2016 Intl IEEE Conferences on Ubiquitous Intelligence & Computing, Advanced and Trusted Computing, Scalable Computing and Communications, Cloud and Big Data Computing, Internet of People, and Smart World Congress

A Survey on Wi-Fi based Contactless Activity Recognition

Junyi Ma, Hao Wang, Daqing Zhang, Yasha Wang, Yuxiang Wang
The Key Laboratory of High Confidence Software Technologies
School of EECS, Peking University
Beijing, China
majunyi@pku.edu.cn, {haowang, dqzhang}@sei.pku.edu.cn, {wangyasha, wyxpku}@pku.edu.cn

Abstract—**Providing accurate information about human's state and activity is one of the most important elements in Ubiquitous Computing. Various applications can be enabled if one's state and activity can be recognized. Due to the low deployment cost and non-intrusive sensing nature, Wi-Fi based activity recognition has become a promising and emerging research area. In this paper, we survey the state-of-the-art of the area from four aspects ranging from historical overview, theories and models, key techniques to applications. In addition to the summary about the principles and achievements of existing work, we also highlight some open issues and research directions in this emerging area.**

Keywords—Activity Recognition; Wi-Fi; Contactless Sensing;

I. INTRODUCTION

Activity recognition is an essential part of context-aware computing and a key enabler for many applications in smart homes and smart cities [37]. Existing activity recognition systems include contact-based activity recognition and contactless activity recognition. Compared to contact-based approaches, e.g. wearable device [38] [48], contactless activity recognition has the advantage of non-intrusiveness, and thus is suitable for long-term sensing. Contactless activity recognition approaches include video-based [39], RF-based [41] [47], ultrasonic-based [40], and other methods. Compared with the most studied video-based approaches [11], RF based approaches are much more privacy friendly. RF based approaches include UWB [45], continuous wave radar [46], ZigBee [25], Wi-Fi [1] and etc. One promising approach is the Wi-Fi based contactless activity recognition, because it is cost-effective as it reuses the existing infrastructure compared with other RF based approaches. Thus, Wi-Fi based activity recognition has attracted a lot of research interests.

In the indoor environment as shown in Fig.1.(a), 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 [11][12]. When people appear in the environment, extra signal transmission path will be introduced by reflection and refraction of human body as shown in Fig.1.(a). In this way, the distortion of Wi-Fi signal affected by human activities will be recorded continuously by receiver. The basic idea behind Wi-Fi RF-based activity recognition is to map different human activities to the received signal records.

In this paper, we would like to conduct a short survey and summarize the related work of this emerging field. First, we would like to provide a historical review of the field by highlighting the key related work in this domain. Then we survey the state of the art from the following three aspects: underlying theories and models, key techniques, and applications. In the end, based on the analysis of the existing work, we identify the pending research issues and problems, and point out the possible research directions for further study.

II. HISTORICAL OVERVIEW

In 2000, Paramvir et al. [1] published a Wi-Fi RSSI based indoor localization method. This is the first research on Wi-Fi based sensing. Since then, the researchers in the area of Wi-Fi based sensing mainly focus their efforts on indoor localization. Until 2013, a Wi-Fi RSSI based activity recognition, called Nuzzer, was published [42]. But Nuzzer can only be used to detect whether people are active, unable to distinguish between different activities. Limited by the ability of RSSI, researchers began to utilize the fine signal processing capabilities of USRP to realize activity recognition such as tracks the 3D motion of a user [43], monitor breathing and heart rate [44] and see through walls with Wi-Fi [2]

In 2011, Halperin et al. [4] published the measuring method and tools of channel state information (CSI) based on Intel 5300 NIC which expands the scope of Wi-Fi based sensing. Since then, researchers start to work on activity recognition based on commercial Wi-Fi devices. In 2014, many of the articles that utilize CSI to achieve contactless activity recognition in commercial Wi-Fi device have emerged, such as WiHear [5], E-eyes [6], WiFall [7], RT-Fall [21], Gestures Recognition [8] and Wi-Fi imaging [9]. Up to now, a large number of related work [10] had published in top conferences and journals about ubiquitous computing, computer network, and communication. These related works have accumulated fruitful achievements in theoretical model, key techniques and applications.

