Effects of Antenna Orientation in Fall Detection Systems Based on WiFi Signals

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***Abstract*—The global increase in human life expectancy has created a need for healthcare and remote monitoring technology suitable for the elderly. One of the biggest health treats to older adults are falls occurring at home during daily activities. This reality has prompted the design of device-free fall detection systems that employ WiFi signals as sensing probes. Several works have addressed the design and development of these detection platforms. However, these works have not considered the impact of the antenna orientation on the system's sensing capabilities. To close the gap, we present a systematic analysis of the effects of antenna orientation on the performance of a WiFi-based fall detection systems. The analysis was conducted on the grounds of an experimental platform that transmits WiFi-like waveforms from which the Doppler signature of a fall event can be computed. Our work shows how the orientation of the antenna affects spectrograms of the received probe signal. The results also show that signals transmitted with a horizontal positioning improve the performance in the classification stage.**

***Index Terms*—WiFi, fall detection, device-free, Doppler signature, spectrogram analysis.**

I. Introduction

THE share of the world population aged 65 years or more will experience a large growth in the next years. The percentage of elderly population in 1990 was 6%, but in 2019, the percentage of elderly population was 9%. Therefore, in the past 30 years, the elderly population had a 3% growth. This proportion is expected to rise to 16% by 2050. These estimates create a need for healthcare and monitoring systems suitable to provide elderly care [1]. According to the World Health Organization, 37.3 million of elderly people require medical attention each year for injuries caused by falls [2]. For this reason, fall detection automation has become a research topic of great interest. A fall is a sporadic action in which the persons lose control of their body and precipitate to the ground.

There are several approaches to human activity monitoring that can be employed to detect when a human fall event has occurred. Systems for event detection based on activity monitoring have been developed using different sensing techniques. A vision system can be used to detect an event. However, these systems are expensive and require a direct line of sight (LOS) with the person under monitoring. Another disadvantage is the violation of user privacy [3]. Another approach is the use of wearable devices with accelerometers or gyroscopes. However, these devices must always be carried by the users, making them invasive. A further approach has emerged in the last years: device-free fall detection based on radio frequency (RF) signals. In this approach, a transmitted probe signal is processed at the receiver to obtain information of ranging and Doppler dispersion caused by moving people [4]. These systems have several advantages: they are not invasive, they do not require a LOS with the moving person and they offer a communication mechanism to send alerts if falls occur. Fall detection systems based on WiFi are under intense research and development due to the ubiquity of these wireless local area networks [5]–[7].

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However, previous research works on WiFi-based fall detection have not considered the impact of the antenna orientation on the system's sensing capabilities. In [8], the accuracy of a fall detection system called WiFall was analyzed by considering different heights of the antennas. Nonetheless, the effect of the antenna orientation was not addressed. Huang et. al. considered different sensing regions of the antennas by introducing multiple sensors in the indoor environment [9]. Notwithstanding, increasing the sensors also increases the system's cost. This previous work did not consider the impact of antenna orientation in the sensing regions.

In this paper, we present an experimental platform for fall detection that allows identifying signal variations caused by the orientations of antennas. This platform emits a pure tone in the range of RF WiFi signals. The signal is transmitted by a typical WiFi monopole antenna. The objective is to replicate the operation conditions of commercial access points but allowing a flexible positioning of the transmitting and receiving antennas. Thereby, it is possible to assess the signal dispersion caused by the multipath effects. In order to measure the impact of the orientation of the antenna, we conducted a series of experiments involving falls of young and middle-age adults from the top of a three-step ladder within an indoor environment.

The analysis of the Doppler signatures of the received probe signal is carried out in accordance with the concept of spectrogram. Spectrograms are used to analyze time-varying and non-stationary signals. These signals provide information on the variations in time of the frequency spectrum. This is performed by estimating the dispersions of the signal's spectral signatures stemming from human motion. Finally, result validation is carried out by extracting the features of the spectrograms using Principal Component Analysis (PCA). The numerical values obtained by this technique are used to quantitatively determine the variations between Doppler signatures of fall events and those of static states.

The remainder of this paper is organized as follows. In Section II, a review of spectrogram analysis through Doppler signatures for fall detection is presented. Then, the instrumental implementation necessary for the sensing platform is described in Section III. The results obtained are shown in the Section IV. Finally, the conclusions are given in Section V.

II. Doppler Signatures and Spectrogram Analysis

The computation of Doppler signatures starts with the transmission of an unmodulated RF signal in an indoor setting. When the signal impinges on a moving body, the carrier signal suffers a frequency shift known as the Doppler effect. This frequency shift together with the multipath propagation generates sidebands in the received signal's spectrum known as Doppler signatures. During a fall event, the speed of the falling body produces certain Doppler signatures that can be characterized to determine the nature of the event. Doppler signatures can be studied using spectrogram analysis. A spectrogram provides information about the spectral density of a signal that varies over time [10].

