WiFall: Device-free Fall Detection by Wireless Networks

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***Abstract*—The world population is in the midst of a unique and irreversible process of aging. Fall, which is one of the major health threats and obstacles to independent living of elders, will aggravate the global pressure in elders' health care and injury rescue. Thus, automatic fall detection is highly in need. Current proposed fall detection systems either need hardware installation or disrupt people's daily life. These limitations make it hard to widely deploy fall detection systems in residential settings. In this work, we analyze the wireless signal propagation model considering human activities influence. We then propose a novel and truly unobtrusive detection method based on the advanced wireless technologies, which we call as WiFall. WiFall employs the time variability and special diversity of Channel State Information (CSI) as the indicator of human activities. As CSI is readily available in prevalent in-use wireless infrastructures, WiFall withdraws the need for hardware modification, environmental setup and worn or taken devices. We implement WiFall on laptops equipped with commercial 802.11n NICs. Two typical indoor scenarios and several layout schemes are examined. As demonstrated by the experimental results, WiFall yielded 87% detection precision with false alarm rate of 18% in average.**

I. Introduction

Falls can be described as the abrupt change of body position from the upright/sitting position to the reclining or almost lengthened position without control [1]. Falls are very prevalent among the elderly. According to the Centers for Disease Control and Prevention, one out of three adults age 65 and older falls each year [2]. In the event of a fall, a lot of injuries can happen which include bruises, internal bleeding and bone fractures. For the worst case, a fall may even lead to the death of the person. The longer time the person lie on the floor, the more server will the injuries be. Studies have shown that the medical outcome of a fall is largely dependent on the response and rescue time [3]. The delay of medical treatment after a fall can increase the mortality risk in some clinical conditions, especially for those who live alone. Falls not only bring a main threat to people's health, they also account for a large part of medical cost in the whole world. For example, in 2000, falls among older adults cost the U.S. health care system over $19 billion dollars and the number increase to $30 billion dollars in 2010 [2]. All of these emphasize the importance of automatic fall detection system to be deployed in the living environment.

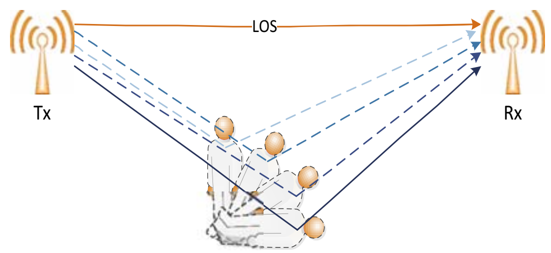

Fig. 1. Signal propagation model when fall happens

Over the past ten years, fall detection (FD) systems using various techniques have been proposed and studied [1] [4] [5]. The existing prototypes can be categorized into four classes: ambient device based, vision based, wearable sensor based and smartphone based techniques.

Ambient device based FD systems [3] [6] [7] try to make use of ambient noise caused by fall activity to detect a risky situation. The ambient noise being used includes vision, audio and floor vibration. In these systems, specific devices need to be implanted in active environment. Sensing pressure or sound of everything in and around the object causes a large proportion of false alarm.

Vision based fall detection systems [8] [9] [10] employ activity classification algorithms on a series of images recorded by a high resolution camera. Image processing can effectively detect a human fall. Nevertheless, problem caused by installing a camera is privacy invasion. Vision based fall detection fails to work in dark environment.

Both wearable sensor based [11] [12] and smartphone based [13] [14] fall detection techniques employ sensors like accelerators to sense the acceleration or velocity on three axis. Sensors are widely used in activities recognition. However, carrying sensors or smartphones is usually user unfriendly.

Although numerous fall detection systems have been proposed and studied, few of them have been widely used in living settings. Thus, falls are still one of the major health threats to elderly who live alone. Based on these motivations and the prosperous development of wireless techniques, this paper aims to investigate if automatic fall detection can be achieved without any equipped and carried devices by using currently commercial wireless products.

In recent years, rapid blossom of wireless network facilities and techniques has motivated variety of research interests in localization [15], motion detection [16] and object tracking [17]. Wireless techniques are promising in identifying environment change. However, there is few work studying the relationship between the wireless signal and human activities. As illustrated in Fig. 1, when a human activity, for instance, fall happens, the signal transmission pathes are changed.

To implement unobtrusive fall detection by wireless networks, we need to solve the following challenges: firstly, we need to find a good representation of wireless signal which should be robust to environmental change but sensible to human disturbance; secondly, when considering complex human activities, current radio propagation model cannot be applied directly; finally, it's difficult to mine the relationship between human activities and wireless signal properties.