III. THEORIES AND MODELS

Due to the lack of accurate theoretical model, early works on Wi-Fi based activity recognition mainly depend on empirical observation and statistical learning [7][13][14]. The path loss

978-1-5090-2771-2/16 $31.00 © 2016 IEEE
DOI 10.1109/UIC-ATC-ScalCom-CBDCom-IoP-SmartWorld.2016.142

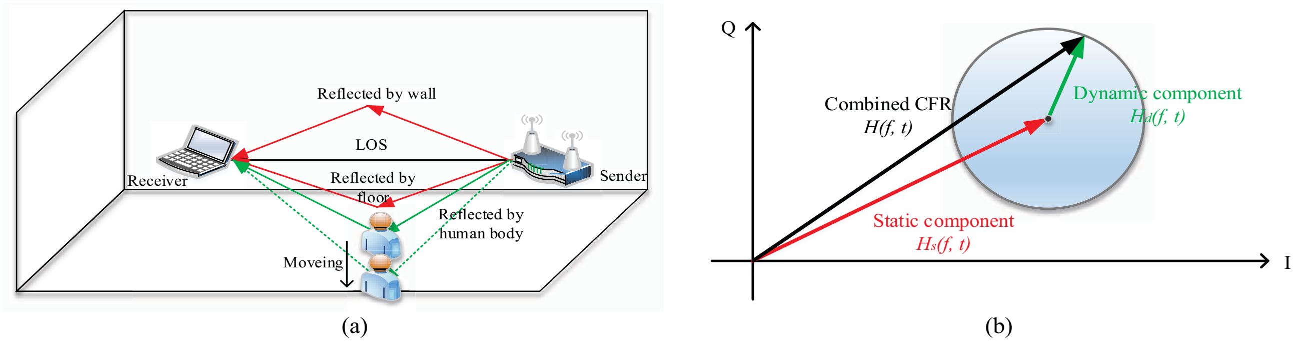

Fig.1. (a) Superposed signals influenced by transmit physical space and extra signal transmission paths introduced by reflection of human body. (b) Superposition of a set of static path and a set of dynamic path.

model proposed in [7] is the only theoretical support to this area. This model considers that, in a typical indoor environment, there is one main path (LOS) and several reflected paths by the surroundings such as roof, floor and wall. If someone presents in the room, there will exist other paths reflected from the human body. Thus, the power received can be represented as [13]:

$$P_r(d) = \frac{P_t G_t G_r \lambda^2}{(4\pi)^2 (d^2 + 4h^2 + \Delta^2)} \quad (1)$$

Where λ is the wavelength; d is the length of LOS between transmitter and receiver; P_t is transmitted power; G_t, G_r is the gain of transmitting antenna and receiving antenna respectively; h is the depth between the reflection points of ceiling or walls and Δ represent the path length of the reflection from human body.

It can be seen that, if the subject is in stationary state, P_r should be relatively stable; When the subject is moving, Δ will change with it, resulting in the fluctuation of the received signal amplitude. However, the path loss model lacks the physical background and quantitative relationship between amplitude dynamics and human activities.

In order to overcome the deficiency of the path loss model, Wang et al. [15] proposed a phase shift model, called CARM, to quantify the correlation between CSI value dynamics and human movements speed [15]. The key point of this model is to imagine received signal as a superposition of a set of static path and a set of dynamic path as shown in Fig.1(b). We assume that a radio signal arrives at the receiver after through N different paths, then the channel frequency response (CFR) *H(f, t)* can be defined as follows :

$$\mathrm{H(f,t)} = e^{-j2\pi\Delta f t} \sum_{k=1}^{N} a_k(f,t)\, e^{-j2\pi f \tau_k(t)} \quad (2)$$

Where $a_k(f,t)$ is a complex valued representation of attenuation and initial phase shift of the k^{th} path; $e^{-j2\pi f \tau_k(t)}$ is the phase shift that the k^{th} path that has a propagation delay of $\tau_k(t)$; $e^{-j2\pi\Delta f t}$ is the phase shift caused by frequency offset Δf between transmitter and receiver.

