

**DEVICE-FREE WIFI SENSING FOR HUMAN
ACTIVITY RECOGNITION**

by
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ABSTRACT

Human activity recognition (HAR) using WiFi signals (WiFi-based HAR) has drawn considerable interest from the research community. In contrast to traditional device-based sensing techniques, WiFi-based HAR possesses several advantages, including convenience, wide availability, and privacy protection, making it an attractive sensing solution for a wide range of applications in smart home, health care, and intelligent monitoring.

Recently, applying deep learning (DL) to WiFi-based HAR has received strong research interest. Assisted by signal processing techniques, DL-based HAR methods are able to automatically extract deep features from input signals, contributing to successful recognitions. Despite its effectiveness in improving recognition performance, DL-based HAR methods suffer from several inherent drawbacks. First, feature extraction is a challenging task that always bottlenecks the recognition performance. Second, DL-based HAR requires a large number of training examples from the testing/targeted environment or/and previously seen environments (PSEs) to train the corresponding DL architectures. When the number of required samples is not sufficient, the sensing performance will drop dramatically. Third, the trained model in one environment cannot be directly applied to another environment without additional effort.

My PhD thesis aims to provide novel solutions to the above WiFi-based HAR issues. Specifically, to extract effective features, we propose two advanced methods together with leveraging the property of DL architectures to enhance the quality of input signals of DL networks and extracted repre-

sentative features. For a reliable recognition with limited training samples, we propose a novel HAR scheme by developing innovative signal processing methods and exploring the characteristics of one-shot learning to reduce the number of required training samples. The proposed HAR scheme is able to accomplish successful recognitions when both the number of PSEs and the amount of samples from the testing environment are quite limited (e.g., one PSE and at the minimum one sample for each activity from the testing environment). To achieve environmental robustness, we propose two novel signal processing algorithms and leverage the features of the matching network. The proposed models are trained once and can be directly applied to various new/testing environments for reliable recognitions without requiring an additional retraining process.

CERTIFICATE OF ORIGINAL AUTHORSHIP

I, ZHENGUO SHI, declare that this thesis, is submitted in fulfilment of the requirements for the award of DOCTOR OF PHILOSOPHY, in the Faculty of Engineering and Information Technology at the University of Technology Sydney.

This thesis is wholly my own work unless otherwise reference or acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis.

This document has not been submitted for qualifications at any other academic institution.

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List of Publications

Journal Publications

- **Zhenguo Shi**, Andrew Zhang, Richard Xu, Qingqing Cheng, Environment-Robust Device-free Human Activity Recognition with Channel-State-Information Enhancement and One-Shot Learning, in IEEE Transactions on Mobile Computing (TMC), doi: 10.1109/TMC.2020.3012433. (Corresponding to Chapter 4)
- **Zhenguo Shi**, Qingqing Cheng, Andrew Zhang, Richard Xu Environment-independent WiFi-based Human Activity Recognition using Enhanced CSI and Deep Learning under review in IEEE Internet of Things Journal (IoT). (Corresponding to Chapter 5)

Conference Publications

- **Zhenguo Shi**, Andrew Zhang, Richard Xu and Gengfa Fang, Human activity recognition using deep learning networks with enhanced channel state information, in 2018 IEEE Globecom Workshops (GC Workshops), Dec 2018, pp. 16. (Corresponding to Chapter 3)
- **Zhenguo Shi**, Andrew Zhang, Richard Xu, Qingqing Cheng, "WiFi-Based Activity Recognition using Activity Filter and Enhanced Correlation with

Deep Learning,” 2020 IEEE International Conference on Communications Workshops (ICC Workshops), Dublin, Ireland, 2020. (Corresponding to Chapter 3)

- **Zhenguo Shi**, Andrew Zhang, Richard Xu, Qingqing Cheng “Deep learning networks for human activity recognition with CSI correlation feature extraction”, in IEEE International Conference on Communications, ICC 2019. (Corresponding to Chapter 4)
- **Zhenguo Shi**, Andrew Zhang, Richard Xu, Qingqing Cheng, Towards Environment-independent Human Activity Recognition using Deep Learning and Enhanced CSI, accepted in IEEE Global Communications Conference (GLOBECOM), 2020. (Corresponding to Chapter 5)

Patent

- Andrew Zhang, Richard Xu and **Zhenguo Shi**. A System and method for event recognition. Under review in Hong Kong Short Term Patent, Application No. 19129029.5

Other Journal Publications

- Qingqing Cheng, **Zhenguo Shi**, Diep N. Nguyen and Eryk Dutkiewicz, Sensing ofdm signal: A deep learning approach, in IEEE Transactions on Communications (TCOM), 2019.
- **Zhenguo Shi**, Zhilu Wu, Zhendong Yin, Zhutian Yang, and Qingqing Cheng. Novel Markov channel predictors for interference alignment in cognitive radio network. *Wireless Netw* 24, 1915-1925 (2018).

Other Conference Publications

- Qingqing Cheng, **Zhenguo Shi**, Jinhong Yuan, Spectrum Sensing in Full-Duplex OFDM Systems using One-Shot Learning in IEEE International Conference on Communications, ICC 2021.
- Qingqing Cheng, **Zhenguo Shi**, Diep N. Nguyen, Eryk Dutkiewicz, “Non-cooperative OFDM Spectrum Sensing Using Deep Learning”, International Conference on Computing, Networking and Communications, ICNC 2020.
- Qingqing Cheng, **Zhenguo Shi**, Diep N. Nguyen, Eryk Dutkiewicz, “An OFDM Sensing Algorithm in Full-Duplex Systems with Self-Interference and Carrier Frequency Offset”, in IEEE Global Communications Conference (GLOBECOM), 2019.