In this paper, we firstly study wireless radio propagation model in indoor environment under the disturbance of human activity. Both theoretically and experimentally, it is proved that wireless signal is affected by human actions. Based on this model, we propose a device-free fall detection system (WiFall) taking advantage of wireless signal properties-Channel State Information (CSI). As CSI is a finer measurement of the wireless propagation channel, it's a good indicator of human interference on wireless signal. The core idea is to mine the change rules of CSI when the environment is affected by human activities. WiFall consists of a two-phase detection architecture: local outlier factor based algorithm to find abnormal CSI series and activity classification using one-class Support Vector Machine (SVM) to distinguish falls. In summary, the main contributions of this paper are as follows.

1) We exploit the feasibility of using fine grained channel state information for device-free fall detection. To the best of our knowledge, this is the first work to leverage PHY layer information CSI for Device-free fall detection in WLANs. Unlike other FD systems, WiFall leverages the prevalent wireless infrastructures existing already. There is no need for hardware modification and environmental setup.
2) We take the advantages (temporal stability and frequency diversity) of CSI to design WiFall, a passive device-free fall detection system. To realize the truly unobtrusive fall detection, we reconstruct the radio propagation model with consideration of human activities. On the basis of motion detection by anomaly detection algorithm, we apply one-class SVM to separate falls.
3) Extensive evaluations of WiFall with commercial 802.11 NICs are conducted in two typical indoor scenarios. These measurements show that WiFall achieves comparable precision as device-based fall detection systems. Furthermore, it can easily be extended for recognizing other human activities.

The rest of this paper is organized as follows. We first introduce the related work in Section. II. This is followed by wireless techniques in Section. III, which includes the detailed introduction of channel state information and the analysis of wireless signal propagation model. Then in Section. IV, the design details and overview system architecture are presented. Section. V gives the methodology and Section. VI describes the implementation and experimental results of WiFall. Finally, the conclusions and future work are given in Section. VII.

II. Related Work

Timely fall detection of the elderly can reduce the damage degree and decrease the chances of mortality. Older people are the most disturbed group by unintentional falls. Fall detection for elderly is always a hot topic in healthcare industry and has attracted a lot of attention from academia in the past two decades. There have been a lot of fall detection techniques proposed since the early 1990s. Noury et al. [1], Yu [4] and Mubashir et al. [5] reviewed the principles and approaches used in existing fall detection (FD) systems. In general, fall detection systems can be classified into four groups: ambient device based techniques, vision based techniques, wearable sensor based and smarphone based techniques.

Ambient device based fall detection techniques attempt to fuse ambient noise information including visual [6], audio [7] and floor vibrational [3] data produced by a fall for the detection purpose. The principle is based on the fact that human movements in a living setting will cause the acoustic change and floor vibration. It is unobtrusive and less intrusive. However, some specific devices need to be implanted in dwelling environment. Moreover, it has a big disadvantage of sensing pressure or sound of everything in and around the object and generating false alarms. For example, a heavy stuff fall from a high height will also cause the similar patter in vibration or sound.

Along with the computer graphics and widely used cameras, other researchers have proposed fall detection systems based on vision techniques. In these kind of systems, a high resolution camera is equipped in the monitoring room and a series of images of the object is recorded. By using activity classification algorithm, the fall activity is distinguished and reported [8] [9] [10]. The problem this method brings is that people may feel uncomfortable with a camera overhead, especially in bathroom. Besides the privacy intrusion, this method is also limited by line of sight problem and fails in darkness. What's more, there will exist dead corner that can not be reached even by several cameras.

Wearable sensor based fall detection systems rely on sensors that are embedded in wearable stuff such as coat, belt and watch. The widely used sensors include accelerators, gyroscopes, mercury tilt swatch and velocity sensors [11] [12]. These detection systems can only work on the premise that all the devices are worn by the object and connected correctly to the body. Such requirements give additional burden on the body and interfere objects' daily life. From the above, wearable devices are an unfavourable choice for the elderly.

Smart phone is one of the tool we use everyday and plenty of applications are available online for downloading. Smart phone based fall detector is new and potential [13] [14]. However, besides the precision concern, it has the same problem with wearable based methods, which is prone to be forgotten. Most users will not take their phone on body all the time, especially at home.

In summary, owing to several kinds of constraints, there still lacks one satisfactory automatic fall detection system.