Now, let us consider how CFR power changes when an object is moving. We assume that an object moves at a constant speed such that the length of the k^{th} path changes at a constant speed v_k for a short time period, e.g. 100 milliseconds. Let $d_k(t)$ as the length of the k^{th} path at time t, and $d_k(t) = d_k(0) + v_k t$. Then the instantaneous CFR power in time *t* can be written as:

$$|H(f,t)|^2 = |H_s(f)|^2 + \textstyle\sum_{k\in P_d} |a_k(f,t)|^2$$
$$+ \textstyle\sum_{k,l\in P_d, k\neq l} 2|a_k(f,t)a_l(f,t)| \cos\left(\frac{2\pi(v_k - v_l)t}{\lambda} + \frac{2\pi(d_k(0)-d_l(0))}{\lambda} + \phi_{kl}\right)$$
$$+ \textstyle\sum_{k\in P_d} 2|a_k(f,t)H_s(f)| \cos\left(\frac{2\pi v_k t}{\lambda} + \frac{2\pi d_k(0)}{\lambda} + \phi_{sk}\right) \quad (3)$$

Where $\frac{2\pi d_k(0)}{\lambda} + \phi_{sk}$ and $\frac{2\pi(d_k(0)-d_l(0))}{\lambda} + \phi_{kl}$ are constants representing initial phase shift. This formula provides a key insight: the total CFR power is the sum of a constant offset and a set of sinusoids, where the frequencies of the sinusoids are related to the speeds of path length changes. By measuring the frequencies of these sinusoids and multiplying them with the carrier wavelength, we can obtain the speeds of path length change. In this way, the quantitative relation between CSI value dynamics and the human movements speed is established.

IV. KEY TECHNIQUES

In this section, we will review the key technologies in previous literatures and summarize a framework for Wi-Fi based contactless activity recognition, consisting of four steps: base signal selection, preprocessing, feature extraction and classification techniques, as shown in Fig.2.

A. Base Signal Selection

There were three kinds of base signals used in current literatures: amplitude, phase and phase difference. Each has its own pros and cons.

1) Amplitude: Amplitude is a widely used base signal, which be applied in fall detection [16][21], gesture recognition[3][8][49] and etc. The fluctuation of the amplitude caused by human body activities has definite physical meaning and some correlations with human movements speed [7]. However, there are also some shortcomings when using amplitude, for example, it is hard to remove the noise from the raw amplitude.

2) Phase: Due to the lack of useful phase information in commercial Wi-Fi devices, calibration is thus needed [19]. One commonly used calibration method is called the linear transformation [19]. Liu [24] et al use this method to realize intrusion detection. However, this phase calibration method has

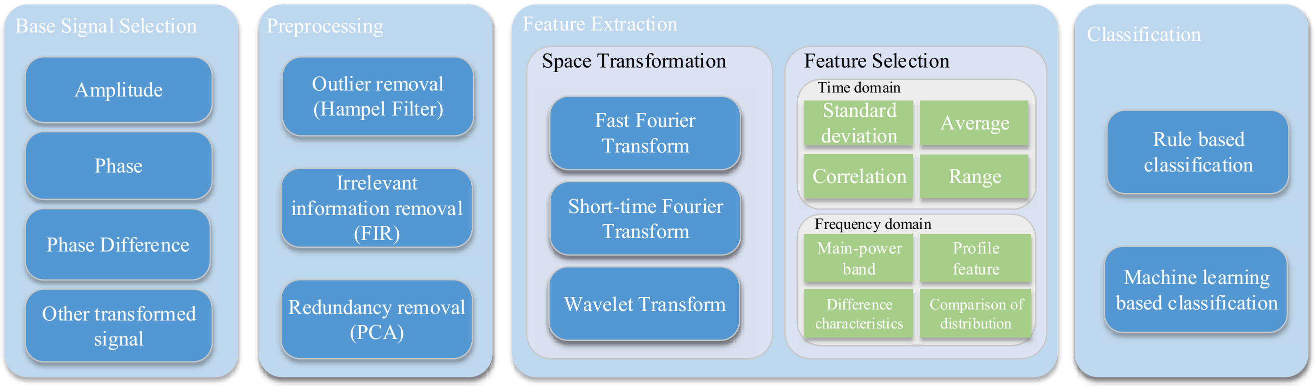

Fig.2. Framework for Wi-Fi based contactless activity recognition.

a side effect: The effects of human activities will be filtered out [15], resulting that the phase signal almost lost the sensing ability.

3) Phase difference: Phase difference has a good ability to capture small human movements, which mainly due to two reasons [17]: Phase difference utilizes the space diversity, and the total sensory sensitivity that we can acquire is the sum of two antenna's sensitivity; It can be proved that there is only a small range of Gaussian random noise in phase difference, clean phase difference can be obtained by a simple denoising method. [16] and [21] achieved fall detection by using phase difference as base signal. We believe that phase difference has more broad application space in the future, and is worth further study.

