IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received April 9, 2020, accepted May 4, 2020, date of publication May 11, 2020, date of current version May 26, 2020.

Digital Object Identifier 10.1109/ACCESS.2020.2993548

RF Cloud for Cyberspace Intelligence

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ABSTRACT Wireless information networks have become a necessity of our day-to-day life. Over a billion Wi-Fi access points, hundreds of thousands of cell towers, and billions of IoT devices, using a variety of wireless technologies, create the infrastructure that enables this technology to access everyone, everywhere. The radio signal carrying the wireless information, propagates from antennas through the air and creates a radio frequency (RF) cloud carrying a huge amount of data that is commonly accessible by anyone. The big data of the RF cloud includes information about the transmitter type and addresses, embedded in the information packets; as well as features of the RF signal carrying the message, such as received signal strength (RSS), time of arrival (TOA), direction of arrival (DOA), channel impulse response (CIR), and channel state information (CSI). We can benefit from the big data contents of the messages as well as the temporal and spatial variations of their RF propagation characteristics to engineer intelligent cyberspace applications. This paper provides a holistic vision of emerging cyberspace applications and explains how they benefit from the RF cloud to operate. We begin by introducing the big data contents of the RF cloud. Then, we explain how innovative cyberspace applications are emerging that benefit from this big data. We classify these applications into three categories: wireless positioning systems, gesture and motion detection technologies, and authentication and security techniques. We explain how Wi-Fi, cell-tower, and IoT wireless positioning systems benefit from big data of the RF cloud. We discuss how researchers are studying applications of RF cloud features for motion, activity and gesture detection for human-computer interaction, and we show how authentication and security applications benefit from RF cloud characteristics.

INDEX TERMS Motion detection, gesture detection, authentication, security, cyberspace, smart world, RF cloud.

I. INTRODUCTION

The holistic view of wireless data communications for office information networking emerged in the mid-1980's [1], [2] and the IEEE 802.11 standardization activity for wireless local area networking, commercially known as Wi-Fi, began in late 1980s to address this industry. Today, when we arrive at a hotel registration desk, the first fundamental questions we ask related to our basic needs are: Where is my room? Where is the restaurant? And how can I connect to the Wi-Fi? Over a billion Wi-Fi access points deployed worldwide connect our mobile, personal, and fixed devices to the Internet and cyberspace. They have become an essential part of our lives to the extent that some people take Wi-Fi as the foundation

FIGURE 2. Density of Wi-Fi access points in Bay Area, Manhattan and Seattle, and the RF cloud data generated around them, including information packets and data embedded in features of RF signal propagation.

The associate editor coordinating the review of this manuscript and approving it for publication was Qilian Liang.

of human needs, where Maslow's hierarchy of human needs lands on (Figure 1, [3], [4]).[1]

In the late 1990s the IEEE 802.15 standardization activities began and introduced Bluetooth, ZigBee, and Ultra-Wideband (UWB) technologies for personal area networking [5]. Radio Frequency Identification (RFID) technologies have emerged as the icon of supply chain management, inventory control, and many other applications [6]. More recently, with the emergence of millimeter wave (mmWave) technology for Wi-Fi and cellular networks, leading manufacturers such as Texas Instruments have introduced short range radar sensor devices employing this technology [7]. Today, the RF signal radiating from over a billion Wi-Fi access points, several hundred thousands of cell towers, and trillions of IoT devices using Bluetooth, ZigBee, UWB, mmWave, and RFID technologies invites innovative opportunistic big data application developments for cyberspace [8]. The RF signals radiating from these devices create an RF cloud reachable to any device with an RF front end to sense their signals. The features of these RF signals such as received signal strength (RSS), time of arrival (TOA), direction of arrival (DOA), channel impulse response (CIR), and channel state information (CSI), provide a fertile ground for numerous innovative opportunistic cyberspace applications.

This paper provides a visionary overview of these emerging cyberspace applications and explains how they benefit from RF cloud to operate. We first discuss the big data contents of features of the RF cloud. Then, we explain how innovative cyberspace applications are emerging to benefit from the big data in these features. We begin with explaining opportunistic wireless positioning benefitting from big data from the RF cloud. Then, we explain how researchers are studying applications of these features for motion, activity and gesture detection as well as authentication and security to open a new horizon for human-computer interaction.

II. BIG DATA IN THE RF CLOUD

Figure 2 explains the concept of RF cloud for Wi-Fi access points in a database of a Wi-Fi positioning system in the Bay Area, Manhattan, and Seattle [9]. The big data embedded inside the RF cloud are divided into two types: 1) the data in the information packets to exchange information among wireless devices, and 2) the data related to the multipath characteristics of RF signals carrying this information. The data embedded in RF propagation features reflects the structure of the environment surrounding the source and destination antennas of the RF devices.

We can also divide wireless devices into two general classes, wireless communication devices and radars (Figure 3). Wireless communication devices (Figure 3a) transmit symbols, each carrying a limited number of bits of information in binary format. The transmitted packet of information consists of a bundle of these symbols carrying an information packet destined to a receiver with information about the system and the devices, which are beneficial for any receiver to gain cyber intelligence. These packets are broadcast and they are accessible to all other devices in the coverage area of the transmitter. In indoor and urban areas where wireless communication devices operate, the received signal arrives through different paths, bouncing off objects between the transmitter and the receiver. As such, the signal contains information related to the objects in the environment, embedded in the characteristics of the RF propagation channel between the transmitter and the receiver. Modern wireless devices measure these characteristics to enhance the quality of the wireless communication link. That way, characteristics of the RF propagation channel are available to end-users. Radars (Figure 3b), similar to communication devices, also transmit electronic waveforms. However, the transmitter and receiver are located in the same location and the received waveforms are compared with the transmitted symbols to measure the characteristics of the paths reflected from surrounding objects in the environment.