III. Preliminaries

A. Channel State Information

Channel state information or channel status information (CSI) is information that estimate the channel properties of a communication link [15]. In wireless communication, the transmitted radio signal is affected by the physical environment, for instance, reflections, diffractions and scattering. CSI describes how a signal propagates in the channel combined the effect of time delay, amplitude attenuation and phase shift.

In frequency domain, the narrowband flat-fading channel with multiple transmit and receive antennas (MIMO) is modeled as

$$y = Hx + n \tag{1}$$

where y is the received vector, x is the transmitted vector, n is the noise vector and H is the channel matrix. As noise is often modeled as circular symmetric complex normal with $n \sim cN(0, S)$, H in the above formula can be estimated as

$$\hat{H} = \frac{y}{x}$$

.

Channel State Information (CSI) is an estimation of H. In Orthogonal Frequency Division Multiplexing (OFDM) system, CSI is represented at subcarrier level. CSI of a single subcarrier is in the following mathematical format:

$$h = |h|e^{j\sin\theta}$$

where $|h|$ and θ are the amplitude and phase respectively.

CSI provides a finer-grained representation of the wireless link compared with Received Signal Strength (RSS). Thus, recent wireless applications tend to employ CSI rather than RSS. In the next section, we give experimental analysis about how to use CSI to indicate environmental changes.

B. Radio Propagation Model

The idea of device-free fall detection is based on the fact that human existence and movement affect the wireless propagation paths. To understand the relation of human movements with received CSI, the wireless propagation model should be first studied. In this section, we examine the wireless propagation model in indoor environment.

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 scattered by the human body. As illustrated in Fig. 2, ignoring the reflected pathes from walls and other surroundings, there is one line-of-sight path plotted in yellow line, two reflected pathes from ceiling and floor that are plotted in green lines and several pathes scattered by human body represented in red line.

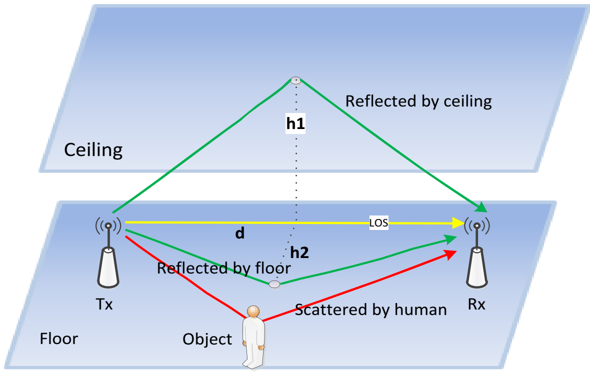

Fig. 2. Signal propagation model in indoor environment

The line-of-sight path suffers from free space path loss. According to the free space model, the received power by a receiver antenna which is separated from a radiating transmitter antenna by a distance d, is given by the Friis free space equation [18],

$$P_r(d) = \frac{P_t G_t G_r \lambda^2}{(4\pi)^2 d^2} \tag{2}$$

where P_t is the transmitted power, $P_r(d)$ is the received power which is a function of the distance d, G_r is the receiver antenna gain, G_t is the transmitter antenna gain, λ is the wavelength in meters and d is the distance from transmitter to receiver in meters.

Considering the reflection pathes by the ceiling and floor, the power received can be represented as [17],

$$P_r(d) = \frac{P_t G_t G_r \lambda^2}{(4\pi)^2 (d^2 + 4h^2)} \tag{3}$$

where h is the distance from reflection point on ceiling or floor to LOS path.

When a person exists in the indoor environment, several scattered pathes are produced by human body. Those scattered power should also be added in the final received power.

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

where Δ is a brief representation of path length caused by human body.

If a person is static in the environment, P_r is almost stable. However, along with the fall of a person, the scattered points become lower and keep in changing. For example, in Fig. 1, the dash light blue lines represent the scattered pathes by a person who is falling. The solid blue line refers to the scattered line by a lying human body. In the process of a fall activity,

