2016 12th International Conference on Mobile Ad-Hoc and Sensor Networks

A Survey on Motion Detection Using WiFi Signals

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***Abstract*—WiFi signals based applications, such as indoor localization, human activity recognition and trace tracking, have been increasing attention in the past decade. WiFi signals are sensitive to the change of indoor environment, so the above mentioned applications encounter challenges which contain dynamic indoor environment, device diversity and motion influence. We mainly survey techniques of motion detecting and estimate changes of WiFi signals reflected by motion behaviors. Moreover, we analyze the impact of motion behaviors on applications based on WiFi signals, and deeply research developmental trend of WiFi signals. Finally, we pay closed attention to opportunities and future research directions in this new and large open area.**

***Keywords*-Motion Detection; WiFi Signals; Motion Pattern; Channel State Information;**

I. Introduction

A. Research Background and Significance

A wireless signal traverses in all radial directions, and reflects off walls, furniture, and other objects. The creative idea is applied to indoor location, human activity recognition, access control, security surveillance and saving hostages in complexity and dynamic environment. Indoor location [1] [2] leverage fine-grained information of WiFi signals to locate people according to the path-loss characteristics. Activity recognition [3] [4] investigates the specific pattern between human activity and WiFi signals by reducing the interruption from around people or environment changes. Detecting motion and estimating influences of motion are a interesting and challenging research topic.

Motions increase several challenges and opportunities to WiFi signals based applications. Mobility information can benefit to indoor location, tracking by increasing extra information. However, it can increase the difficulty of signals processing. Recent works leverage the change of WiFi signals reflected by motion behavior to detect human motion [5]–[8]. Speed and orientation are two properties of motion behavior. Some works mainly resolve dynamic speed motion [8] [9]. High speed motion promote the change rate of WiFi signals in dynamic environment [10]. On the basis of detecting mobility, motion tracking [11] [12] has a quickly development in recent years.

B. Challenges and Issues

This paper mainly surveys techniques of motion detecting, and estimates the motion impact on applications based on WiFi signals. All in all, how to efficiently estimate the influence of motion behavior will face the following challenges.

- How to distinguish target motion from non-target motion in complex indoor environment. This challenge mainly comes from two aspects, one is that target close to non-target; another one is motion detecting based on device-free.
- How to design a framework for efficient estimation of motion behavior. Existing works propose methods to deal with special motion behavior in experiment environment, and can not apply to a new environment.
- How to estimate the relationship between motion behaviors and changes of WiFi signals in the random indoor environment. This relationship concerns how to distinguish macro-mobility from micro-mobility, and how to estimate the quality of data set from different experiment environments.

II. WiFi Signals and Motion Types

A. WiFi Signals

Wireless radio propagation in complexity environment could be modeled as a superposition of large-scale path-loss, middle-scale shadowing, and small-scale multi-path fading [13]. Early works mainly research received signal strength (RSS) which is easily gained in wireless environment. However, RSS is sensitive to multi-path effect. Then, several works select channel state information (CSI) instead of RSS to detect motions. SpotFi [14] proposes the super-resolution algorithms that can accurately compute the angle-of-arrival (AoA) of multi-path components, and achieves a median accuracy of 40cm. Chronos [15] can compute sub-nanosecond time-of-flight (ToF) using commodity WiFi cards, and achieve accuracy of 65cm. Table I show features of WiFi signals which are exploited in different applications based on WiFi signals.

978-1-5090-5696-5/16 $31.00 © 2016 IEEE
DOI 10.1109/MSN.2016.39

Table I: Features of WiFi Signals

Techniques	Features
RSS	Mean, Variance, Standard Deviation Signal Envelope
CSI	Amplitude, Phase, Standard Deviation, Signal Entropy, Velocity of Signal Change, Correlation Coefficient, Eigenvalues
AoA	AoA of the Direct Path
ToF	Difference of ToF, Absolute ToF

B. Motion Types

Motion patterns are dived into three classes as shown in the Fig. 1. First, target motions has a relatively large impact on WiFi signals in practical daily life. Second, non-target motions result in change of WiFi signals which affects the accuracy of the motion target detecting. It is the most important challenge for current applications based on WiFi signals. Third, influences of wireless device jitter also is an important part of motion pattern.

