Demo Abstract: Technology-agnostic Approach to RF based Human Activity Recognition

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***Abstract*—Human activity recognition (HAR), as an essential component of many emerging smart applications, has attracted an increasing interest in recent years. Various radio-frequency (RF) sensing technologies, such as Radio-Frequency Identification (RFID), WiFi, and RF radar, have been utilized for developing non-invasive HAR systems. However, most of the RF based HAR solutions are closely designed for the specific, chosen RF technology, which incurs a significant barrier for the wide deployment of such systems. In this demo, we present a *t*echnology-*a*gnostic approach for *RF*-based HAR, termed TARF, which aims to overcome such constraints and perform HAR with various RF sensing technologies.**

***Index Terms*—Human Activity Recognition (HAR), Technology-agnostic RF sensing, Internet of Things (IoT), Domain Adversarial Learning.**

I. Introduction

Human activity recognition (HAR) has been identified as a critical technology for many emerging smart Internet-of-Things (IoT) applications, such as health-care monitoring, smart homes, and safety surveillance [1]. Traditional HAR systems are mostly developed with vision data or wearable sensors, which are restricted by the lighting and non-line-of-sight (NLOS) conditions, and are inconvenient for long time usage. Various RF technologies, such as RFID [2], [3], WiFi [4], and different types of RF radars, have been utilized to alleviate such restrictions. With advanced deep learning models, such RF-based approaches have been shown to achieve a high performance for HAR. However, since the deep neural network is designed for the specific, chosen RF technology, the proposed system is closely tailored to the chosen wireless platform. Being tied up with a specific technology or platform will hinder the deployment of large-scale and easy-to-deploy HAR systems. Considering the increasing demand for large-scale and flexible HAR systems, the limitations of the existing RF technologies should be addressed.

In this demo, we present TARF, a generalized, **t**echnology-**a**gnostic **RF** HAR system for flexible and accurate HAR performance using a variety of RF technologies. To address the limitations of existing systems, we first calibrate the RF data collected by different RF sensing technologies to represent them in a generalized Short Time Fourier Transform (STFT) RF feature tensor format. We then propose a Domain Adversarial Neural Network (DANN) to compensate for the discrepancy in the translation of RF signals.

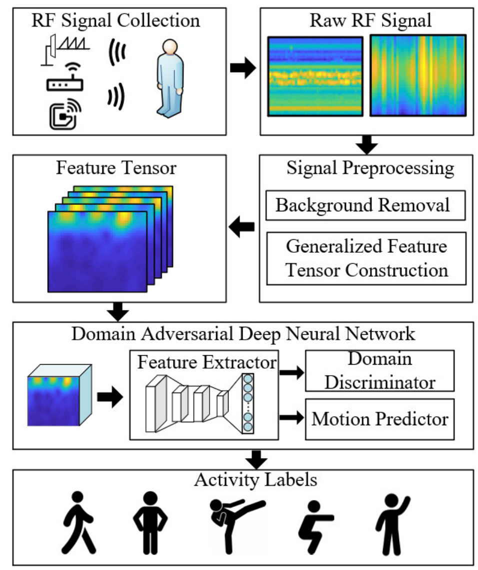

Fig. 1. Architecture of the proposed technology-agnostic RF sensing system.

II. System Overview

A. System Architecture

TARF is designed to be generalizable to diverse RF data measured using different RF sensing technologies to perform technology-agnostic HAR. Fig. 1 provides an overview of the system architecture, which is composed of three main components, including (i) RF signal collection, (ii) generalized RF signal preprocessing, and (iii) domain adversarial deep neural network based activity recognition.

B. Generalized RF Signal Preprocessing

In the RF data collection module, raw RF signals are sampled by several different RF sensing platforms. Depending on the RF platforms, different RF data are utilized for HAR. For example, range profile can be collected using an FMCW radar, phase data can be collected using RFID tags, and CSI data can be collected from WiFi platforms. In the proposed TARF system, the signals will be treated using the same generalized signal preprocessing module, no matter which RF technology is used for sensing. Generalization to different RF technologies should begin with a unified RF data format. The system utilizes a generalized RF data preprocessing module, where the measured RF signal is treated as a group of different

