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# 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 and sensorless sensing is not the 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.

**Key words:** Channel State Information (CSI); sensorless sensing; WiFi; indoor localization; device-free human detection; activity recognition; wireless networks; ubiquitous computing

## 1 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. As 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 shown in Fig. 1, sensorless sensing with WiFi infers the surrounding environments by analyzing received WiFi signals, with increasing levels of sensing contexts.

It is not a 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 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 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.

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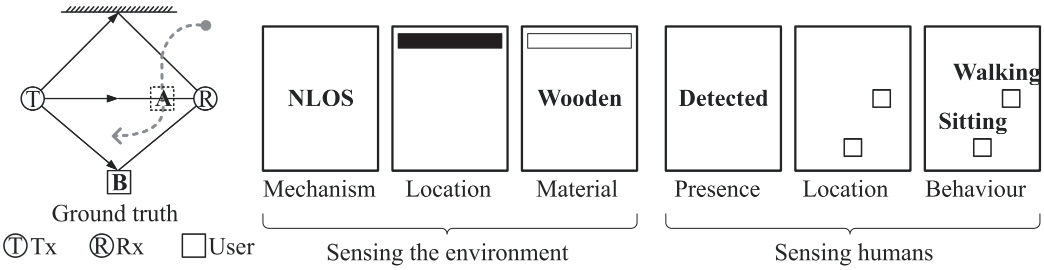


**Fig. 1 Illustration of setups and sensing tasks for wireless sensing in multipath propagation environments.**

On the other hand, contactless sensing technology is of rising demand in our everyday world. For instance, passive human detection has raised extensive research interest in the past decade[2–5]. By *Passive* (also termed as *device-free* or *non-invasive*), it refers to detecting users via wireless signals, while the users carry no radio-enabled devices[2]. Such contactless and privacy-preserving mode can stimulate various applications including security surveillance, intrusion detection, elderly monitoring, remote health-care, and innovative human-computer interaction.

One solution to passive human detection is to deploy extra sensors like UWB radar systems. Yet a more attractive alternative is to reuse the ubiquitous WiFi infrastructure for 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 often fails to support sophisticated radar signal processing. It is thus urgent to break 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 innovations in mobile computing. Pioneer researchers have termed this largely unexplored field as *Wireless Sensing*, *Sensorless Sensing* or *Radio Tomography Imaging*[3], and we will use *wireless sensing* and *sensorless sensing* throughout this paper. In this paper, 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[6–10] and we expect wireless, sensorless, and contactless sensing to leap towards industrial products in the coming few years.

## 2 From Received Signal Strength (RSS) to Channel State Information (CSI)

How can we infer environment information from wireless signals? As a toy example, weak WiFi signal strength may indicate long distance from the access point. Though intuitive, RSS is widely used to infer environment information such as propagation distances. The past two decades have witnessed various sensing applications using RSS, with RSS-based localization as the most representative.

### 2.1 Received signal strength

RSS acts as a common proxy for channel quality and is accessible in numerous wireless communication technologies including RFID, GSM, WiFi, and Bluetooth. Researchers also utilize RSS for sensing, such as indoor localization and passive human detection. In theory, it is feasible to substitute RSS into propagation models to estimate propagation distance, or take a set of RSS from multiple access points as fingerprints for each location, or infer human motions from RSS fluctuations. However, in typical indoor environments, wireless signals often propagate via multiple paths, a phenomenon called multipath propagation. In presence of multipath propagation, RSS may no longer decrease monotonically with propagation distance, thus limiting ranging accuracy. Multipath propagation can also lead to unpredictable RSS fluctuations. Studies showed that RSS can fluctuate up to 5 dB in one minute even for a static link[11]. Such multipath-induced RSS fluctuation may cause false match in fingerprint-based localization. Since RSS is single-valued, it fails to depict multipath propagation, making it less robust and reliable. Hence RSS-based sensing applications often resort to dense deployed wireless links to avoid the impact of multipath via redundancy[3].

### 2.2 Channel state information

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

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

where $a_i$, $\theta_i$, and $\tau_i$ denote the amplitude, phase, and delay of the $i$-th path. $N$ is the number of paths and $\delta(\tau)$ is the Dirac delta function. Each impulse represents a propagation path resolvable by time delays. Multipath propagation also leads to constructive and destructive phase superposition, which exhibits frequency-selective fading. Therefore multipath propagation can also be characterized by Channel Frequency Response (CFR), the Fourier transform of CIR given infinite bandwidth.

Obtaining high-resolution CIR or CFR often involves dedicated channel sounders. Yet the physical layer of WiFi, especially Orthogonal Frequency Division Multiplex (OFDM) based WiFi standards (e.g., IEEE 802.11a/g/n), offers a sampled CFR at the granularity of subcarriers. With only slight firmware modification and commercial WiFi network interface cards[12], these sampled versions of CFR measurements can be revealed to upper layers in the format of CSI. Each CSI estimates the amplitude and phase of one OFDM subcarrier:

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

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

### 2.3 RSS vs. CSI

Compared with RSS, CSI is able to depict multipath propagation to certain extent, making it an upgrade for RSS. Analogously speaking, CSI is to RSS what a rainbow is to a sunbeam. As shown in Fig. 2, CSI separates signals of different wavelengths via OFDM, while RSS only provides a single-valued amplitude of superposed paths. As physical layer information, CSI conveys channel information invisible in MAC layer RSS. On one hand, CSI estimates CFR on multiple subcarriers, 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 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.