Receivers in both radars and wireless communication devices can measure the magnitude, phase, and time of flight of multiple paths reflected from surrounding objects in the environment. As objects move in the environment, the data associated with paths fluctuate and an intelligent receiver can use this to design motion-related cyberspace applications for positioning, tracking, motion and gesture detection, authentication, and security. In recent years, many cyber intelligent applications have evolved benefitting from the contents of data broadcast from wireless devices and the data associated with RF channel characteristics measured by RF receivers.

A. DATA CONTENTS OF FLOATING PACKETS

Figure 4a shows typical fields in a packet used for wireless communications. It consists of a preamble, starting delimiter (SD), destination/source addresses (DA/SA), control bits, information data, and a checksum code. The length of the packet depends on the information length and the rest of the data is considered as the overhead of the packet. Figure 4b shows the type of data contents in each field of a packet. The header is different in different technologies and it contains data on the type of technology used for the packet communication. Addresses contain data about the source and destination and can associate the packet to the physical location of the source. In wireless communications, coverage of the devices is limited. As a result, when we read a packet from a transmitter, we know we are at a certain distance from its location. Control data contains information on communication links, and sometimes channel information that can be used for environmental monitoring. The data itself and the checksum code is aimed for communication applications. This data does not contain any special information for intelligence, however, they affect the length of the packet and variations of the length contain information. For example, variation of the length of data arriving from a specific device can reflect unique behavior of the source as a measure for authenticity.

[1] This paper is based on an invited keynote speech with the same title as this paper, presented by the lead author at Cyberspace Congress (CyberCon), Beijing, China, on Dec 17, 2019.

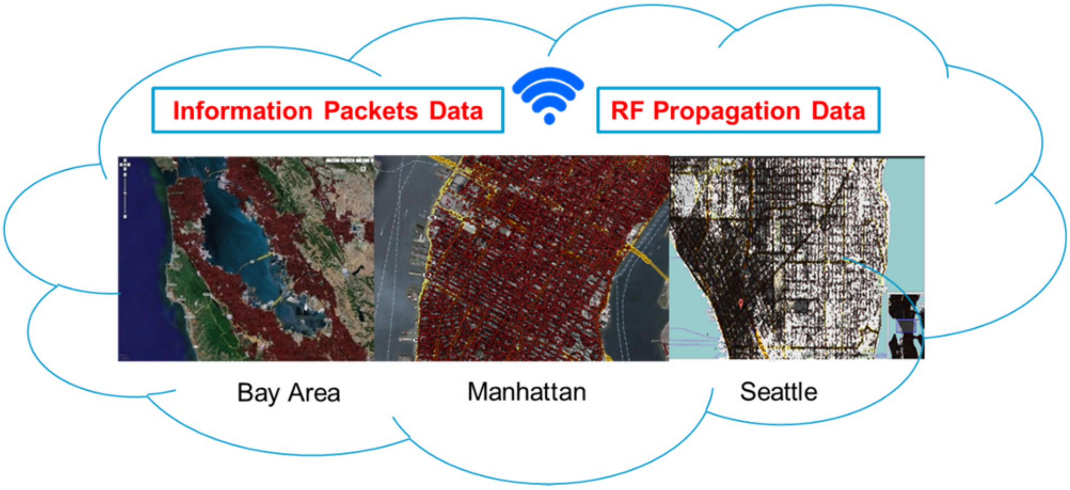

FIGURE 1. Maslow's hierarchy of human needs and its perceived relation to Wi-Fi [3], [4].

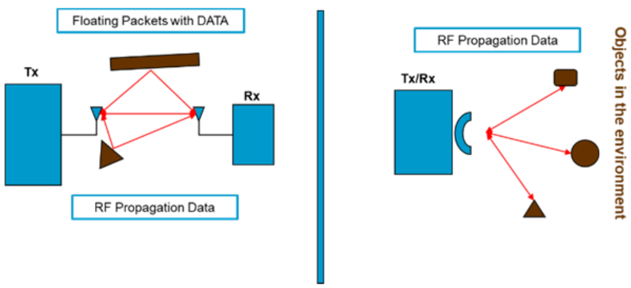

FIGURE 3. Two classes of wireless devices: (a) wireless communication devices, with transmitter (Tx) and receiver (Rx) in different locations, and, (b) Radars with integrated Tx and Rx.

Preamble	SD	DA	SA	Control	Data	Checksum

(a)

Tech Type	Addresses	Comm Channel Char	Device Chrac	Length

(b)

FIGURE 4. (a) Typical fields in a wireless communication packets, (b) typical common data in floating packets.

B. DATA CONTENTS IN FEATURES OF RF PROPAGATION

Motion in the environment affects RF propagation features including the received signal strength (RSS), embedded in the amplitude of the carrier of the received signal, and time of flight or time of arrival (TOA), which is embedded in the phase of the carrier of the received signal. The TOA can also be measured using the envelope of the carrier signal but it is much less reliable than that obtained from the measurement of the phase of the signal. Using multiple antennas, we can also extract direction of arrival (DOA) by utilizing the differences among the TOAs in antenna arrays. The quality of TOA ranging for measuring the distance between a transmitter and a receiver is superior to RSS based ranging. However, TOA-based ranging is extremely sensitive to excessive multipath propagation conditions and if it is not controlled, it may perform worse than RSS-based ranging. Multipath conditions increase as we go into partitioned spaces: in open space areas there is no multipath, in suburban areas we have some multipath, in dense urban areas multipath increases significantly, and in indoor areas it is extensive. If the receiver is capable of measuring the characteristics of the individual multipath components, there is an opportunity to take care of multipath effects using signal processing algorithms [10].

The Channel Impulse Response (CIR) for wireless devices operating in multipath indoor and urban areas is commonly represented by:

$$h(\alpha_i;\, \tau_i;\, \theta_i,\, \psi_i) = \sum_{i=1}^{N} \alpha_i e^{j\theta_i} \delta(t-\tau_i)\delta(\psi-\psi_i), \tag{1}$$

where $(\alpha_i;\, \tau_i;\, \theta_i;\, \psi_i)$ are the magnitude, TOA, phase, and DOA of the i-th path. In this equation the TOA is related to the phase of the arriving path by:

$$\tau_i = \frac{\theta_i}{2\pi f_c} = \frac{d}{c}, \tag{2}$$

where f_c is the carrier frequency of the signal, d is the length of the path, and c is the speed of light.

