Passive Human Sensing with COTS Wi-Fi

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ABSTRACT

Recent advances in wireless sensing show promise for ubiquitous human activity recognition interface with Wi-Fi. Despite its attractiveness, multiple challenges still exist in bottom-up translation from CSI values to human activities, making existing approaches unready for practical use. To this end, we recognize three key challenges, non-coherent CSI measurements, context-dependent features and diverse human activities. Our preliminary results demonstrate the feasibility of CSI cleaning and passive human tracking. Based on the initial efforts, we propose the plan for further research.

CCS CONCEPTS

• **Human-centered computing → Ubiquitous and mobile computing systems and tools**;

KEYWORDS

Wireless Sensing; Activity Recognition; CSI

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1 INTRODUCTION

Human activity awareness is a key enabler for a wide range of applications, such as smart homes, security monitoring, and fitness tracking. Traditional approaches are based on cameras, radars or wearable sensors, which, however, suffer from several limitations. Camera based approaches are sensible to lighting condition and line-of-sight condition, and breach user privacy significantly. Sonic and RF radar solutions require high-cost installation and instrumentation. Wearable sensors based approaches pose inconvenience since users need to wear or take specific devices and thus are inapplicable in some scenarios such as security surveillance.

Recent innovations in wireless communications shed light upon passive human sensing with Wi-Fi signals. By exploiting the phenomenon that human motions distort multipath profiles during signal propagation, various wireless sensing approaches have been proposed for activity classification, tracking and vital signs monitoring. These RF based approaches are more attractive than previous solutions since they do not require the user to carry a device, support omni-directional coverage even in Non-Line-of-Sight (NLoS) scenarios, and preserve user privacy gracefully.

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The key limitation of these pioneer works is the lack of a general framework that accounts for both ubiquity and diversity of activity recognition. Specifically, some works rely on statistical characteristics of Wi-Fi signals, and employ learning based techniques for recognition of pre-defined sets of activities. In contrast, works that quantitatively model the relationships between signal and human motion only track coarse motion information (e.g. location, velocity) or single activities such as respiration and heartbeat. A reasonable solution is to combine learning-based approaches and model-based approaches. In my dissertation research, I will explore and investigate the feasibility of deriving context-free features from noisy CSI for learning-based activity recognition.

2 CHALLENGES

The challenges of implementing a general Wi-Fi based human sensing framework mainly come from three folds.

Non-coherent CSI measurements. Wi-Fi NICs measure channel discretely in time (packet), frequency (subcarrier) and space (antenna) for equalization during communication. With slight driver modification, CSI is portrayed to upper layer and can be used in human sensing. However, due to asynchronization between transceivers and hardware imperfection, CSI measurements consist various phase noises, which vary across packets, subcarriers and antennas, and need to be carefully calibrated to obtain meaningful CSI values for activity recognition.

Context-dependent features. Existing works capture statistical characteristics of Wi-Fi signals, such as Doppler frequency shifts and distributions of signal strength to distinguish different human activities. These features, however, are dependent on human motion status and environments, and cannot generalize to context-free ubiquitous cases. For example, Doppler frequency shift is dependent on both relative location and velocity (speed and direction) between the person and the devices. Theoretically, it requires users to perform activities at the same location and towards the same direction for successful recognition. Thus, how to extract context-free features from wireless signals remains a challenging problem to wireless sensing.

Diverse human activities. Human activities are widely different in both time scale and space scale, from small short activities such as pushing hands to large long activities such as exercising. Many sensing systems only classifies a small set of activities, lacking of a universal semantic representation for all activities at multiple time and space resolutions. Hierarchical characteristics of human activities requires multi-resolution learning structure (e.g. deep neural network), and is another for wireless sensing.

3 INITIAL EFFORTS

Our initial efforts include CSI cleaning [2, 5] and passive tracking [3, 4].

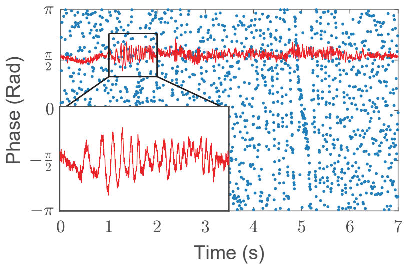

Figure 1: CSI cleaning.