B. Preprocessing

After the base signal selection, the goal of preprocessing is improving the reliability of the signal by outlier removal, irrelevant information removal and redundancy removal.

1) Outlier removal: Some outliers will appear in the received signal due to hardware defects or environment interference, which can significantly reduce the ability of recognition. [18] utilizes Hampel filter with moving average to achieve outlier removal. However, Hampel Filter only fits the signal that only has Gaussian noise and moving average will reduce the sensibility of human activity caused high frequency. So, the length of the sliding window cannot be too long.

2) Irrelevant information removal: The raw date we received may contains a large amount of irrelevant information. Taking breathing detection as an example, people usually breath in the frequency range of 0.15Hz~0.55Hz. Since the received signal always be disturbed by other frequency components which do not belong to breathing, it is very hard to directly distinguish the cyclical changes in the time domain signal. [20] utilizes Finite Impulse Response (FIR) filter, specifically the band-pass filter, to remove irrelevant information from received signal and achieved breathing detection. Similarly, [21] applies band-pass filter to distinguish the fall and fall-like activities.

3) Redundancy removal: Redundancy will be inserted into received signal due to CSI streams provided by commercial Wi-Fi devices are extremely noisy. One major source of the noise in CSI streams is the internal state transition in transmitter and receiver Wi-Fi NICs such as transmission power changes, transmission rate adaptation, and internal CSI reference level changes [15]. [15] use principal component analysis (PCA) to extract redundancy. They claim that redundancy was separated out in the first principal component, as human *movements* impact was keep in other principal components. Even so, using PCA to remove redundancy is still imperfect because of three difficulties: redundancy is not always appear in the first principal component. Experiments found that redundancy may appear in any of the first five principal components; redundancy is not always appearing in one principal component. It means that we can't reliable mark redundancy by only one principal component; It is hard to choose the most suitable signal in other principal component, especially when the effect of redundancy separation is not good. Thus, we think that using PCA to remove redundancy still dependent on empirical process. We need explore the reasons behind it in the further.

C. Feature Extraction

Feature Extraction is the process of refining the raw data. The most commonly used feature extraction method in current literatures is hand-designed features, which can be divided into two steps: space transformation and feature selection. In the following, we will introduce the details of these two steps

1) Space transformation: Space transformation is a process that mainly transforms signal from time domain to frequency domain. Now, three methods are commonly used: Fast Fourier Transform (FFT), Short-time Fourier Transform (STFT) and Wavelet Transform (WT). FFT is one of the most basic time-frequency analysis method that directly transforms signal from time domain to frequency domain. For example, [20] using FFT to confirm the specific breathing frequency of people by finding the peak in the frequency range of 0.15Hz~0.55Hz. However, FFT is only applicable to the stationary signal and without the ability to capture the instantaneous frequency component caused by human movements. So there are STFT and WT. STFT is a window based Fourier transform, which be used in RT-Fall [21] and Anti-Fall [16]. This method does FFT for each window of time domain signal, and the window slides backwards according