We can calculate the RSS of the received signal from:

$$\begin{aligned} RSS &= P_r = |r(t)|^2 \\ &= \left|\sum_{i=1}^{N} \alpha_i e^{j\theta_i} \delta(t-\tau_i)\delta(\psi-\psi_i)\right|^2 = \left|\sum_{i=1}^{N} \alpha_i\right|^2 \end{aligned} \tag{3}$$

We can easily measure the RSS from a transmitting wireless device without any synchronization with the source, while measurement of TOA needs tight synchronization between the devices as well as some additional signal processing.

As the objects or the wireless devices move in the environment or we change the frequency of operation, characteristics of the multipath features fluctuate drastically and cause fading in the received signal. In the wireless communication literature, this phenomenon is discussed under temporal, frequency-selective and spatial fading [11]. By taking

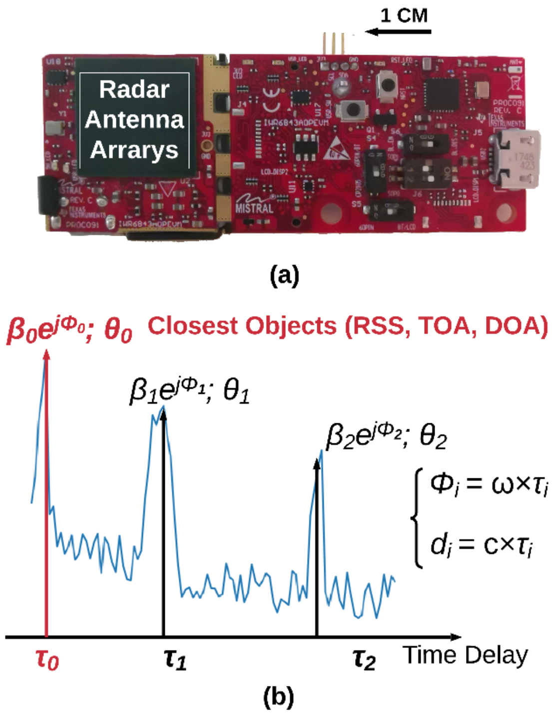

FIGURE 5. **Overview of the TI's mmWave Radar, (a) the physical appearance, (b) abstraction of CIR. (c) A typical measure of range-amplitude profile.**

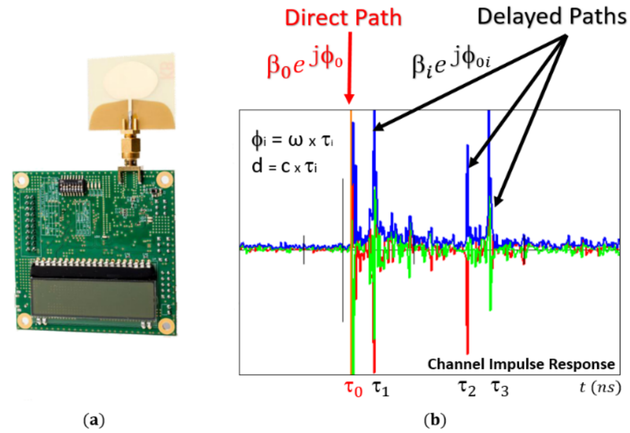

FIGURE 6. **Overview of DecaWave EVK100 UWB wireless communication and ranging system, (a) physical appearance, (b) a typical Channel Impulse response measurement, with abstraction of CIR.**

the Fourier Transform of these fluctuations we can measure the speed of movement of the objects. Different wireless devices measure some of these parameters for enhancing their communication quality and those measurements are available for development of other cyberspace applications, which we present in this paper.

1) RF DATA CONTENT OF RADARS

The popularity of millimeter Wave (mmWave) technology operating at around 60GHz for the 5G and 6G cellular networks has enabled implementation of low-cost short-range radars at these frequencies. The Texas Instruments mmWave sensor radar device is a popular example of such devices operating at 76-81 GHz [7]. This compact and low-cost radar, shown in Figure 5, emits chirp signals to capture distance, velocity and angle of objects surrounding the device. This information includes the RSS, TOA, DOA and velocity of motion of these objects. This mmWave radar features a flat 8×8 Multiple-Input-Multiple-Output (MIMO) array antenna enabling the device to capture refined spatial information from detected objects. Operation at high GHz has enabled the device to have a small array and advancements in microelectronics has integrated this device in a finger-sized package. Availability of this device in the market initiated a number of interesting research projects in micro-gesture detection. We will discuss more details on research on these topics in section III.B.

Figure 5 shows the basics of TI's radar characteristics. Figure 5a shows the physical appearance of the device with size metrics. Fig. 5b illustrates a sample range-amplitude profile captured by the radar receiver from different surrounding objects, representing the CIR. In this measurement, the first peak associates with the gesture of a hand kept close to the device and other major peaks are reflection from the environment located at longer distances.

2) RF DATA CONTENT OF WIRELESS COMMUNICATIONS

The enormous success of the wireless communication industry has nurtured a number of successful technologies that include, Wi-Fi, cellular, Bluetooth, ZigBee and UWB [11]. In addition to the common data available in the floating packets (Section II.B.1), devices using these technologies also have access to data from features of RF propagation reflecting motions in the environment. All of these devices support measurement of the RSS. As a result, RSS of Wi-Fi, Bluetooth and ZigBee have found their ways in a variety of cyberspace applications.

