12-2015

Sensorless sensing with WiFi

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Abstract—**Can WiFi signals be used for sensing purpose? The growing PHY layer capabilities of WiFi has made it possible to reuse WiFi signals for both communication and sensing. Sensing via WiFi would enable remote sensing without wearable sensors, simultaneous perception and data transmission without extra communication infrastructure, and contactless sensing in privacy-preserving mode. Due to the popularity of WiFi devices and the ubiquitous deployment of WiFi networks, WiFi-based sensing networks, if fully connected, would potentially rank as one of the world's largest wireless sensor networks. Yet the concept of wireless, sensorless and contactless sensing is no simple combination of WiFi and radar. It seeks breakthroughs from dedicated radar systems, and aims to balance between low cost and high accuracy, to meet the rising demand for pervasive environment perception in everyday life. Despite increasing research interest, wireless sensing is still in its infancy. Through introductions on basic principles and working prototypes, we review the feasibilities and limitations of wireless, sensorless and contactless sensing via WiFi. We envision this article as a brief primer on wireless sensing for interested readers to explore this open and largely unexplored field and create next-generation wireless and mobile computing applications.**

I. Introduction

Technological advances have extended the role of wireless signals from a sole communication medium to a contactless sensing platform, especially indoors. In indoor environments, wireless signals often propagate via both the direct path and multiple reflection and scattering paths, resulting in multiple aliased signals superposing at the receiver. Since the physical space constrains the propagation of wireless signals, the wireless signals in turn convey information that characterizes the environment they pass through. Herein the *environment* refers to the physical space where wireless signals propagate, which includes both ambient objects (e.g. walls and furniture) and humans (e.g. their locations and postures). As illustrated in Figure 1, sensorless sensing with WiFi refers to characterize the surrounding environments by analyzing received WiFi signals, with increasing levels of sensing contexts.

It is no brand-new concept to exploit wireless signals for contactless environment sensing. Aircraft radar systems, as a representative, detect the presence of *outdoor* aircrafts and determine their range, type and other motion information by analyzing either the wireless signals emitted by the aircrafts themselves or those broadcast by the radar transmitters and reflected by the aircrafts afterwards. Recent research has also explored to use Ultra-Wide Band (UWB) signals for *indoor* radar systems [1]. Primarily designed for military context, however, these techniques either rely on dedicated hardware or extremely wide bandwidth to obtain high time resolution and accurate range measurements, impeding their pervasive deployment in daily life.

On the other hand, contactless sensing technology is of rising demand in our everyday world. For instance, passive human detection has attracted increasing research interest in the past decade [2]–[6]. By *passive* human detection, (also termed as *device-free* or *non-invasive* human detection), it refers to detect or localize users via wireless signals, while users carry no radio-enabled devices [2]. Such contactless and privacy-preserving operation mode can stimulate various applications including security surveillance, intrusion detection, elderly and children monitoring, remote health-care, and innovative human-computer interaction.

One solution to passive human detection is to deploy extra sensors like UWB indoor radar systems. Yet a more convenient alternative is to reuse the ubiquitously deployed WiFi infrastructure indoors to enable pervasive, cost-effective, and easy-to-use passive human sensing. Such WiFi-based sensing is challenging in two aspects: standard WiFi signals have limited bandwidth and insufficient time resolution compared with dedicated radar signals; commercial WiFi hardware is often incapable of sophisticated radar signal processing. It is thus urgent to breaks away from traditional radar systems and develop theory and technology for high-resolution wireless sensing with off-the-shelf WiFi infrastructure.

Although neither WiFi nor radar alone yields new concepts, their combination sparks interesting innovation in mobile and ubiquitous computing. Pioneer researchers have termed this largely unexplored field as *Wireless Sensing*, *Sensorless Sensing* or *Radio Tomography Imaging* [4], and we will use the two picturesque terminologies of *wireless sensing* and *sensorless sensing* throughout this paper. In this article, we reviewed the emergence of wireless, sensorless and contactless sensing via WiFi. We focus on the principles and the infrastructure advances that enable wireless and sensorless sensing on commodity devices. Over the past five years researchers have developed a series of WiFi-based contactless sensing prototypes with increasing functionalities [7]–[11] and we expect wireless, sensorless and contactless sensing to leap towards industrial products in the coming few years.