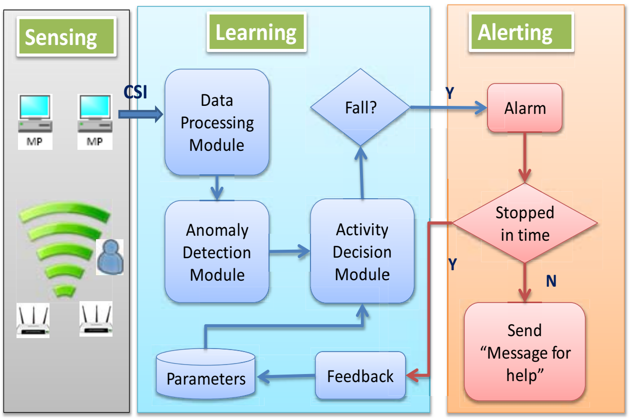

Fig. 3. Overview of System Architecture

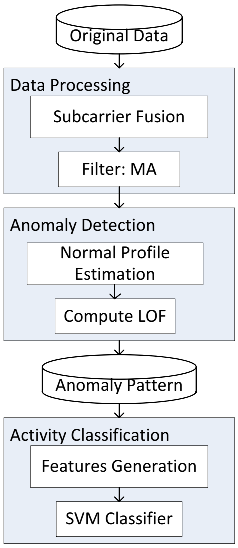

Fig. 6. System Flow Chart

the scattered pathes change in a fast speed. This results in the variance in received signal power.

The total received power by the receiver is the sum of received power from multiple propagation pathes. Suppose the intensity magnitudes of the line-of-sight path, the roof reflection path, the ground reflection path, and human scattering pathes are E_{los}, E_{ref1}, E_{ref2}, E_{sca} respectively. For simplicity, the total received power P can be expressed as

$$P \propto |E_{los} + E_{ref1} + E_{ref2} + E_{sca}|^2 \tag{5}$$

In the above formula, E_{los}, $E_{ref1}E_{ref2}$ are nearly constant in a special environment. The component E_{sca} is also constant when the person in the environment is static. However, when the person is active, E_{sca} will be variational over time. In the following section, the focus is on the instable part E_{sca}, which can represent human motions.

IV. System Design

WiFall leverage PHY layer information CSI to indicate the human activities in indoor environment and then learn the specific pattern related with a fall activity. Figure 3 gives an overview of the system. WiFall system is consisted of three main phases: the sensing phase, the learning phase and the altering phase.

In the sensing phase, the transmitters propagate wireless beacon signals. The receivers in the same interesting area collect the wireless physical information-CSI and send to the next phase. The transmitters are typically access points well the receivers can be any existing devices at home, e.g. laptops. They will be named as Access Points (APs) and Monitoring Points (MPs) hereafter.

There are four modules in the learning phase, namely data processing, anomaly detection, activity classification and feedback. They are implemented on an application server. Data filtering techniques are required first for the reason that wireless signal is also affected by the change in the environment such as temperature, air pressure and humidity. Then moving average is applied to reduce noise in the data. As motionless human body cause no change of wireless signal in time domain, by using time series anomaly detection algorithm, human motions (walk, sit, stand up and fall) are detected. The corresponding anomaly patterns are extracted and stored. Activity classification module depends on the anomaly information and selected features to decide what activity is happening, especially to report a fall. The last one, feedback, cooperates with the altering phase and gives a feedback that can refine the detection and decision making algorithms.

The final phase, altering, is an emergency alarm trigged by the fall detected. When a fall is detected, the application will pop up an alarm. The object can turn off the alarm if he/she does not need any help. Otherwise, if no action is taken for a fixed time, a message for help will be sent out.

V. Methodology

The flow chart of WiFall is given in Fig. 6. There are mainly there steps in the process:

1) Data Processing: CSI is collected in thirty subcarriers and nine streams, which reflect the signal diversity in frequency and space. We analyze the property of CSI and pick the best ones for detection. What's more, CSI is also slightly influenced by environmental noise besides human activities. To reduce the noise, we smooth CSI with weighted moving average.
2) Anomaly Detection: Static human body does not affect CSI in time domain. Human activities, such as walk, sit, stand up and fall are active and will result in the variance of CSI. Compared with stationary, human activities can be considered as anomaly. and be detected by anomaly detection algorithm.