Other devices measure the CIR with different levels of precision. UWB devices provide an accurate estimate of the CIR suitable for opportunistic applications in human-computer interfaces. The popularity of UWB technology operating at around 3-10GHz for positioning and communication applications has enabled implementation of low-cost UWB devices. The DecaWave's EVK1000 UWB positioning system is a good example of these devices [12]. This small size, low-cost accurate indoor positioning system (Figure 6) uses UWB signals to measure the CIR between a transmitter and a receiver and position a device in an unknown location using known location of several reference devices. Figure 6a shows the physical appearance of the device, Figure 6b illustrates a typical measurement of the CIR, and detected direct and reflected paths. In addition to accurate positioning applications for a system consisting of several reference points and a tag, the CIR between any two transmitters and receivers provides

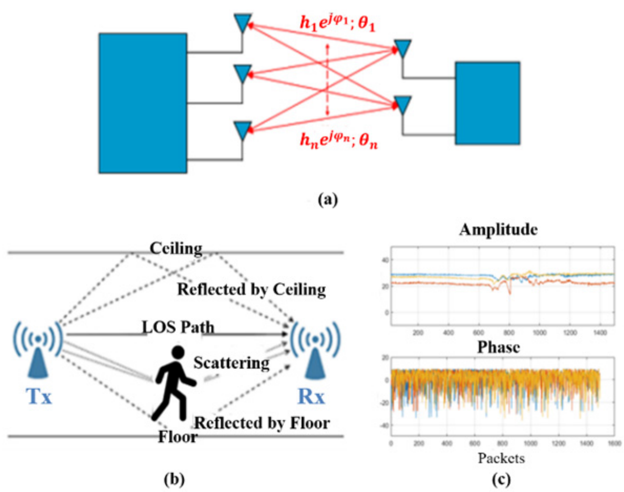

FIGURE 7. A typical wireless communication scenario using MIMO and multiple CIR and DOA information.

multi-channel data stream that is useful for human-computer interaction and other cyberspace applications.

Today, orthogonal frequency division multiplexing (OFDM) is the most popular wireless communication technology for Wi-Fi and cellular networks. An OFDM signal consists of a large group of narrowband transmission systems modulated over neighboring carrier frequencies. In theory, if we have N-carriers, we have N-streams of magnitudes and phases. However, unlike the CIR multiple data streams, the multiple streams of OFDM data are highly correlated. It is possible to obtain CIR from OFDM signals and most OFDM receivers estimate the CIR to enhance the quality of transmission [11]. However, users should notice that the quality of CIR estimates is proportional to the bandwidth and UWB systems provide a much better estimate of CIR.

Wireless communication systems with MIMO antennas, shown in Figure 7, are commonly used in Wi-Fi and cellular networking technologies. These systems are capable of providing for multiple streams of CIR and DOAs. MIMO antenna systems transmit multiple streams through different paths at different arrival angles, each carrying the magnitude and phase of the signal. In the MIMO literature, these streams of information are referred to as Channel State Information (CSI) [13]. The CSI is another rich signal space with multiple streams, which has been popular in recent literature for motion related cyberspace application development. Table 1 summarizes the features of signals embedded in the RF cloud of wireless devices.

3) RF DATA CONTENT OF COMMUNICATION DEVICES

Digital wireless communications take place through symbol transmissions, each symbol carrying a group of information bits. As shown in Figure 8a, transmitted symbols are represented by a signal constellation. Due to the thermal noise, carrier synchronization error, and nonlinearities of the receiver amplifiers, the received symbols arrive around the targeted transmitted symbol and the signal constellation has

TABLE 1. Summary of signals and features in RF cloud.

	Time-Domain Features	Frequency-Domain Features
RSS	Mean, Standard Deviation (STD), Peak-to-Peak	Spectrum (mean, STD, entropy)
CSI (MIMO, OFDM)	Same as RSS with multiple streams and sub-carriers	Doppler Spectrum (spread, decay, entropy, n-th order moment)
CIR (UWB)	Mean, STD, Power of direct/**multi-path**, Time Delay, Root-Mean-Square Time Delay	Spectrum (centroid, n-th order moment, entropy)
CIR (Radar)	Mean, STD, Power of direct/**reflected path**, Time Delay, Root-Mean-Square Time Delay	Same as CIR (UWB)

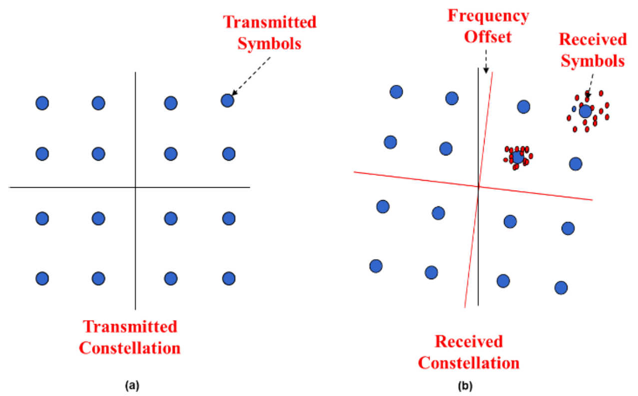

FIGURE 8. (a) Transmitted and, (b) received signal constellation reflecting frequency offset and nonlinearities of the device.

a frequency offset (Figure 8b) [11]. The statistical pattern of the noise around the transmitted symbol changes with nonlinearity of the receiver electronic that is unique to any device. We can benefit from these unique electronic features of the communication devices obtained from statistical behavior of the received symbols in the signal constellation to identify a device type.

III. OPPORTUNISTIC CYBERSPACE APPLICATIONS OF RF CLOUD

Section II described the RF cloud and its big data contents. We showed that the RF cloud radiating from wireless devices surrounding is a valuable source of information. Each wireless device has a unique address and if fixed, a unique location, and it radiates an RF signal with different coverage, which changes its features with motions. One can create a database of these addresses and the available signal features (RSS, TOA, DOA, CIR and CSI) associated with the addresses to develop opportunistic cyberspace applications.

Section III describes examples of these cyberspace applications, which have evolved around the RF cloud from wireless devices. The most widespread cyberspace applications of RF cloud are related to indoor positioning using wireless signals of opportunity [10]. Other applications using RF cloud include gesture and motion detection and using signals of opportunity for authentication and security. We provide an overview of these three categories of RF cloud applications in the next three subsections.