II. From RSSI to CSI

How can we infer environmental information from wireless signals? As a toy example, weak WiFi signal strength may indicate long distance from the access point or blockage in the way. Though intuitive, Received Signal Strength (RSS) is

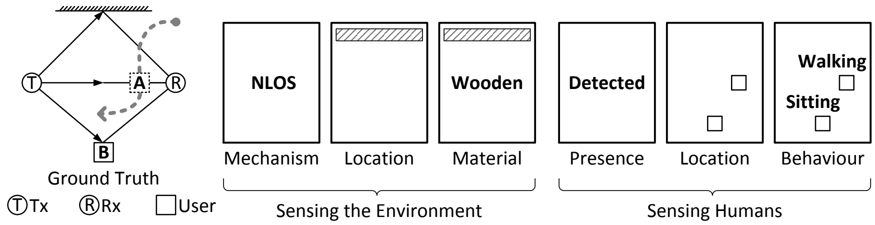

Fig. 1. Wireless sensing in multipath propagation environments.

widely used to infer environment information such as propagation distances. The past two decades have witnessed extensive sensing applications via RSS, with RSS-based wireless indoor localization as the most representative.

A. Received Signal Strength

Traditionally, RSS serves as an indicator for channel quality and is accessible in a range of wireless communication technologies including RFID, FM, GSM, WiFi, ZigBee and so on. Due to its ubiquity, researchers also explored to utilize RSS for sensing, such as wireless indoor localization [12] and passive human detection [2]. In theory, it is feasible to substitute RSS into propagation models to estimate propagation distance, or take a set of RSS as one radio fingerprint for each location, or infer human motions from the fluctuation of RSS. However, in indoor environments, RSS may not decrease monotonically with propagation distance due to small-scale multipath fading, thus limiting ranging accuracy. Multipath propagation indoors can also lead to significant fluctuation of RSS. Some study showed that RSS can fluctuate up to 5dB within one minute even for a stationary link in a typical laboratory environment [13]. Such multipath-induced RSS fluctuation may cause false match of fingerprint-based localization schemes. Since RSS is a single-valued indicator, it fails to characterize the rich multipath propagation indoors, making it less robust and reliable. Consequently, most RSS-based sensing applications often resort to dense deployed wireless links to avoid the impact of multipath via redundancy [4].

B. Channel State Information

As RSS is only a MAC layer feature, recent efforts have dived into the PHY layer to combat the impact of multipath propagation indoors. In the wireless communities, multipath propagation is often depicted by Channel Impulse Response (CIR). Under the time-invariant assumption, CIR can be is modeled as a temporal linear filter:

$$h(\tau) = \sum_{i=1}^{N} a_i e^{-j\theta_i} \delta\left(\tau - \tau_i\right) \tag{1}$$

where a_i, θ_i and τ_i denote the amplitude, phase and delay of the i^{th} path, respectively. N is the number of resolvable paths in the time domain and $\delta(\tau)$ is the Dirac delta (impulse) function. Each impulse represents one propagation path resolvable by time delays. Multipath propagation also leads to constructive and destructive phase superposition, which

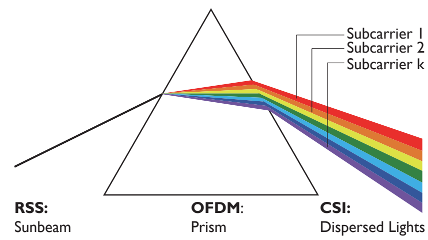

Fig. 2. An analogous illustration of RSS and CSI.

exhibits frequency-selective fading in the frequency domain. Thus multipath propagation can be equivalently characterized by Channel Frequency Response (CFR), which is the Fourier transform of CIR given infinite bandwidth.

While neither CIR nor CFR is accessible in the MAC layer, the PHY layer of WiFi, especially Orthogonal Frequency Division Multiplex (OFDM) based WiFi standards (i.e. IEEE 802.11a/g/n), is capable of measuring a sampled version of CFR for channel measurement purposes. Typically, high-resolution measurements of channel responses (CIR or CFR) require dedicated channel sounders. However, as OFDM-based WiFi standards require a subcarrier level channel measurement to improve decoding performance, they naturally provide coarse-grained CFR measurements at the granularity of OFDM subcarriers. With slight firmware modification and commercial WiFi network interface cards [14], these sampled versions of CFR measurements can be revealed to upper layers in the format of Channel State Information (CSI). Each CSI estimates the amplitude and phase of one OFDM subcarrier:

$$H(f_k) = \|H(f_k)\| e^{j\angle H} \tag{2}$$

where $H(f_k)$ is the CSI at the subcarrier of central frequency f_k, amplitude $\|H(f_k)\|$ and phase $\angle H$, respectively.