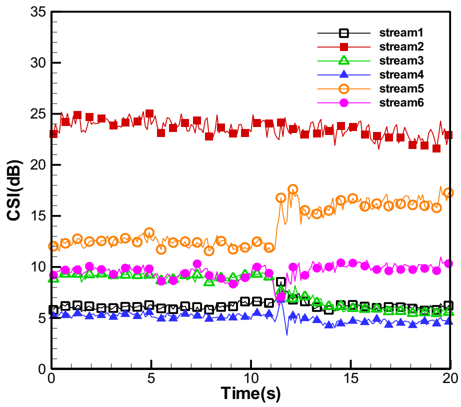

Fig. 4. CSI variance of 1th subcarrier in different streams

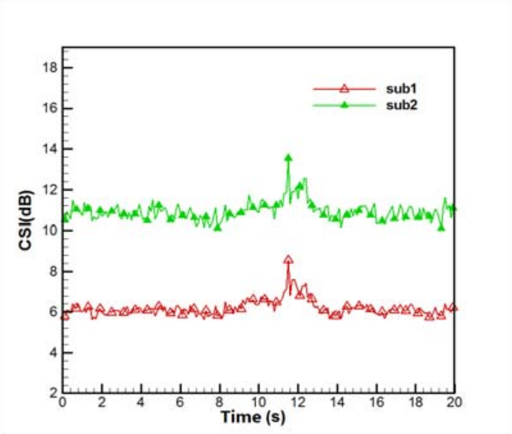

Fig. 5. CSI variance of different subcarriers in one stream

3) Activity Classification: Several human motions can cause anomaly patterns of CSI. It's difficult to distinguish them by anomaly detection. So more features need to be exacted and we use one-class support vector machine algorithm to recognize fall from other human motions.

A. Data Processing

The CSI is collected from received packages in the monitoring point. Based on OFDM system, CSI information is divided into 9 streams (if use 3×3 MIMO system) and 30 subcarriers in each stream. In other words, from each packet, there 270 groups of data can be extracted. They are represented in the following format:

$$\begin{aligned}
\mathbf{CSI}^1 &= \{CSI^{1,1}, CSI^{1,2}, ...CSI^{1,30}\} \\
\mathbf{CSI}^2 &= \{CSI^{2,1}, CSI^{2,2}, ...CSI^{2,30}\} \\
&\quad\cdots\cdots\cdots \\
\mathbf{CSI}^9 &= \{CSI^{9,1}, CSI^{9,2}, ...CSI^{9,30}\}
\end{aligned}$$

where in $\mathbf{CSI}^{i,j}$, i is the indicator of stream and j is the indicator of subcarrier number.

From the experiment, we find that human activities affect the 9 streams independently whereas affect different subcarriers in a similar way, as illustrated in Fig. 4 and Fig. 5. In Fig. 4, CSI amplitude of six different streams in the first subcarrier are plotted with different colors. The six streams are received by the same pair of MP and AP but show different patterns in context of human interference. In Fig. 5, the green line refers to CSI in the $1th$ subcarrier of one stream, while the pink line refers to the CSI in the $30th$ subcarrier of the same stream. Although different in absolute value, they present similar pattern under the influence of human motions.

Based on these two observations, we aggregate CSI in 30 subcarriers into one single value CSI^i (i is the stream number). Several methods can be employed. One simple method is to get the average CSI of five successive subcarriers. Finally, we get nine values of CSI at one time point.

Environmental factors such as temperature and room settings may also cause the received CSI fluctuate. WiFall system reduces environmental noise by employing weighted moving average. Specifically, in a CSI series, says $\{CSI_1, CSI_2, \cdots, CSI_t\}$, the CSI value at time t is averaged by the previous m values. The latest CSI has weight m, the second latest $m-1$, etc., down to one

$$\begin{aligned}
CSI_t = &\frac{1}{m + (m-1) + ... + 1} \times (m \times CSI_t \\
&+ (m-1) \times CSI_{t-1} + ... + 1 \times CSI_{t-m+1})
\end{aligned} \tag{6}$$

where CSI_t is the averaged new CSI. The value of m decides in what degree the current value is related with historical records.

B. Anomaly Detection

Anomaly detection aims to detect the anomaly change in wireless signal. The activities WiFall system focuses include walk, sit, stand up and fall. Although various immobile human postures results in different signal power at MPs, they have same signal change patterns in time domain, which is steady over the time. Human motions-walk, sit, stand up and fall lead to obvious fluctuation of CSI. By using Local Outlier Factor based anomaly detection algorithm, WiFall finds human motions and isolates the corresponding anomaly patterns.

Local outlier factor (LOF) is introduced as the suspicious score of anomaly detection. LOF is first proposed by Markus M. Breunig et al. [19] for finding anomalous data points by measuring the local density of a given data point with respect to its k-nearest neighbours. The local density is estimated by a specific distance at which a point can be reached from its neighbors. Concretely, the local density of p is defined as

$$lrd(p) = 1/(\frac{\sum_{o \in k(p)} reach-dist_k(p,o)}{k}) \tag{7}$$

where $k(p)$ is the set of k-nearest neighbors of p, k is the number of chosen nearest neighbors. $reach-dist_k(p,o)$ is called reachability distance. Let $k-distance(p)$ be the

Fig. 7. Scenario 1: Chamber

Fig. 8. Scenario 2: Laboratory

Fig. 9. Scenario 3: Dormitory

distance of object p to the k nearest neighbors and $d(p,o)$ be the distance from p to o, $reach-dist_k(p,o)$ can be calculated in the following.

$$reach-dist_k(p,o) = max\{k-distance(p), d(p,o)\} \quad (8)$$

Local Outlier Factor is defined as the ratio of average local densities of one object's neighbors to the local density of the object. LOF of point p is computed as follows.

$$LOF(p) = \frac{\frac{1}{k}\sum_{o\epsilon k(p)} lrd(o)}{lrd(p)} \quad (9)$$

LOF denotes the degree of outlier-ness. LOF value of approximately 1 indicates that the point is located in a region of homogenous density. Higher LOF values signify an outlier, as it is a degree of being an outlier, but the scaling is different for different datasets.