A. WIRELESS POSITIONING WITH RF CLOUD DATA

In late 1990s, indoor geolocation science and technology began to evolve to extend the coverage of Global Positioning System (GPS) to indoor areas [14], [15]. The high cost of dense infrastructure, needed for proper operation of these systems, moved this industry towards opportunistic positioning using RF cloud data from the existing Wi-Fi access point infrastructure [16], [17]. A Real Time Localization System (RTLS) industry, with a limited vertical market, evolved around this idea for applications in specific areas, such as museums, warehouses, and hospitals. Fingerprinting of the RF cloud for RTLS systems are done manually by surveying inside the building for the site of application. Manual sight survey is expensive and that restricts scaling to large areas of coverage. In the mid-2000s the Wireless Positioning System (WPS) industry evolved around the same idea with a new method for fingerprinting. In WPS, the RF cloud fingerprinting takes place by driving in the streets and tagging the collected data using a GPS receiver. This automated process enabled WPS systems to scale to metropolitan areas. For that reason, WPS was adopted for the original iPhone and it became integrated in all smart phones and smart devices since [9]. In the remainder of this section, we explain how WPS works and how it is evolving to enhance the opportunistic wireless positioning industry.

1) WI-FI RSS POSITIONING AND WPS

Today, the most popular positioning system is WPS, which is the main positioning engine for hundreds of thousands of applications on smart devices. Skyhook, Google, and Apple own the three major Wi-Fi location databases of access points (APs) for these systems. The database of Skyhook, the pioneer of the technology, receives over a billion hits per day and includes close to a billion Wi-Fi access point addresses with their estimated locations. In the original WPS systems, cars driving in the streets of a city collected the RSS fingerprint of Wi-Fi devices identified by their MAC addresses provided in the floating beacon packets and tags them with the GPS readings of the locations. Intelligent algorithms process the big database of these readings to estimate the location of any device from its Wi-Fi readings in an unknown location. Therefore, WPS relies on GPS because it is a database associating Wi-Fi addresses with GPS readings in the streets. The advantage of WPS is that it works indoors, where GPS does not work.

Initially cars driving in the streets of different cities collected the database. Then, organic RSS reading data from devices searching for their unknown location augmented the database of access point addresses and locations. The accuracy of WPS systems are typically around 10-15 meters [9], which is on the order of the average coverage of Wi-Fi. This accuracy is adequate for turn-by-turn navigation of cars in streets to differentiate building addresses from each other in urban areas. To increase the precision of WPS for indoor positioning applications, demanding a few meter accuracy to differentiate different rooms from each other, we need indoor manual fingerprinting, similar to RTLS, and that is expensive.

2) LOCATION INTELLIGENCE: AN OUTCOME OF WPS

GPS is a physical real time system providing position information based on current readings of TOA from satellites. WPS is a cyberspace information system built on a big database and an intelligent search engine with intelligent algorithms.

Each time we agree that an application on our smart device can use our location address, we send a packet to the WPS database and WPS knows our device location. With around one billion hits per day, WPS service providers can extract cyberspace intelligence about our location. We can use this new outcome of WPS technology to implement location-time traffic analysis, geo-fencing (for supporting elderly people, animals, prisoners, and suspicious people), real-world consumer behavior analysis, location certification for security and privacy, positioning IP addresses, and customizing content and experiences [10]. These are secondary outcomes of WPS technology, enabling other cyberspace applications for location intelligence.

3) FUTURE DIRECTIONS OF WPS

As we mentioned in section III.A.1, the current state of the art WPS technology without indoor fingerprinting has 10-15m accuracy. For accuracy in the range of meters, we need expensive indoor site surveys and fingerprinting. Typical smart devices carry a number of other sensors such as accelerometer, gyroscope, magnetometer, barometer, step counter and compass. These devices provide information on speed and direction of movements of the device. Using hybrid AI algorithms, we can integrate these motions related information with the absolute position estimate from the WPS to enhance the positioning and to refine the tracking in indoor areas [10], [18]–[20].

Wi-Fi access points are installed in office buildings approximately 30 meters apart. In a typical office building such as Atwater Kent Laboratory at the Worcester Polytechnic Institute (approximately 50mX100m), each floor is covered only with 3-7 Wi-Fi access points. That is why we need fingerprinting to increase the precision to a few meters to differentiate rooms from each other. With the increase in 'smartness' of office buildings, every room of this building has at least two IoT devices controlling the light and the temperature. IoT devices use Bluetooth Low Energy (BLE), ZigBee or other active RFID technologies, which have smaller coverage than Wi-Fi. Smaller coverage indeed helps the precision. Imagine we have an RFID with coverage of one meter, if we read its signal, we know our location with one-meter accuracy. With such density of deployment of small coverage IoT devices, we may not need indoor fingerprinting anymore. It can be shown that the precision of Wi-Fi positioning in a typical building (e.g. WPI's Atwater Kent Laboratory), with three Wi-Fi APs in 90% of locations is better than 15 meters, while with only eight randomly distributed IoT devices in that floor this precision comes close to two meters [21], [22]. In practice, design of such systems is practical because all devices measure their RSS and they are connected to the Internet, therefore they can pass that information to a positioning database to enhance the precision of positioning.

4) CELL TOWER RSS POSITIONING

RSS based Wi-Fi positioning is a device-based positioning system. The metric data used for positioning is collected by the device independent from the communication network provider. We can apply this technology to cell tower positioning using fingerprinting of cell towers [23]. The advantage of this approach for cell tower positioning is that the positioning system takes advantage of cell towers from all cellular providers without any specific coordination. The positioning service provider drives in the streets to identify cell towers and develop a database of their fingerprints tagged with the GPS location. Then using the RSS readings of the cell towers around a device, the service provider can come up with a position estimate for the device. The device needs to have a cellular chipset to read the RSS values of the cell towers.