C. RSSI vs. CSI

Compared with RSS, CSI depicts multipath propagation to certain extent, making it an upgrade for RSS. Analogously speaking, CSI is to RSS what a rainbow is to a sunbeam, where components of different wavelengths in CSI are separated, while RSS only provides a single-valued amplitude of superposed paths (Figure 2). As physical layer information, CSI conveys richer channel information invisible in MAC layer RSS. One the one hand, CSI estimates the channel frequency response on multiple subcarriers per received packet, thus depicting the frequency-selective fading of WiFi channels. On the other hand, CSI measures not only the amplitude of each subcarrier, but its phase as well. Thus CSI provides richer and finer-grained channel information in the frequency domain. Since CIR is the inverse Fourier transform of CFR, CSI also enables coarse-grained path distinction in the time domain.

CSI brings about more than richer information. With proper signal processing, CSI can exhibit different site-specific amplitude and phase patterns in different propagation environments, while its overall structure remains stable in the same environment. Hence it holds potential to extract finer-grained and more robust signal features from CSI via machine learning and signal processing techniques, rather than simply adding up the amplitudes over subcarriers (a similar processing approach as RSS). Although currently CSI is only accessible on certain platforms, e.g. IEEE 802.11a/g/n compatible devices, the continuing popularity of WiFi and its ubiquitous deployment indoors still makes CSI a relatively pervasive signal feature.

Compared with the precise CIR/CFR measured by dedicated channel sounders, the resolution of CSI is limited by WiFi bandwidth. Given a bandwidth of 40MHz, its time resolution still fails to distinguish individual paths. Nevertheless, we envision WiFi standards with increasingly wider bandwidth (e.g. IEEE 802.11ac) would provide finer-grained information on multipath propagation in the near future.

III. Sensorless Sensing via WiFi

How does CSI benefit wireless sensing? Since CSI can be regarded as an upgrade for RSS, it is natural to adopt CSI to boost performance of conventional RSS-based applications. For instance, in RSS-based indoor localization, RSS can be used as either a location-specific fingerprint or to calculate the distance between the mobile client and the access point based on propagation models. Similarly, CSI can be employed as a finer-grained fingerprint as it carries both amplitude and phase information across subcarriers; or for more accurate ranging by accounting for frequency-selective fading. We refer interested readers to [15] for a more comprehensive overview on CSI-based wireless indoor localization. In general, RSS-based applications usually consider multipath propagation as harmful, since it is unable to resolve multipath propagation and suffers from unpredictable fluctuation in dense multipath propagation. In contrast, CSI manages to resolve multipath effect at subcarrier level. Albeit coarse-grained, it offers opportunities to harness multipath in wireless sensing applications.

A. Sensing the Environment

In multipath propagation environments, propagation paths can be broadly classified into Line-Of-Sight (LOS) and Non-Line-Of-Sight (NLOS) paths, where NLOS paths often pose major challenges in designing wireless communication and mobile computing applications deployed indoors. Severe NLOS propagation may deteriorate communication link quality and degrade theoretical signal propagation models. A prerequisite to avoid the impact of NLOS propagation is to identify the availability of the LOS path. Since CSI depicts multipath propagation at the granularity of subcarriers, researchers explored to exploit CSI for LOS identification [16] [17]. Some extracted statistical features from CSI amplitudes in both the time and frequency domains, and leveraged receiver mobility to distinguish LOS and NLOS paths based on their difference in spatial stability [16]. Others utilized CSI phases of multiple antennas for real-time LOS identification for both static and mobile scenarios [17]. Phase information offers an orthogonal dimension to traditional amplitude-based features, and has been successfully adopted in a range of applications e.g. millimeter-level localization [18].

Another more concrete environment characteristic is the shape and the size of rooms and corridors, which make up part of the indoor floor plan. Floor plan is often assumed to be offered by location-based service providers and researchers have shown increasing interest to build up indoor floor plans by combining wireless and inertial sensing. Some work have also demonstrated the feasibility of using wireless sensing only to recover part of the floor plan information. For instance, researchers distinguished straight pathways, right-angle and arc corners by analyzing the difference in the trend of CSI changing rates while the WiFi device moves [19]. With channel measurements on multiple receiving antennas, the authors in [20] developed a space scanning scheme by calculating the angle-of-arrivals of multiple propagation paths simultaneously and recovering the locations of the reflecting walls. Despite its bulky size currently, the working prototype holds promise for sensing the physical environment wirelessly and contactlessly.