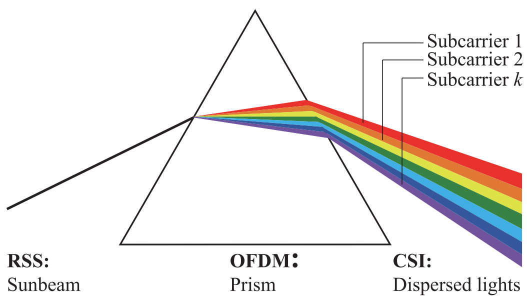


**Fig. 2 An analogous illustration of RSS and CSI.**

CSI brings more than richer information. With proper processing, CSI can exhibit site-specific patterns in different environments, while retaining stable overall structure in the same environment. Hence we may extract finer-grained and more robust signal features from CSI via machine learning and signal processing, rather than obtain only a single value by simply adding up the amplitudes over subcarriers (a similar processing approach as RSS). Although currently CSI is only accessible on certain platforms, the continuing popularity of WiFi and its ubiquitous deployment still make CSI a relatively pervasive signal feature.

However, the resolution of CSI is limited by the operating bandwidth of WiFi. Even with a bandwidth of 40 MHz (IEEE 802.11n with channel bounding), its time resolution still fails to distinguish individual paths. We envision WiFi standards with increasingly wider bandwidth (e.g., IEEE 802.11ac) would provide finer-grained multipath propagation information in future.

## 3 Sensorless Sensing via WiFi

How does CSI benefit wireless sensing? As an upgrade for RSS, it is natural to adopt CSI to boost performance of RSS-based sensing applications. For instance, in RSS-based localization, RSS can be used as either a location-specific fingerprint or to calculate the distance between the mobile client and the access point. 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. Here we refer interested readers to Ref. [13] for a more comprehensive overview on CSI-based indoor localization. To sum up, RSS-based applications often consider multipath harmful, since RSS is unable to resolve multipath propagation and suffers unpredictable fluctuation in dense multipath propagation. In contrast, CSI manages to resolve multipath effect at subcarrier level. Though coarse-grained, CSI offers opportunities to harness multipath in wireless sensing applications.

### 3.1 Sensing the environment

In multipath 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 for wireless communication and mobile computing applications. Severe NLOS propagation may deteriorate communication 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 at the granularity of subcarriers, researchers have explored CSI for LOS identification[14, 15]. Zhou et al.[14] 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. Wu et al.[15] utilized CSI phases of multiple antennas for real-time LOS identification for both static and mobile scenarios[15]. 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[16].

Another concrete environment characteristic is the shape and the size of rooms and corridors, which make up part of the floor plan. Floor plan is often assumed to be offered by service providers and researchers have shown increasing interest to draw floor plans by combining wireless and inertial sensing. Some works also demonstrated the feasibility of using wireless sensing alone to recover part of the floor plan information. For instance, Wang et al.[17] distinguished straight pathways, right-angle, and arc corners by analyzing the difference in the trend of CSI changing rates when the WiFi device moves. With channel measurements on multiple receiving antennas, the authors in Ref. [18] developed a space scanning scheme by calculating the angle-of-arrivals of multiple propagation paths and inferring the locations of the reflecting walls. Despite its bulky size, the working prototype holds promise for scanning the physical space wirelessly and contactlessly.

### 3.2 Sensing humans

Humans, as part of the environments wireless signals propagate within, are of utmost interest in wireless sensing. In passive human detection, CSI can detect tiny human-induced variations from both LOS and NLOS paths, thereby enhancing detection sensitivity and expanding sensing coverage. Zhou et al.[4] utilized CSI as finer-grained fingerprints to achieve omnidirectional passive human detection on a single transmitter-receiver link, where the user approaching the receiver from all directions can be detected. With fusion of multiple links, CSI also facilitates fine-grained passive human localization[19]. Xi et al.[5] extended human detection to multi-user scenarios by correlating the variation of CSI to the number of humans nearby for device-free crowd counting.

Pioneer research has marched beyond 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 work demonstrated the feasibility of general-purposed daily activity recognition by using CSI as fingerprints for the hybrid of locations and activity patterns[7]. Others targeted at more concrete scenarios, e.g., fall detection[20], adopting similar principles with scenario-tailored optimization. On the other hand, ambitious CSI-based sensing applications strive to detect micro body-part motions at increasingly finer granularity. Some reported over 90% accuracy of distinguishing multiple whole-body[6] and body-part gestures[9], while others claimed accurate breath detection[10] or even lips reading[8]. Nevertheless, researchers have reached no concursus on to what extent of motion granularity and variety is CSI capable of distinguishing in practice.

### 3.3 One leap further: WiFi radar

Over the past five years, CSI has spawned various 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 not a 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 practice, as well as seek other techniques to extend CSI-based sensing to general WiFi-based sensorless sensing or *WiFi radar*. In Ref. [21], researchers pointed out via ambiguity function analysis that the range resolution of WiFi-compatible passive bistatic radars can only reach meters, which is fundamentally constrained by the bandwidth of WiFi signals. To overcome this intrinsic constraint, researchers alternatively incorporate Multi-Input-Multi-Output (MIMO) technology. Researchers in Ref. [22] exploited antenna cancellation techniques to eliminate the impact of static clutters to enable through-wall sensing of human movements. In Ref. [23], 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.

## 4 Conclusions

Wireless and sensorless sensing seeks breakthroughs in the contradiction between the limitation of WiFi and the growing demand for environment perception in daily life, seeks 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 the capability of wireless sensing to finer granularity and higher sensitivity, which will in turn foster various new applications. This article only serves as an introduction on the concept of *wireless and sensorless sensing*, and we refer interested readers to the corresponding references for in-depth information.

If we consider WiFi as a side sensor, then WiFi-based sensorless sensing can be regarded as one of the world's largest 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 want 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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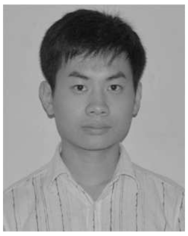

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