As compared with Wi-Fi positioning, the density of cellular networks is far less: we have billions of Wi-Fi access points as compared with hundreds of thousands of cell towers worldwide. Therefore, the accuracy of these RSS based cell-tower positioning systems (CPS) is around 100-250 meters, which is significantly lower than WPS [9], [23]. However, CPS has a more comprehensive coverage, which includes highways as well as urban areas. The original iPhone did not include GPS and it used CPS as a backup for WPS for these areas. With the increase in density of deployment in 5G and 6G cellular networks, the gap between precision of WPS and CPS should reduce significantly. This intuitive observation needs to be justified by empirical research data.

5) CELL TOWER TOA POSITIONING

WPS, CPS and GPS are device-based positioning systems, in which the device measures the features of the RF cloud for positioning. Another approach to positioning is network-based positioning, where cell towers or access points measure the features of RF signals from the device and send that to a central computational server to locate the device. The first popular application of this approach was the Uplink-Time Difference of Arrival (U-TDOA) positioning systems, designed in 2G cellular networks to comply with FCC regulations for E911 services for cell phones [10]. These TOA based systems utilize the difference between arriving signals from a cell phone to locate the device. One of the advantages of this approach is that we can locate a device without its active participation in the positioning process.

The U-TDOA provides for approximately 100m precision for E-911 service using existing cell tower signals [24]. This level of precision is not adequate for many popular indoor and urban area positioning and navigation applications, but it has a comprehensive coverage, which makes it appealing for emergency response.

The U-TDOA was a patch solution to position because 2G standard organizations had not included positioning in their agenda. If we consider positioning as a part of the standardization of communication protocols, we should be able to achieve higher precisions using TOA and DOA technologies. The fundamental challenge for TOA based systems are sensitivity to multipath effects and need for atomic clock synchronization to achieve sub-meter precision. By integrating GPS clock with the cellular system standards, we can have a practical solution for synchronization, but multipath effects are serious, in particular with indoor areas [12].

Ultra-wideband transmission controls the effects of multipath arrivals by isolating them from one another, antenna beamforming focuses the transmission to a single path, and we can design algorithms for positioning in the absence of direct path [25]. The emerging 5G and 6G cellular system with massive MIMO and mmWave technologies benefit from ultra-wide band transmission as well. In theory, these characteristics of 5G/6G technologies can enable high precision TOA based positioning. However, implementation of these systems to make it available for precision sensitive positioning applications needs algorithm and system design with focus on performance evaluation in realistic positioning application scenarios. In general, standards organizations are focused on the increase in capacity, which directly affect the user experience. They need to increase their attention to positioning and navigation as a fundamental enabling technology for millions of applications. More details on design and performance evaluation of positioning systems are available in the lead author's recent book in this area [10].

B. MOTION, ACTIVITY & GESTURE DETECTION WITH RF CLOUD

Motions of the wireless device or objects close to the antennas of the wireless devices cause temporal fluctuations of characteristic of RF cloud features measured at the receiver antennas. Recently, a number of researchers have studied these characteristics of RF cloud from wireless devices for activity, motion and gesture detection. This area of research expects to revolutionize human-computer interaction and introduce a variety of other cyber space applications by taking advantage of the variations in RF cloud features due to motions in the environment.

1) DETECTION OF RF FEATURES DUE TO MOTION

Wireless communication receivers measure features of the RF cloud reflecting motions in the environment. Signal process-

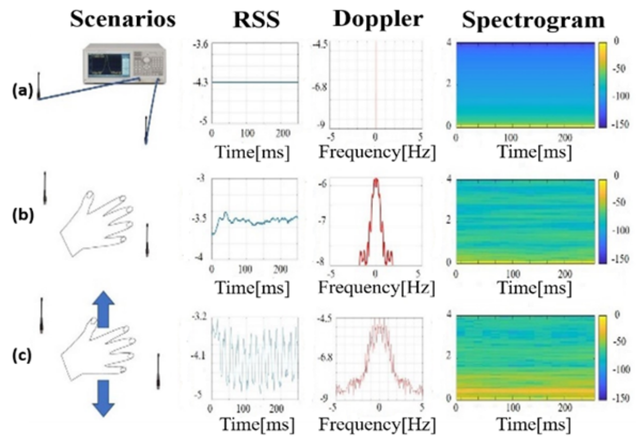

FIGURE 9. The temporal variations of RSS for a receiver antenna in proximity of a transmitting antenna and its Doppler Spectrum and Spectrogram (a) with no-motion, (b) with a hand with natural motions, (c) with a moving hand between the antennas.

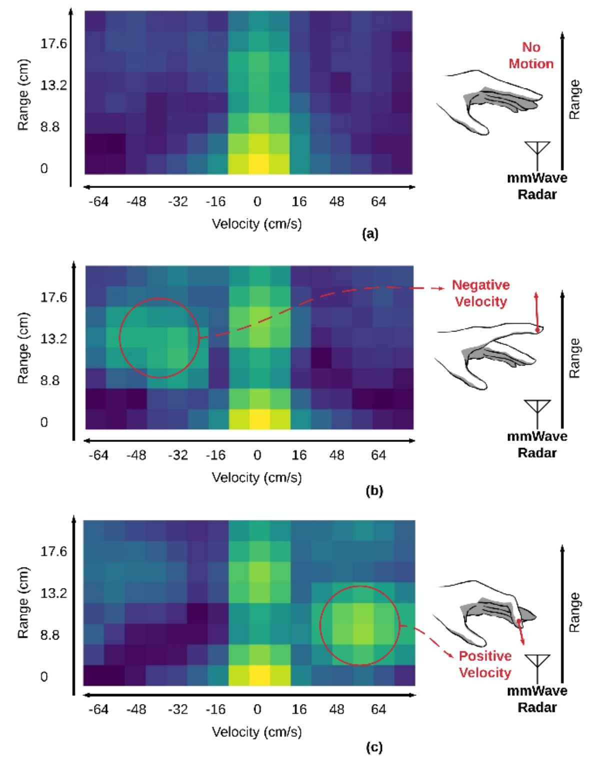

FIGURE 10. Range-velocity Profile of TI's mmWave Radar with (a) the hand staying still in front of the radar device (b) a finger tilting backward (c) a finger tilting forward.

ing techniques help detect these motions and prepare them for cyberspace application development. Figure 9 illustrates the temporal variations of RSS of a receiver antenna in proximity of a transmitting antenna. The figure also shows the Fourier transform of the signal representing the Doppler spectrum and the short-term Fourier transform representing its spectrogram. Figure 9a shows a situation with no-motion, Figure 9b shows a situation with a hand held between the two antennas, and Figure 9c shows the results when the hand moves between the antennas. As the speed of motions increases, the bandwidth of the Doppler spectrum and the contrast of colors in the spectrogram increases. We can benefit from this change in depiction of the RSS characteristics, to develop hand motion related applications. All modern wireless devices measure RSS and many other features of the RF cloud that are available and accessible with software, opening an interesting area for motion related cyberspace applications.