1) Target Motion: Target motion describes the behavior of the monitored object in indoor environment [6]. Movement speed and orientation of target are important elements for estimating the impact of motion behavior on WiFi signals. Target motion can change the distance between target and transmitter, enrich multi-path effect, and increase environment complexity. Changes of WiFi signals reflected by target motion can predict target traces, and target behavior.

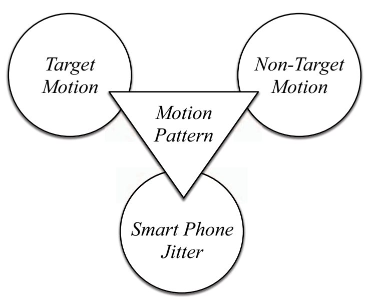

Figure 1: Motion Pattern

2) Non-target Motion: Non-target objects mean people who do not participate in experiment, however, it impacts on WiFi signals in experiment environment. Changes of WiFi signals reflected by non-target motions are more quickly than static targets. In this event, how to distinguish influence of non-target motions from static targets is an important problem for applications based on WiFi signals. DeMan [4] leverages the signal patterns caused by chest motions to distinguish static target from non-target motion.

3) Wireless Device Jitter: Handhold mobile device is hard to keep the steady state in mobility scenarios. Mobile device jitter results in a small change of WiFi signals caused by the arm movement of target. This small change is hard to distinguish it from non-target motion if it only depends on WiFi signals. For example, keyword recognition systems [16]–[18] obtain the relationship model between different keywords and different changes of WiFi signals reflected by keystrokes on the basis of imposing restrictions of the environment.

III. Techniques and Performance

A. Techniques

1) Probability Model based: Probability model is constructed by training the collected information. However, probability model based method is not pervasive for different environments. Horus [2] shows that the model has invalidation when environment occurs change. We show two points about weakness of probability-based technique.

- Environment Dependence: The same device collects information from the same environment is difference in different time. Moreover, probability model of each training also has a little difference, and this difference causes a large error to application based on WiFi signals.
- Instability: Probability model not only depends on experiment environment, but also relay on the training set and training techniques. Once training set happens to change as well as training techniques, probability model will change.

2) Fingerprint-based: Fingerprint-based method includes two phases: first, collecting RSS of each location to construct fingerprint database inside a building; second, matching the measuring RSS with fingerprint database. Fingerprint-based works can provide meter-level accuracy at the expense of explicit site-survey. However, its high deployment cost and low adaptiveness to environment change hinders the practical effectiveness. We show three points about weakness of fingerprint-based techniques.

- High-Cost: Fingerprint-based applications collect abundant location information by using a large number of labors and devices to construct fingerprint database. The more richer collect location information, the higher accuracy indoor location obtains.
- Low Adaptiveness: Once indoor environment changes, fingerprint database needs to update in time. This limitation enhances burden of systems in practical environment.
- Choice of Optimal Location: Some works select some locations of indoor maps to decrease the high-cost and also keep high accuracy. In other words, a few locations

can represent indoor maps by the coarse way. The challenge is how to select some locations to represent the indoor maps with high accuracy.

3) Crowdsourcing-based: Crowdsourcing-based applications leverage a large of mobile devices which locate in different locations of indoor environment to collect data information [19], and reduce cost of people, financial resources. However, crowdsourcing-based applications have some challenges in the practical environment as shown in following.