C. Activity Classification

After anomaly detection, several human motions are detected as anomaly patterns. They are similar because they can cause a large and obvious variance of CSI in time domain, which is abnormal compared with the steady situation.

To distinguish human fall, an one-class Support Vector Machine (SVM) is applied based on the features extracted from anomaly patterns. We choose the following seven features to characterize the activity: (1) the normalized standard deviation (STD) of CSI, (2) the offset of signal strength, (3) the period of the motion, (4) the median absolute deviation (MAD), (5) interquartile range (IR), (6) signal entropy, (7) the velocity of signal change. Based on the observation in Section. V-A, different streams present different change laws when affected by human activities. To explore the spatial diversity, each stream generates the above seven features respectively and they together constitute the input of classification algorithm. Example of four features are shown in Fig. 10-Fig. 13.

One-class SVM is an extended algorithm of SVM [20]. In one-class SVM, all the samples are divided into objective class and non-objective class. To solve the non-linear classification problem, it maps input samples into a high dimensional feature space by using a kernel function and find the maximum margin hyperplane in the transformed feature space. The hyperplane includes all the objective samples inside and non-objective samples outside.

In our application, fall is the objective class, denoted as F. Other human motions belong to non-objective class. Specifically, the problem can be formalized in the following way: Given some training anomaly pattern set X in the form,

$$X = \{x_1, x_2, ..., x_m\} \subset \chi \quad (10)$$

χ is the feature set in the original space.

Let $\Phi\colon X \to H$ be a kernel map that transforms the training examples to another high dimensional space. Then, to separate the data set from the origin, one needs to solve the following quadratic programming problem:

$$\underset{w,\xi,\rho}{\mathbf{min}} \quad \frac{1}{2}||w^2|| + \frac{1}{\upsilon l}\sum_i \xi_i - \rho \quad (11)$$

$$\textbf{Subject to} \quad (w \cdot \phi(\mathbf{X_i})) \geq \rho - \xi_i, \xi_i \geq 0 \quad (12)$$

From this, one can get a discriminant function f such that

$$f(x) = sign(w \cdot \Phi(x) - \rho) \quad (13)$$

This classification rule is used to assign a label to a test example x. If $f(x) > 0$, then x is labeled as Fall. The kernel we use in this model is Gaussian kernel: $K(x,y) = e^{-||x-y||^2/(2\sigma^2)}$, where σ^2 is the variance.

SVM classifier requires a training data set. In the process of construct classification model. We took the data from testbed in one week, which consists of four human subjects performing four activities. Each sample lasts 20 seconds. We use LOF to extract the anomaly series and build the classification model by utilizing LibSVM, a freely SVM libratory implemented by Chang and Lin [21].

VI. Experimental Results

This section illustrates the implementation and experimental evaluation of WiFall. Firstly, we describe experimental settings. Then, we analyze the signal properties of different activities and examine the effective detection range of a single wireless link. Finally, we evaluate the performance of WiFall.