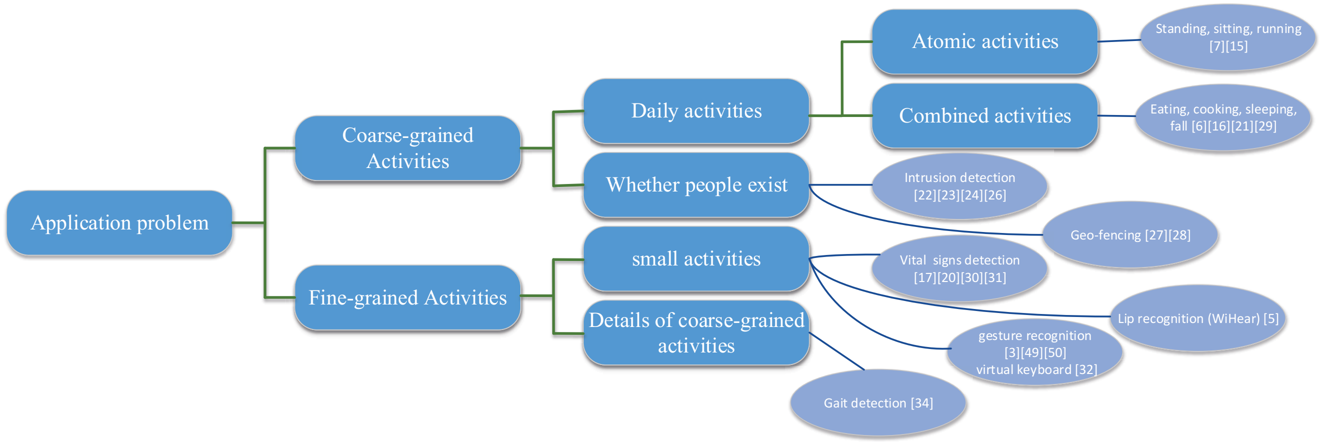

Fig.3. Summary of the applications based on Wi-Fi contactless activity recognition.

to the overlap coefficient. In this way, we can capture instantaneous frequency of each moment. However, the frequency resolution of STFT is not as accurate as WT. WT uses a completely different basis, namely wavelet basis to realize high-precision instantaneous frequency capture, such as [5] and [15]. However, discrete wavelet transform has high efficiency but low resolution, while continuous wavelet transform has high resolution but low efficiency. Hence, we need a tradeoff between real-time requirement and resolution in practical applications.

2) Feature selection: After space transformation, what we need to do is selecting appropriate feature according to our requirements. The commonly used time domain features are standard deviation, average, correlation, range and etc. The commonly used frequency domain features are main-power band, difference characteristics, profile feature and etc.

D. Classification Techniques

There are two main classification techniques in current activity recognition: rule based classification and machine learning based classification. Rule based method is mainly used in "binary problem" which can be depicted by a threshold. As for multidimensional complex problem or unstable relationship, machine learning method is more suitable.

1) rule based classification: Rule based classification methods often are used to identify some "binary" problems, such as whether someone is present in the environment [22][23][24] or whether someone is doing activities in the environment [15]. [16] and [21] use the standard deviation threshold to determine whether a "fall-like activity" happened and divided activities into two categories: fall-like and not-fall. However, the main problem of rule based classification methods is that, a stable and clear relationship is required between the signal and the target of classification and this relationship must can be depicted by a set of threshold or a threshold choose method.

2) Machine learning based classification: Machine learning based classification method is widely used, but most of the related works haven't mentioned the classifier they chose. It is generally recognized that the result of mainstream machine learning algorithm such as support vector machine (SVM), neural network, and genetic algorithm has no significant difference when using small data set.

In current works, different classification methods are used in different applications. Anti-Fall [16] and RT-Fall [21] utilize support vector machine (SVM) to achieve real-time fall detection, keystroke [32] uses k-nearest neighbor algorithm (kNN) to achieve gesture recognition, and Wang et al. [15] uses Hidden Markov Model (HMM) to build CSI activity models that consist of multiple movement states.

V. Applications

Wi-Fi based contactless activity recognition has accumulated rich achievements in the past 3 years. As shown in Fig.3, research on application problem of Wi-Fi based activity recognition can be roughly divided into two directions: coarse-grained activities and fine-grained activities.

A. Coarse-gained activities

For the activity recognition in macro level, existing main work can be divided into two categories: Whether people exist, and what people are doing in the given environment. The main applied background of the first category is intrusion detection. The challenge is how to realize reliable detection when a person appears in a given environment and how to keep a static posture in the location of different distance from the Wi-Fi device (stand up, move slowly etc.). In the related work, the team led by Liu [23][24] and Ni [22] keep a close eye on this problem. Through their incessant improvement, it has got a proven solution with high precision (close to 100%). And it derives a kind of interesting sub problems combined with its deep understanding in positioning, we call it Geo-fencing. The aim of Geo-fencing is detecting whether people appear in the specific zones established in the given environment [27][28]. The main application of the other category is daily activity recognition, including atomic activities like running, standing, sitting, lying, fall [7][15] and combined activities such as eating, cooking, washing gargle and sleeping [6][29]. Now, a great challenge of daily activity recognition is real-time activity segmentation problem. Activities of people are continuous and diverse in daily life, and even if the same person does the same activity many times, the duration and speed are not exactly the same. Thus, the real-time segmentation problem is more difficult than classification problem. For such problems, [16] and [21] achieved a fall detection, which can segment fall-like activities from the continuous activity stream and then detect the fall activity from the fall-like activities [33].