B. Sensing Humans

Humans, as part of the environments wireless signals propagate within, have been of utmost interest in the area of wireless and sensorless sensing. In passive human detection, CSI is able to detect tiny human-induced variations in both LOS and NLOS paths, thereby enhancing detection sensitivity and expanding sensing coverage. Some researchers exploited CSI as finer-grained fingerprints to achieve omnidirectional passive human detection on a single transmitter-receiver link, where the user approaching from all directions can be detected [5]. With fusion of multiple links, CSI also facilitates fine-grained passive human localization, which substantially outperforms RSS-based schemes [21]. Other researchers extended human detection to multi-user scenarios by harnessing the frequency diversity of CSI and correlating the variation of CSI to the number of humans nearby for device-free crowd counting [6].

Pioneer research has marched beyond passively detecting simply the presence of humans. On the one hand, CSI-based wireless sensing shifts from locating users in the physical coordinates to offering more context-aware information. Some demonstrated the feasibility of general-purposed daily activity recognition by using CSI as fingerprints for the hybrid of locations and activity patterns [8]. Other work targeted at more concrete scenarios, e.g. fall detection [22] adopting similar principles with scenario-tailored optimization. On the other hand, ambitious CSI-based sensing applications aim to explore detecting micro body-part motions at increasingly finer granularity. Some reported over 90% accuracy of distinguishing multiple whole-body [7] and body-part gestures [10], while others claimed highly accurate breath detection [11] or even lips reading [9]. Nevertheless, researchers have reached no concursus on to what extent of motion granularity and variety is CSI capable of distinguishing in practice.

C. One Leap Further: WiFi Radar

Over the past five years, CSI has spawned a broad range of applications and its application scenarios continue to expand. As an upgrade for RSS, it is natural to improve performance of some applications simply by replacing RSS with CSI. CSI also enables various applications infeasible with RSS alone, such as gesture recognition, breath detection, and complex environment sensing. Nevertheless, CSI is no panacea, and its improvement in sensing granularity is still incomparable with radar signals. Some envisioned applications might have already gone beyond the capability of CSI.

Apart from further exploring and exploiting the frequency diversity and the phase information of CSI, researchers also began to identify its limitations in certain application scenarios, as well as seek other techniques to extend CSI-based wireless sensing to general WiFi-based sensorless sensing or *WiFi radar*. In [23], researchers pointed out ambiguity function analysis that the range resolution of passive bistatic radars based on current WiFi standards can only reach meters, which is fundamentally constrained by the operating bandwidth of WiFi signals. Consequently, researchers are striving to overcome this intrinsic constraint by incorporating Multi-Input-Multi-Output (MIMO) technology. In [24], researchers exploited antenna cancellation techniques to eliminate the impact of static clutters to enable through-wall sensing of human movements. In [25], the authors achieved computational imaging using WiFi, and built a MIMO-based prototype on software defined radio platforms. They experimentally demonstrated that the size, material, and orientation of the target objects can significantly affect the performance of WiFi imaging, and a one-fit-all solution is still to be explored.

IV. Conclusion

Wireless and sensorless sensing seeks breakthroughs in the contradiction between the limitation of WiFi signals and the growing demand for environmental perception in everyday life, searches for a balance between low cost and high accuracy, explores solutions via frequency diversity and spatial diversity, and creates applications that are previously infeasible in wireless communications and mobile computing. We envision technological advances would boost sensing capability to finer granularity and higher sensitivity, which will in turn foster various new applications. This article only serves as a brief introduction on the concept of *wireless and sensorless sensing*, and we refer interested readers to the corresponding references throughout this article for more in-depth information.

If we consider WiFi as a side sensor, then WiFi-based contactless sensing can be regarded as one of the world's most large-scale wireless sensor networks, spreading over office buildings, shopping malls, other public places and homes, and silently watching the activities of humans therein. Living inside such a network, every individual in the physical world has been bestowed with unique being in the digital world. So the next time you would like a secret meeting, after shutting the doors, pulling down the curtains and even checking for wiretaps beneath the table, do not forget to turn off the WiFi!

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