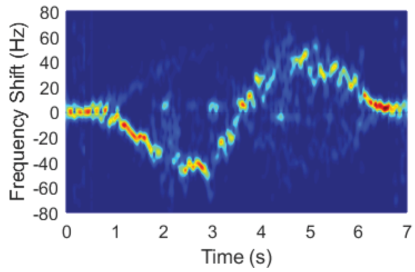

Figure 2: Doppler frequency profile.

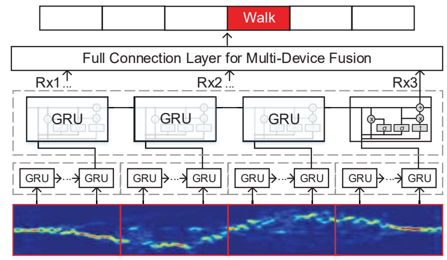

Figure 3: Preliminary framework.

Cleaning CSI. The phase noises in CSI can be modeled as:

$$\Delta\phi(i,j,k) = 2\pi\Delta f_j \epsilon_{t_i} + 2\pi\Delta t_i \epsilon_f + \zeta_k \quad (1)$$

where Δt_i is the arrival time of the i-th packet, Δf_j is the frequency of the j-th subcarrier; ϵ_{t_i}, ϵ_f and ζ_k are the timing offset, carrier frequency offset and initial phase offset of the k-th antenna. WiDance [5] leverages the observation that phase noises are consistent across antennas, and calculate the conjugate multiplication of CSIs of a pair of antennas to remove phase noises. Figure 1 shows the phase of conjugate multiplication of CSIs when a person is walking. Random phase noises are removed while motion-induced sinusoid-like waveforms are retained. In indoor environments, aggregate static response (e.g. LoS signal or reflection by static walls and furnitures) is much stronger than the dynamic response by the moving target. As a result, the time-varying terms in conjugate multiplication of CSIs approximately have the same Doppler frequency shifts as that in original CSI, and can be used for activity recognition.

Passive human tracking. Existing works [1, 5, 6] decompose CSI and extract Doppler frequency shifts, which are further used for tracking human motion status (i.e. location and walking velocity) [1, 3, 4]. Figure 2 shows an an example of Doppler shift profile, where a target walks away from and then back towards the link. Nonetheless, these works treat the human as a rigid body and estimate the translation velocity of the torso, which is insufficient for recognition of various activities.

4 RESEARCH PLAN

This section discusses the plan for further research of the challenges.

Extracting context-free features.

Fortunately, we may leverage the initial tracking results from these works. For example, while Doppler frequency shifts caused by human activities are effective indicators for these activities, they are coupled with the orientation of the target:

$$f_D = \frac{<\vec{v}, \hat{e}>}{\lambda} \quad (2)$$

where $\vec{v}$ is the pivot velocity of the target, $\hat{e}$ is the radial unit vector from the target to the transceivers and λ is the wavelength. Given the location of the target, the radial unit vector $\hat{e}$ can be directly calculated. To compensate the impact of orientation in Doppler shift profile, two links are required:

$$P_{D_0} = <\hat{e}_1, \hat{v}> P_{D_1} + <\hat{e}_2, \hat{v}> P_{D_2} \quad (3)$$

Where $\hat{e}_i$ and P_{D_i} are radial unit vector and Doppler shift profile for the i-th link respectively, and $\hat{v}$ is the unit vector of pivot velocity.

The further research against this challenge may consist of two steps. First, it needs to adapt existing walking tracking approaches to activity tracking scenarios, where both moving object and range are much smaller and may pose new challenges. Second, upon knowing the pivot moving direction, it needs to decouple the activity profile (e.g. Doppler frequency shifts) from context-dependent target orientation.

Hierarchical activity recognition. Currently, we adapt a deep learning framework for activity recognition with time-series data [7]. Figure 3 shows the preliminary design of deep learning framework. The input is Doppler shift profiles of some human activity observed from multiple links, and is split into a series of data intervals along time. Specifically, the framework uses hierarchical recurrent neural networks (HRNN) for capturing features at different scales. We test different activities, including boxing, clapping, jumping, running, standing up, sitting down, walking, falling down, turning, striking and waving. However, the average recognition accuracy is only about 70%. The future research include integrating of context-free features into the learning process and designing of frameworks that are free from individual and environment diversities [8].

5 CONCLUSION

In this abstract, we discuss key challenges for human sensing systems, including non-coherent CSI measurements, context-dependent features and diverse human activities. My dissertation research aims at investigating the feasibility of solving these challenges, and stitching all parts into a general human sensing framework.

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