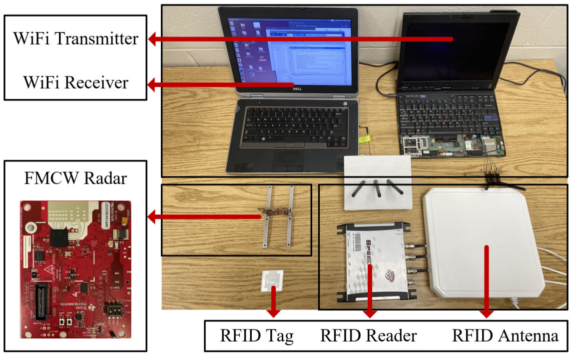

Fig. 2. RF platforms used in our implementation and experiments.

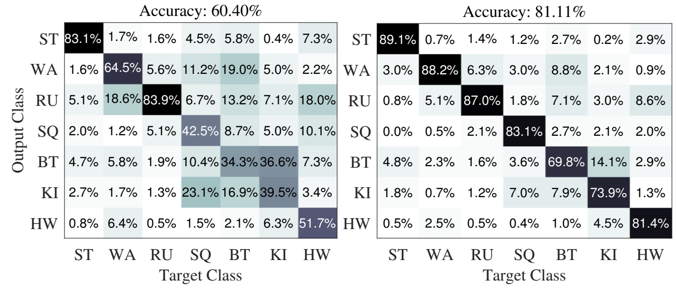

Fig. 3. Confusion matrix of HAR obtained using four RF technologies (i.e., FMCW radar, 2.4 GHz WiFi, 5 GHz WiFi, and RFID). Left: the CNN-based baseline scheme; Right: TARF.

observations of the same source signal (i.e., human activity) and is converted to a generalized input data matrix. Then general background removal is implemented with Hampel filters, where the interference from the common static background is removed. The collected data sequence are reordered in a matrix according to their signal strength to mitigate the sensitivity diversity across different RF devices, which is then transformed into generalized feature tensors with STFT.

C. Domain Adversarial Neural Network

Generalized feature tensors are constructed and fed into a domain adversarial deep neural network [5] for activity classification. Compared with the traditional CNN models, the domain adversarial neural network can further optimize the feature extractor with the domain discriminator. The network used in TARF is composed of a CNN based feature extractor, an activity predictor, and a domain discriminator. The domain discriminator is used to combat the diversity between different domains, i.e., different RF technologies in this paper. Thus, the network will learn the generalized human activity related features and discard the specific features associated with the specific RF technology.

III. Implementation and Evaluation

1) Hardware Platforms: To evaluate the proposed technology-agnostic HAR system, we develop a prototype using several RF technologies, including UHF RFID, FMCW radar, 2.4 GHz WiFi, and 5 GHz WiFi. The hardware platforms are shown in Fig. 2. The FMCW radar employed in the system, as shown in the figure, is an IWR1843 BOOST single-chip FMCW mmWave sensor that operates in the $76 \sim 81$ GHz band. The WiFi devices are integrated with a standard Intel 5300 network interface card (NIC), which operates at either 2.4 GHz or 5 GHz. The RFID platform consists of three S9028PCR polarized antennas, one Impinj R420 reader, and ALN-9634 (HIGG-3) passive RFID tags.

2) Evaluation and Results: The corresponding RF data are collected by sampling activities performed by a subject in front of the RF sensing platforms. The individual conducts seven types of different activities in these experiments. For convenience, we label different activities with the following acronyms: standing still (ST), walking (WA), running (RU), squatting (SQ), body twisting (BT), kicking (KI), and hand waving (HW). To demonstrate the performance of the TARF system, we compare it with a baseline scheme, which implements the traditional CNN based classification network [6].

We examine the system performance when all the four RF sensing technologies are used for data acquisition. Fig. 3 presents the confusion matrices when all the four technologies are utilized for human activity recognition. The confusion matrix on the left is obtained with the CNN-based baseline method, whose overall accuracy is 60.40%. The results demonstrate the significant interference caused by diverse RF data collected from four different platforms. In contrast, the right confusion matrix shows that TARF achieves an overall accuracy of identification of 81.11%. Such robustness to diverse RF data is achieved by the domain discriminator used in TARF. The technology-agnostic learning approach is quite effective to adapt to different RF technologies.

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