The mmWave radar development environment (Fig. 5) also supports other aspects helpful in classification of motions. Figure 10 shows the range-velocity profile of the device illustrating motions of the finger in different directions. The mmWave sensor extracts velocity information, and consolidates it with the range data to form the range-velocity profile. Figure 10a shows a hand, which is a strong reflector, at close distance from the radar and its corresponding profile. Figure 10b and 10c demonstrate that the finger movement creates radical velocities relative to the radar, and thus mirrored in the profile below. These depictions of motions open an opportunity for micro-gesture detection from finger motions.

2) MOTION RELATED CYBERSPACE APPLICATIONS

In recent years, a number of researchers have benefited from RF cloud features to introduce innovative cyberspace applications. As a simple example, using an algorithm measuring variations of the RSS above its average value, one could detect the number of people attending a class [26], or monitor newborn babies in a hospital [27]. More complex cyberspace applications using opportunistic signals available in the RF cloud is achievable by using artificial intelligence algorithms and taking advantage of more complex features of the signal, such as CIR, CSI, TOA, and DOA. In recent years, a number of research laboratories have pursued this idea.

At the Worcester Polytechnic Institute, variations of the RSS of body-mounted sensors is used for activity monitoring of first responders to find out if a fire fighter carrying a device is standing, walking, laying down, crawling, or running [28]–[30]. These states of motion reflect the temporal behavior of the fire fighter, revealing the seriousness of the situation she or he is facing. The work in [28] uses traditional characteristics of the fading, such as coherence time, rms Doppler spread, and threshold crossing rate of the RSS of simple devices such as Bluetooth, to differentiate different motions and the work presented in [29] integrates AI algorithms into the motion detection process. The work presented in [30] benefits from more complex CSI signals of Wi-Fi devices along with more complex AI algorithms such as Long-short-term-memory Regressive Neural Network (LSTM-RNN), to increase the capacity of the system in differentiating different motions on a flat floor or when climbing the stairs. As we explained in section II.B.2, CSI provides multiple streams of RSS and more diversified variations of the signal. In [31], the research group demonstrates the use of mmWave radar in tracking the motion of a finger, opening up further study in gesture-based application controls in the human-computer interaction (HCI) research area.

Researchers at the University of Washington [32] have used Wi-Fi signals for hand gesture recognition to differentiate nine different hand motions. Multiple RSS stream from different channels of the OFDM signal of Wi-Fi are depicted by a spectrogram to generate frequency-time characteristics color images. The AI algorithm classifies the image to detect the nine gestures of the hand motion. At Michigan State University [33], the CSI of a Wi-Fi signal is use for keystroke detection. When typing a certain key, the hands and fingers move in a unique formation and direction, there is a unique pattern of CSI RF fingerprint. By training an AI algorithm, they have detected the keystrokes of the keyboard user. At the Massachusetts Institute of Technology [34], researchers have used radar signals similar to the Wi-Fi signals with multiple antennas, for human pose estimation through walls and occlusions. They demonstrated detection of multiple human postures through the walls using the RF signal and a neural network algorithm. They used visual data captured by a camera during the training period for the AI algorithm. At Stanford University [35], commodity Wi-Fi signals are used for tracking hand motion for virtual reality applications to replace existing infrared devices.

In parallel with academic studies, practical applications of RF signals for motion and gesture detection and tracking are emerging in industry. As an example, Google [36] uses RF radar signals at mmWave frequencies obtained from antenna arrays, for micro-motion tracking of hand and finger gestures for applications such as connection less winding or rolling over the surface of a wristwatch. RF signal variations can replace any application using mechanical sensors. For example, the interactive electronic games commonly use mechanical sensors such as an accelerometer, and an accelerometer mounted on the gait of a patient has been used to measure the extent of progress in Parkinson decease [37], [38]. The RF cloud of UWB devices, measuring the CIR, can replace many of these mechanical sensors and be used in interactive electronic gaming [39], to help visually impaired [40]; and to provide gait motion detection.

Building on the advances in motion, activity and gesture detection using RF Cloud, researchers have begun to explore the possibilities for future HCI applications. Early work explored using unmodified GSM signals to enable recognition of eight tapping gestures, four hover gestures and two sliding gestures around a mobile device, to enable incoming call management as well as phone navigation from a distance [41]. More recent work, has demonstrated an mmWave gesture recognition pipeline [36] as well as the recognition of eleven gestures with short-mmWave radar with a goal of them being used in human-computer interaction [42]. Other work explored mmWave gesture recognition for in-car infotainment control [43]. Radar signals have also been explored for automatically classifying everyday objects to support various applications including a physical object dictionary that looks up objects that are recognized, context-aware interaction,