B. Fine-grained activities

For the activity recognition in micro level, there are also exist two research problems: subtle activity recognition and detailed the details of coarse-grained activity recognition. Now researchers pay more attention to monitoring vital signs [17][20][30][31]. It reflects the healthy status and sleep quality by analyzing the breath and heartbeat of people when they are sleeping. WiHear achieved lip recognition [5], Keystroke implemented a virtual keyboard [32] and Nandakumar et al. [49] conducted gesture recognition. But for now, this kind of work is limited in a controlled environment. How to achieve fine-grained activity recognition in real and challenging environment such as others working normally in the same room is one important research direction in the future. The other direction is understanding the details of coarse-grained activity. As the activity details often inform a person's characteristics. We can realize user authentication based on Wi-Fi signals associated with one's gait [34] and gesture features.

VI. Issues and future directions

Although the Wi-Fi based contactless activity recognition has made remarkable achievements, there still exist many problems worth exploring.

As for theories and models, the existing phase shift model lacks the description of the spatial propagation properties of radio frequency, when the path length change patterns are different, the phase shift change patterns are also different (e.g. moving perpendicular to the LOS and moving parallel to the LOS,). Thus, there exists a deviation in the relationship between human movements speed and CSI dynamics. How to combine the phase shift model and spatial propagation properties is an important research problem.

As for key techniques, in the base signal selection step, the quantitative relationship between the phase difference and the human movements have not been established, and we envision that more base signals will be proposed in the future. For example, a division of two amplitudes extracted from two antennas. In the preprocessing step, we still lack a comprehensive understanding of the source of noise. Thus, further research is needed to effectively remove the noise from different sources. In the feature extraction step, hand-designed feature relies heavily on empirical observations. Another research direction is to use representation learning such as deep learning [35][36] to achieve auto-generated features.

As for applications, we still have a few questions unanswered: how to push studied applications from the laboratory environment to the practical environment? Where is the boundary of the detectable problem? e.g. under which situation which activities are detectable and which are not?

To sum up, we need a more complete theoretical model that combines the propagation model and the phase shift. We also need a general technique or framework for Wi-Fi based activity recognition, because existing research only focusing on a particular application and corresponding technology based on model or observation. Moreover, we need more mechanism research such as building a human body model that links the signal to the characteristics of the human body. As a cost effective and pervasive sensing technique, there will be an increasing number of researchers engaged in this area. Thus, we can foresee that in the near future, Wi-Fi based contactless activity recognition will expect significant progress in theoretical model, key techniques and applications.

References

[1] Bahl P, Padmanabhan V N. RADAR: An in-building RF-based user location and tracking system[C]//INFOCOM 2000. Nineteenth Annual Joint Conference of the IEEE Computer and Communications Societies. Proceedings. IEEE. Ieee, 2000, 2: 775-784.

[2] ADIB F, KATABI D. See Through Walls with Wi-Fi![J]. Computer communication review, 2013, 43(4): 75-86.

[3] Pu Q, Gupta S, Gollakota S, et al. Whole-home gesture recognition using wireless signals[C]//Proceedings of the 19th annual international conference on Mobile computing & networking. ACM, 2013: 27-38.

[4] Halperin D, Hu W, Sheth A, et al. Tool release: Gathering 802.11 n traces with channel state information[J]. ACM SIGCOMM Computer Communication Review, 2011, 41(1): 53-53.

[5] Wang G, Zou Y, Zhou Z, et al. We can hear you with Wi-Fi![C]//Proceedings of the 20th annual international conference on Mobile computing and networking. ACM, 2014: 593-604.

[6] Wang Y, Liu J, Chen Y, et al. E-eyes: device-free location-oriented activity identification using fine-grained wifi signatures[C]//Proceedings of the 20th annual international conference on Mobile computing and networking. ACM, 2014: 617-628.

[7] Han C, Wu K, Wang Y, et al. WiFall: Device-free fall detection by wireless networks[C]//INFOCOM, 2014 Proceedings IEEE. IEEE, 2014: 271-279.

[8] Melgarejo P, Zhang X, Ramanathan P, et al. Leveraging directional antenna capabilities for fine-grained gesture recognition[C]//Proceedings of the 2014 ACM International Joint Conference on Pervasive and Ubiquitous Computing. ACM, 2014: 541-551.