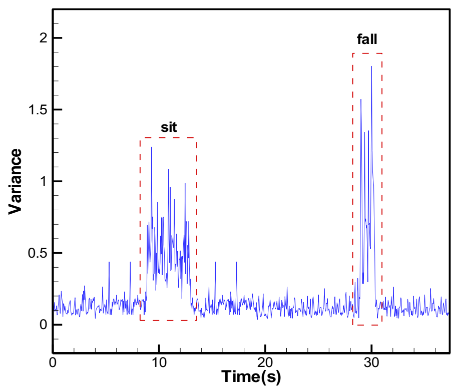

Fig. 10. Variance comparison of sit and fall

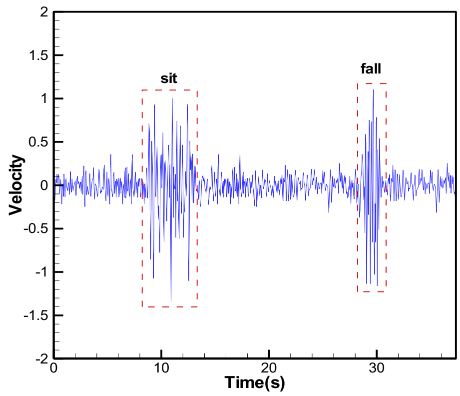

Fig. 11. Velocity comparison of sit and fall

A. Experimental Setting

In the experiment, we use two HP laptops with 2.4GHz dual-core CPU as the MPs and implement WiFall on both laptops. The laptops are equipped with Intel WiFi Link 5300(iwl5300) 802.11n NICs. We modify the driver as in [22] to collect CSI. Two TP-LINK routers act as APs. All the NICs and routers are equipped with three antennas. The 3×3 MIMO system produces nine streams and achieves the spacial diversity. The two MPs and APs form two wireless links and run on 5GHz to get free from crowded 2.4GHz interference in the experimental environment.

Most of the interested activities happen in several seconds. In order to capture the signal affected by those short time activities, we increase the beacon rate to 100 packets per second, which is 100Hz. MPs gather the packets and extract CSIs from the wireless NICs. We conduct experiments under three different indoor scenarios:

1) Chamber. We first set up a testbed in a $3m \times 4m$ chamber as shown in Fig. 7. Chamber is a RF shielding system, where wireless signal will be absorbed instead of reflection. Typically, chamber is a free space indoor environment where there is no multipath phenomenon. In our experiment, besides LOS signal, multipaths caused by human also exist. This is an ideal environment to test the influence of human activities on CSI.
2) Laboratory. The second experiment is conducted in a $8m \times 9m$ laboratory as shown in fig. 8. Because laboratory is big and spacious, we can test the effective range of one wireless link. In the laboratory, we place one AP and MP on opposite positions. The MP is mounted on a 1 meter high table and the AP is placed on a wheeled chair so we can adjust the distance between AP and MP easily. In the process of gathering signal, three students were working as normal in the neighborhood.
3) Dormitory. Finally, we deployed WiFall in a student's dormitory, which is $4m \times 5m$ as shown in fig. 9. There is some furniture around. The dormitory can estimate one typical living room.

B. Signal Analysis of Different Activities

Previously work [17] [23] has proved that the existence and movement of human will affect the wireless signal propagation, which results in the change in RSSI or CSI values. However, there is few work about how the activities of human will affect the wireless channel. The key of fall detection problem is to discriminate fall from other human activities, like sitting, walking and standing up. In our work, the information we can get is only the indirect wireless data that is affected by the activities. Therefore, we have to first understand what effects different human activities will produce on the wireless propagation channel.

To testify whether different activities have different CSI change patterns, we conducted the first experiment in chamber. Both LOS and non-LOS locations are examined. Because the chamber is too small for walk activity, the test activities set is {sit,fall}.

We select two features to represent the result. From Fig. 10, it is obvious that when the subject is motionless, CSI values have low variance. Sit and fall both cause great variance in the CSI amplitude. Compared with sit, fall has a higher variance value with shorter duration. The result is in accord with our model analysis. Similarly, as shown in Fig. 11, the velocity which stands for the signal change speed between fixed periods, is very different between motionless, sit and fall. For motionless, the signal is almost stable. For sit, the change is bigger than motionless but smaller than fall.

The experiment in dormitory is similar. Walk and stand up are added in the test set. Interquartile range and median absolute deviation of different activities are compared in Fig. 12-Fig. 13.

C. Performance Evaluation

Two metrics are used to analyze the performance of WiFall: detection rate and false alarm rate. Detection rate is the probability that the system can detect a fall. It can be computed through (14). False alarm rate refers to the proportion that the system generates an alarm when there is no fall happens,