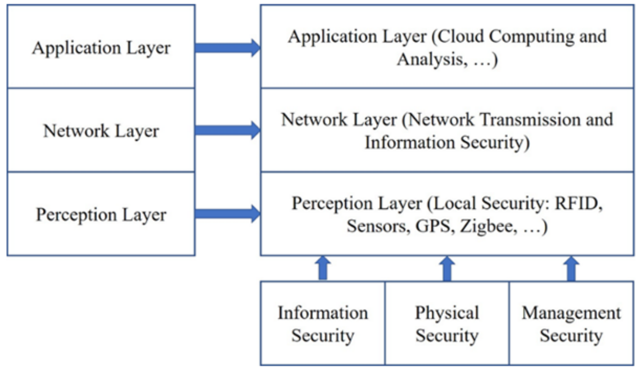

FIGURE 11. **Security architecture for applications involved in the RF clouds.**

as well as future applications such as automatic sorting of different types of waste, assisting the visually impaired and smart medical uses [44]. Using radio signals and one external sensor hanging on the wall, researchers have demonstrated that gait velocity and stride length, which are important health indicators, can be monitored, enabling health-aware smart homes [45]. Taking advantage of indoor WiFi signals to identify motion direction, researchers have created a contactless dance "exergame" [46] as well as sign language gesture recognition [47]. Other work demonstrated that 5GHz WiFi can be used to achieve decimeter localization accuracy of up to four users as well as activity recognition of up to three users doing six different activities [48].

C. SECURITY AND AUTHENTICATION WITH RF CLOUD

In recent years, several researchers have shown interest in developing authentication and security applications benefitting from big data embedded in the RF cloud. These researchers look into various kind of devices, including Wi-Fi, Bluetooth, Zigbee and RFID, to evaluate the threat, to assess vulnerability of the systems, and to propose frameworks for specific authentication and security schemes.

To analyze the security of the networks, it is customary to refer to a layered architecture [49]. Figure 11 shows a general layered architecture and the relations among different layers. The architecture of the security system in this figure consists of three layers: perception layer, network layer, and application layer. The functionality of the perception layer is data collection, preprocessing of data, and secure transition of this data to the network layer. The network layer checks the security of data and transmits it to the application layer. The application layer analyzes and process the data to support the application.

Since most of the RF data collection sensors are deployed in environments with no human supervision, and the data is collected through a wireless medium, this data can be easily monitored, intercepted and modified. In these environments, an attacker can access the sensor and take control of the device or damage these sensors or physically remove them from their assigned location. As a result, most of the security designers for RF cloud applications implement their measures at the perception layer.

Application of machine learning methods for classification of devices for authentication and security has been very popular in the recent literature [50]. The time-domain features of the RF cloud from Wi-Fi have been used to train a classifier to differentiate between trusted and un-trusted devices operating in close vicinity of each other [51]. Researchers have also examined physical authentication using a unique coding technique to generate location-related public keys based on RF cloud signature in a given location [52].

In section II.B.2, we introduced the main features of the RF cloud, which includes RSS, TOA, CIR, and CSI and how we can process them for extraction of traditional statistical features such as mean and standard deviation, as well as Doppler spectrum related features. At the perception layer of security systems, we can use the fingerprint of these feature for RF authentication. Fingerprinting is the process of identifying radio transmitters by examining their unique transient characteristics at the beginning of transmission. A complete identification system has been presented, which includes data acquisition, transmission detection, RF fingerprint extraction, and a variety of classification subsystems [53]. Following this pioneering work, a number of researchers have examined different machine learning methods for RF cloud related research in authentication and security.

Using non-parametric and multi-class ensemble classifiers for RF fingerprinting, researchers demonstrated improved ZigBee device authentication over the traditional algorithms [54]. Other work extracted novel RF fingerprint features to design a hybrid and adaptive classification scheme adjusting to the environment conditions, and carries out extensive experiments to evaluate the performance of these systems [55]. A low-cost system has been introduced for bit-level network security, benefitting from physical unclonable functions, which is challenging to replicate [56]. A device recognition algorithm based on RF fingerprint has also been proposed [57]. In this work, a Hilbert transform and principal component analysis are used to generate the RF data fingerprint of the device and traditional machine learning algorithms are used to classify the devices. The accuracy of RF fingerprinting employing low-end receivers has been evaluated showing that receiver impairment effectively decreases the success rate of impersonation attack on RF fingerprinting [58].

Another area of emerging security and authentication research related to RF cloud applications is the design of testbeds for risk analysis for IoT-based physically secure systems. To assess security risks, researchers have proposed testbeds and methodologies for risk analysis and evaluation of vulnerability [59], [60]. There are other works proposing a testbed for authentication of IoT objects benefiting from RF fingerprinting, along with a machine learning technique [61], [62].

IV. CONCLUSIONS AND FUTURE DIRECTIONS

The success of wireless networks has resulted in the deployment of a huge infrastructure as well as development of inexpensive wireless devices. Big data from the RF cloud of the infrastructure and devices has enabled a number of intelligent cyberspace applications in positioning and tracking, motion and gesture detection, and security and authentication. These innovative cyberspace applications have the potential for creating a major paradigm shift of untethered human-computer interfacing and development of popular applications in the heath and gaming industries.

Research challenges facing this industry include learning how to integrate multiple sensors to enhance positioning and tracking for universal operation in all environments. Another challenge is in finding methods for systematic performance evaluation of alpha-beta classification capability of micro-gestures and performance evaluation of motion and micro-motion tracking techniques. Designing a universal data acquisition interfaces for multiple RF sources is another technical challenge facing the existing devices for practical applications in health, interactive gaming, and human-computer interaction.

ACKNOWLEDGMENT

The authors would like to thank the AI Research Group at the Center for Wireless Information Networking Studies, at the Worcester Polytechnic Institute, An Yan, Zhengyuan Lei, for discussion on radar applications, and Zhuoran Su, Pengyu Zhang, for discussion on CSI research. In addition, authors would like to express their gratitude to Prof. Rick Brown for his valuable editorial comments. They are grateful to all the people that enlighten their research and bring them the passion to finish this visionary paper.

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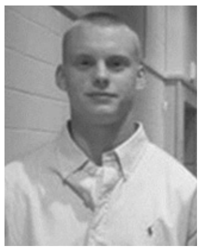

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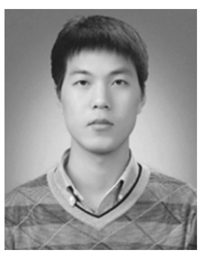

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