Commodity WiFi Devices. IEEE Transactions on Mobile Computing 16, 2 (Feb 2017), 511–526.

10. Ju Wang, Hongbo Jiang, Jie Xiong, Kyle Jamieson, Xiaojiang Chen, Dingyi Fang, and Binbin Xie. 2016. LiFS: Low Human-effort, Device-free Localization with Fine-grained Subcarrier Information. In *Proceedings of the 22nd Annual International Confer- ence on Mobile Computing and Networking (MobiCom '16)*. ACM, New York, NY, USA, 243–256.

11. Wei Wang, Alex X. Liu, and Ke Sun. 2016. Device-free Gesture Tracking Using Acoustic Signals. In *Proceedings of the 22Nd Annual International Conference on Mobile Computing and Networking (MobiCom '16)*. ACM, New York, NY, USA, 82–94.