[9] Huang, Donny, Rajalakshmi Nandakumar, and Shyamnath Gollakota. "Feasibility and limits of wi-fi imaging." Proceedings of the 12th ACM Conference on Embedded Network Sensor Systems. ACM, 2014.

[10] See published articles list. http://dhalperi.github.io/linux-80211n-csitool/

[11] Zimu Zhou, Chenshu Wu, Zheng Yang, and Yunhao Liu. Sensorless Sensing with WiFi[J]. TSINGHUA SCIENCE AND TECHNOLOGY.2015 Feb. Vol 20.

[12] Yang Z, Zhou Z, Liu Y. From RSSI to CSI: Indoor localization via channel response[J]. ACM Computing Surveys (CSUR), 2013, 46(2): 25.

[13] Tse D, Viswanath P. Fundamentals of wireless communication[M]. Cambridge university press, 2005.

[14] D. Zhang, J. Ma, Q. Chen, and L. M. Ni, “An rf-based system for tracking transceiver-free objects,” in Pervasive Computing and Communications, 2007. PerCom’07. Fifth Annual IEEE International Conference on. IEEE, 2007, pp. 135–144.

[15] Wang W, Liu A X, Shahzad M, et al. Understanding and Modeling of WiFi Signal Based Human Activity Recognition[C]//Proceedings of the 21st Annual International Conference on Mobile Computing and Networking. ACM, 2015: 65-76.

[16] Zhang D, Wang H, Wang Y, et al. Anti-fall: A Non-intrusive and Real-Time Fall Detector Leveraging CSI from Commodity WiFi Devices[M]//Inclusive Smart Cities and e-Health. Springer International Publishing, 2015: 181-193.

[17] Wu C, Yang Z, Zhou Z, et al. Phaseu: Real-time los identification with wifi[C]//IEEE INFOCOM. 2015.

[18] Davies L, Gather U. The identification of multiple outliers[J]. Journal of the American Statistical Association, 1993, 88(423): 782-79

[19] Sen S, Radunovic B, Choudhury R R, et al. You are facing the mona lisa: spot localization using phy layer information[C]//Proceedings of the 10th international conference on Mobile systems, applications, and services. ACM, 2012: 183-196.

[20] Liu J, Wang Y, Chen Y, et al. Tracking Vital Signs During Sleep Leveraging Off-the-shelf WiFi[C]//Proceedings of the 16th ACM International Symposium on Mobile Ad Hoc Networking and Computing. ACM, 2015: 267-276.

[21] Hao Wang, Daqing Zhang, et al. RT Fall: A Real-time and Non-intrusive Fall Detector with Commodity WiFi Devices. IEEE Transactions on Mobile Computing. 2015.

[22] Xiao J, Wu K, Yi Y, et al. Fimd: Fine-grained device-free motion detection[C]//Parallel and Distributed Systems (ICPADS), 2012 IEEE 18th International Conference on. IEEE, 2012: 229-235.

[23] Qian K, Wu C, Yang Z, et al. Passive Detection of Moving Targets with Dynamic Speed using PHY Layer Information[J].

[24] Wu C, Yang Z, Zhou Z, et al. Non-invasive Detection of Moving and Stationary Human with WiFi[J].

[25] Patwari N, Wilson J. Rf sensor networks for device-free localiztion: Measurements, models, and algorithms[J]. Proceedings of the IEEE, 2010, 98(11): 1961-1973.

[26] Liu W, Gao X, Wang L, et al. Bfp: Behavior-Free Passive Motion Detection Using PHY Information[J]. Wireless Personal Communications, 2015: 1-21.

[27] Zhou Z, Yang Z, Wu C, et al. Towards omnidirectional passive human detection[C]//INFOCOM, 2013 Proceedings IEEE. IEEE, 2013: 3057-3065.

[28] Zhou Z, Yang Z, Wu C, et al. Omnidirectional coverage for device-free passive human detection[J]. Parallel and Distributed Systems, IEEE Transactions on, 2014, 25(7): 1819-1829.

[29] Yunze Zeng, Parth H. Pathak, and Prasant Mohapatra. Analyzing Shopper's Behavior through WiFi Signals. ACM WPA 2015.

[30] Liu X, Cao J, Tang S, et al. Wi-Sleep: Contactless Sleep Monitoring via WiFi Signals[C]//Real-Time Systems Symposium (RTSS), 2014 IEEE. IEEE, 2014: 346-355.