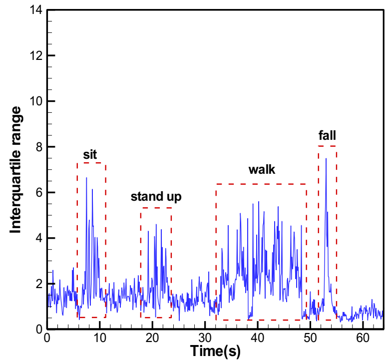

Fig. 12. IR comparison of different activities

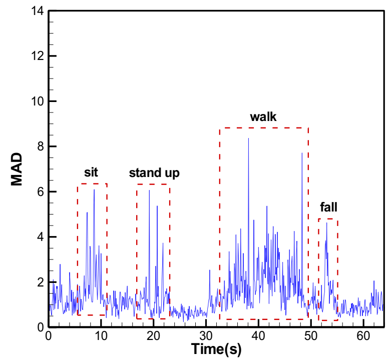

Fig. 13. MAD comparison of different activities

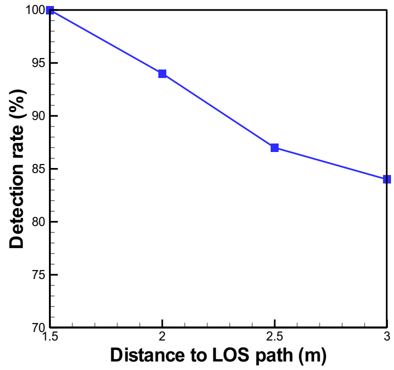

Fig. 14. Anomaly DR when distance to LOS increases

which is computed in (15).

$$DR_{fall} = \frac{\#\, of\, truly\, detected\, fall}{\#\, of\, total\, fall} \tag{14}$$

$$FA = \frac{\#\, of\, wrongly\, detected\, fall}{\#\, of\, detected\, fall} \tag{15}$$

The experiments are conducted in three scenarios: chamber, laboratory and dormitory. Activities set tested in chamber is {sit, stand up, fall}. Activities set tested in the remaining two scenarios are {walk, sit, stand up, fall}.

In chamber, one object did the activities each with three times. In the 36 instances of each activity, the motion detection rate is 100%. Fall detection rate and the false alarm is listed in Table. I.

In the laboratory, we examine two kinds of deployment of APs and MPs. The first one is same as the experiment in previous experiment. One pair of AP-MP communication link has limited effective range. In order to increase the detection rate, we deployed two APs and MPs in the laboratory. Each MP receives from the opposite AP. The whole covered area is $7.2m \times 7.5m$. Four objects simulated walk, sit, stand up and fall each with 5 times. Eight locations are tested. The result is listed in Table. I.

Finally, we implement the user interface of WiFall in MATLAB platform and evaluate the system in dormitory. The interface is shown in Fig. 15. The input box of train points to training data folder. The test input box are the folder where the received CSI data files are stored. In the user interface, we add an function that can confirm or cancel a fall. When a fall is correctly detected, the new CSI features are embedded into the classification model as objective instance. When there is a false alarm, the corresponding patterns are labeled as non-objective instance, which can further improve accuracy of WiFall. In the demo, we did four activities at each location. Each activity was repeated four times. Two times are used as training set and two times are used as test set. Among all the 72 anomaly activities, four fall are missed and there appears three false alarms.

Fig. 15. User interface of WiFall

TABLE I
EXPERIMENT RESULTS

	Precision	False Alarm
chamber	94%	22%
laboratory-one link	85%	17%
laboratory-two links	91%	15%
dormitory	78%	21%

Averaging the experimental results in typical indoor environments-laboratory and dormitory, WiFall realizes 87% detection rate and 18% false alarm rate.

VII. CONCLUSIONS AND FUTURE WORK

Fall has become one of the major health threats and major obstacles to independent living for elders. With the increased attention and needs for automatic fall detection, various systems have been proposed and implemented. However, owing to the strict limitations of these systems (e.g. requirement of instrument installation, privacy invasion and inconvenient devices on body), few can be widely deployed in living settings. Inspired by wireless signal utilizations in motion detection and localization, we propose a WiFi based device-free fall detection solution-WiFall.

The device-free fall detection system in this paper takes advantages of the wireless physical information-Channel State Information (CSI) in widely deployed commercial wireless infrastructure. To demonstrate the feasibility and effectiveness, we implemented WiFall system on Linux platform with commercial 802.11n NICs. The experiments were conducted in three different scenarios with various deployments. According to our observations from experiments, the received signal presents different patterns if wireless propagation space is affected by human activities. Experimental results show that WiFall can achieve an acceptable detection and false alarm rate.

VIII. ACKNOWLEDGEMENT

This research is supported in part by Program for New Century Excellent Talents in University (NCET-13-0908), Guangdong Natural Science Funds for Distinguished Young Scholar (No.S20120011468), Hong Kong RGC Grant HKUST617212, New Star of Pearl River on Science and Technology of Guangzhou (No.2012J2200081), Guangdong NSF Grant (No.S2012010010427), China NSFC Grant 61202454, 61202377, China NSFGD Grant S2012040006682, the Shenzhen Science and Technology Foundation (Grant No. JCYJ20120613173453717), Major State Basic Research Development Program (973 Program) under Grant 2013CB329006.

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