- Device Diversity: Difference among these devices is a challenge in wireless environment. WiFi signals not only are sensitive to indoor environment, but also are more sensitive to different types of devices [15] [20]. However, we often neglect the influence of device diversity for collecting data.
- Instability of Data Source: Mobile devices which crowdsourcing-based technique employs are invisible and stranger, and are unable to guarantee the authenticity of the data.
- Time Synchronization: According to the characteristics of WiFi signals, crowdsourcing-based techniques need the time synchronization of these devices which participate in collecting data. However, many mobile devices keep the time synchronization is difficult in the current technical level.

B. Performance

The goal of existing works is to obtain better performance at the low cost. We show the performance of existing works in the following.

1) Accuracy: RSS is sensitive to dynamic environment and multi-path effect, and existing works still employ RSS information to detect motion due to easily obtained by commodity WiFi infrastructure. Several systems combine WiFi signals with human mobility to achieve a high accuracy as shown in table.1. WiSee [21] leverages doppler shifts of radio signals to recognise human activity with an average accuracy of 97% as well as 92% from E-eyes [22]. Smokey [23] leverages the patterns of smoking behavior which leaves on CSI to identify the smoking activity in the NLOS and through-wall environments. An interesting point is that the system designs foreground detection based motion acquisition method to extract the meaningful information from multiple noisy sub-scarriers even influenced by posture changes.

2) Cost: In earlier research, researchers had a common view: the more APs we deploy, the higher accuracy we can get. Early works often deploy some APs to obtain a high accuracy. Horus [2] achieves an error of less than 0.6m on the average by 4-6 APs. With the development of techniques and increasing the awareness on WiFi signals, recent works also achieve the same level accuracy by the single AP such as Chronos [15] with a median error of 65cm.

3) Robustness: Robustness is an important indicator to estimate the quality of systems in the dynamic indoor environment. Some works propose schemes with high accuracy in the LOS, not apply to NLOS, even obtain the worst accuracy in the NLOS. Recent works [6] [23] can provide the robustness with different techniques. Smokey [23] can identify the smoking activity in the LOS, NLOS and through-wall environments.

IV. Motion Influence

A. Advantage

Previous works have been designed to avoid motion behavior because motion behavior has the great impact on the change of WiFi signals. We survey a large amount of papers in recent years to study mobility detecting techniques and influence. There are three points are summarized as follows.

1) Enrich Multi-path Information: Multi-path effect is the ubiquitous in indoor environment. In general, there are 6-8 paths in common indoor environment. Understanding patterns of human movement can be valuable in identifying hot spots and corridors that help energy management and commercial site selection. Human movement can reset floor plan of indoor environment, and multi-paths will change adaptively. LiFi [27] identifies LOS by using skewed distribution of CSI. Moreover, PhaseU [28] completes real-time LOS identify in indoor environment. Other works select several paths from multi-paths to complete indoor localization or human activity recognition [29].

2) Reducing Cost of Device: WiVi [30] proposed a moving object to simulate the antenna array as shown in Fig. 2. It can reduce the cost of devices, and improve performance of applications such as indoor localization, human tracking and access control. It leverages MIMO interference nulling to eliminate reflections off static objects and focus the receiver on a moving target. If people do not move, we are unable to identify the number of people without the help of an antenna array in a closed room.

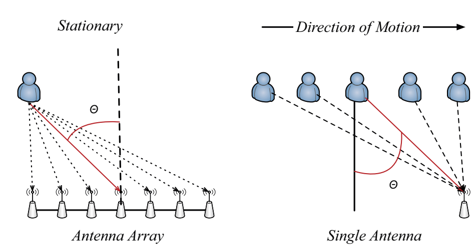

Figure 2: A Moving Object as an Antenna Array

3) Dropping the Dependence of Indoor Environment: Wireless signals are sensitive to indoor environment. Signatures of WiFi signals certainly vary over time and environment. Unfortunately, this characteristic brings more