[31] Liu, X., Cao, J., Tang, S., Wen, J., & Guo, P. Contactless Respiration Monitoring via WiFi Signals. IEEE Transactions on Mobile Computing. TMC 2016

[32] Ali K, Liu A X, Wang W, et al. Keystroke Recognition Using WiFi Signals[C]//Proceedings of the 21st Annual International Conference on Mobile Computing and Networking. ACM, 2015: 90-102.

[33] https://youtu.be/WgTnKjr5xow

[34] Tianben Wang, Daqing Zhang, Zhu Wang, Jiangbo Jia, Hongbo Ni and Xingshe Zhou, Recognizing Gait Pattern of Parkinson's Disease Patients Based on Fine-Grained Movement Function Features, in Proceedings of the 12th IEEE Conference on Ubiquitous Intelligence and Computing (UIC 2015), Aug 10-14, 2015, Beijing, China.

[35] Xuyu Wang, Lingjun Gao, Shiwen Mao, and Santosh Pandey. Nc. DeepFi: Deep Learning for Indoor Fingerprinting Using Channel State Information. IEEE WCNC 2015.

[36] Lingjun Gao. Channel State Information Fingerprinting Based Indoor Localization: a Deep Learning Approach. Ph.D. Thesis, Auburn University, 2015.

[37] Zheng, Yu, Licla Capra, and Ouri Wolfson. "Urban Computing: Concepts, Methodologies, and Applications."

[38] F. Foerster, M. Smeja, and J. Fahrenberg, "Detection of posture and motion by accelerometry: a validation study in ambulatory monitoring," Computers in Human Behavior, vol. 15, no. 5, pp. 571–583, 1999.

[39] Aggarwal J K, Ryoo M S. Human activity analysis: A review [J]. ACM Computing Surveys (CSUR), 2011, 43(3): 16

[40] Turaga P, Chellappa R, Subrahmanian V S, et al. Machine recognition of human activities: A survey[J]. Circuits and Systems for Video Technology, IEEE Transactions on, 2008, 18(11): 1473-1488.

[41] Scholz M, Sigg S, Schmidtke H R, et al. Challenges for device-free radio-based activity recognition[C]//Proceedings of the 3rd workshop on Context Systems, Design, Evaluation and Optimisation (CoSDEO 2011), in Conjunction with MobiQuitous. 2011, 2011.

[42] Seifeldin M, Saeed A, Kosba A E, et al. Nuzzer: A large-scale device-free passive localization system for wireless environments[J]. Mobile Computing, IEEE Transactions on, 2013, 12(7): 1321-1334.

[43] Adib, Fadel, et al. "3d tracking via body radio reflections." 11th USENIX Symposium on Networked Systems Design and Implementation (NSDI 14). 2014.

[44] Adib, Fadel, et al. "Smart homes that monitor breathing and heart rate." Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems. ACM, 2015.

[45] Lai C P, Narayanan R M. Through-wall imaging and characterization of human activity using ultrawideband (UWB) random noise radar[C]//Defense and Security. International Society for Optics and Photonics, 2005: 186-195.

[46] Postolache O, Girão P S, Postolache G, et al. Cardio-respiratory and daily activity monitor based on FMCW Doppler radar embedded in a wheelchair[C]//Engineering in Medicine and Biology Society, EMBC, 2011 Annual International Conference of the IEEE. IEEE, 2011: 1917-1920.

[47] Woyach K, Puccinelli D, Haenggi M. Sensorless sensing in wireless networks: Implementation and measurements[C]//Modeling and Optimization in Mobile, Ad Hoc and Wireless Networks, 2006 4th International Symposium on. IEEE, 2006: 1-8.

[48] O. X. Schlmilch, B. Witzschel, M. Cantor, E. Kahl, R. Mehmke, and C. Runge, "Detection of posture and motion by accelerometry: a validation study in ambulatory monitoring," Computers in Human Behavior, vol. 15, no. 5, pp. 571–583, 1999.

[49] Nandakumar R, Kellogg B, Gollakota S. Wi-fi gesture recognition on existing devices[J]. arXiv preprint arXiv:1411.5394, 2014

[50] He, Wenfeng, et al. "WiG: WiFi-Based Gesture Recognition System." Computer Communication and Networks (ICCCN), 2015 24th International Conference on. IEEE, 2015.