Table II: Fine-grained Information and Mobility

Citation	Techniques	Accuracy	Precision
CUPID [24]	AoA + Human Mobility	Single AP: 4.5m and 2-3 APs: 2.7m	LOS: 20°and NLOS: 60°
ArrayTrack [25]	AoA	37cm	LOS: 7.4°and NLOS: 15.2°
SAIL [26]	ToF + Human Mobility	2.3m	N/A
SpotFi [14]	AoA	40cm	LOS: 5°and NLOS: 10°
Chronos [15]	ToF	LOS: 65cm and NLOS: 98cm	LOS: 0.47ns and NLOS: 0.69ns

challenges for WiFi based applications. Fingerprint-based indoor location cannot widespread apply because signature will change with environment changes. Most of authors attempt to propose a pervasive method to deal with motion behavior in the dynamic environment.

B. Disadvantage

1) Contaminating Data Sets of WiFi Signals: In general, data sets of WiFi signals contain RSS and CSI collected by receiver in indoor environment. Motion behaviors have more important impacts on WiFi signals than static behaviors. We collect data sets which contain target's data, motion data and other noise data. Therefore, it is difficult to distinguish targets'data from collecting data sets without using special techniques. For other noise data, researchers propose a few available methods to resolve them.

2) Making the Preprocessing more Difficult: Preprocess phase becomes harder than previous phase without motion behaviors due to the complication of motion behaviors. Static behaviors can cause a small change of WiFi signals, but motion behaviors can cause a large change. Meantime, it is a hard problem to distinguish outlier from motion behavior by using the collecting data from the receiver.

3) Increasing the Consumption of Hardware Cost: Motion behavior increases instability of data sets collected by mobile devices, and reduces performance of WiFi-based systems. In order to get high accuracy, it needs to increase APs (5-6) and other sensors (Accelerator, Gyroscope). At present, some works combine WiFi signals with sensor data information to achieve the same goal which only depends on WiFi signals without motion behavior.

V. Future Trends

With the in-depth research on the related technologies of WiFi signals, fine-grained information of WiFi signals describes micro-mobility behavior with high accuracy by using machine learning algorithm, senses surroundings and predicts the unknown behavior. Several research groups pay more attentions on device-free detecting motion by using WiFi signals.

- Detecting Non-invasive Human: Researchers attract more attentions to detect non-invasive human. Non-invasive means that people do not need to attach any device, and passive participant in detecting. Applications based on non-invasive can enhance the freedom of people (convenience), and decrease the cost of hardware. In the meantime, it brings severe challenges such as high quality data, effective algorithm, and dependence of environment.
- Detecting Different Motions: The wireless channel between the client and the AP is expected to vary under dynamic environment or device mobility. The fine-grained multi-path structure may change if there are several moving objects in the environment, or the device itself moves. Small variation of the wireless channel can not be captured by using RSS because it only captures an aggregate indicator of all the multi-path components. Therefore, we exploit the relationship between motions and signal changes to distinguish different motions by using CSI or AoA in the complexity environment.
- Tracking User Behavior: Tracking user behavior leverages the characteristics of WiFi signals reflected by human behavior to record the human behavior and predict the unknown behavior [11] [31]. Shopper's behaviors [31] around the entrance can be analyzed by using WiFi signals. We leverage fine-grained information of WiFi signals to track the trace of human, and analyze the human behavior.

VI. Conclusion

This paper surveys motion detecting techniques, and motion has an important impact on WiFi signals. First, we introduce information of WiFi signals and motion types. Next, we describe techniques of mobility detecting including probability model based, fingerprint-based, and crowdsourcing-based. Moreover, we show how to estimate the influence of motion for applications in indoor environment. Finally, we introduce new applications based on WiFi signals in the future.

Acknowledgment

This work is supported by Natural Science Foundation of China under Grants No. 61272524 and Dalian University of Technology under the Haitian Scholar grant. We thank the anonymous reviewers for their helpful feedbacks on earlier versions of this paper.

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