A spectrogram is calculated by dividing the span of a time-varying signal into short-time segments. These segments are a representation of the signal in a short period of time. Then, a Short Time Fourier Transform is applied to each segment as shown in Eq. 1.

$$X(f,t) = \int_{-\infty}^{\infty} x(t)h(\tau - t)e^{-j2\pi f t}dt. \quad (1)$$

According to (1) $x(t)$ is a signal that varies in time t and $h(\tau - t)$ is an even and positive window function. The spectrogram $S(f,t)$ is defined as

$$S(f,t) = |X(f,t)|^2. \quad (2)$$

Once the spectrogram of the signal has been calculated, an analysis of the Doppler signatures can be performed. The spectrogram provides a visual map of a signal's spectral variations over time. Doppler signatures are obtained from analyzing a series of spectrograms. The process of obtaining a Doppler signature involves examining a large set of data. There are several techniques that can be used to extract valuable information of a large set of data. The most popular technique is PCA. PCA is based on singular value decomposition and it unveils important features of a high-dimensional data collection with only a few components [11].

The first two components computed using by PCA contain the most significant features of the frequency spectrums. These components are used to classify the Doppler signatures into two categories: a fall event or a state of no movement. Furthermore, the classification achieved by using the principal components of the signal can be used to compare the effects

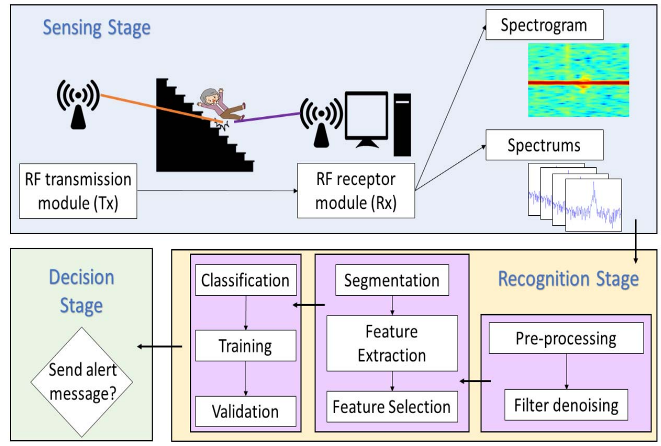


Fig. 1. General diagram of a fall detection system based on radio frequency signals.

of varying position and orientation of the antennas in the experiment setting.

III. Sensing System for Fall Detection

A. Experimental Setup

A fall detection system is composed of three stages: sensing, recognition and decision. A general diagram of a fall detection platform is illustrated in Fig. 1. Our work focuses on the sensing stage of the system. In the sensing stage, an RF signal is transmitted by a transmitter (Tx) through an indoor environment and captured by a receiver (Rx). In our experiments, a platform operating in the frequency range of commercial WiFi systems (IEEE 802.11) was implemented. Furthermore, this platform allowed us to experiment with different orientation and positions of the antennas. The transmitted signals are collected by a spectrum analyzer that makes it possible to record a series of snapshots of the signal's dispersion in the frequency domain throughout the indoor environment. With this information it is possible to compute the spectrograms of the signal.

The experiments are conducted in a controlled environment to avoid interfering signals generated by reflections from moving objects other than the target. The indoor environment includes three-step ladder. The falls were developed by a group

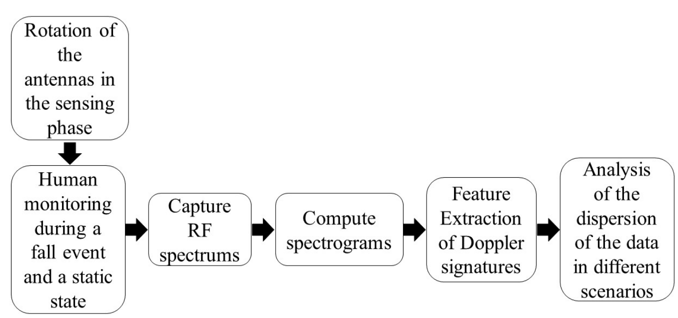


Fig. 2. Block diagram of the experimental process.

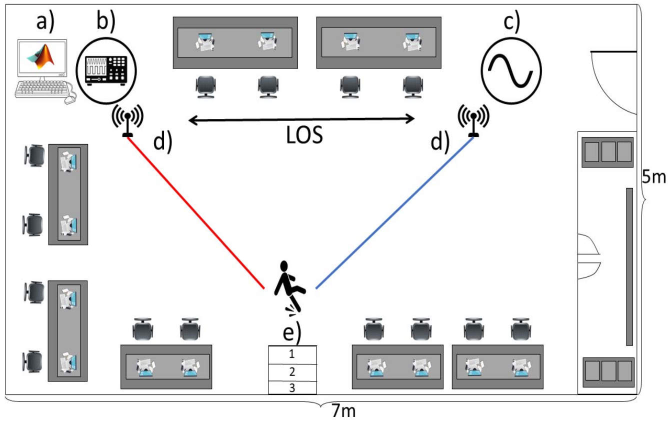


Fig. 3. Schematic of the test scenario: a) control and analysis computer, b) spectrum analyzer (Tx), c) RF generator (Rx), d) omni-directional antennas, e) ladder.

of subjects who made it possible to record signal's dispersions during this event.

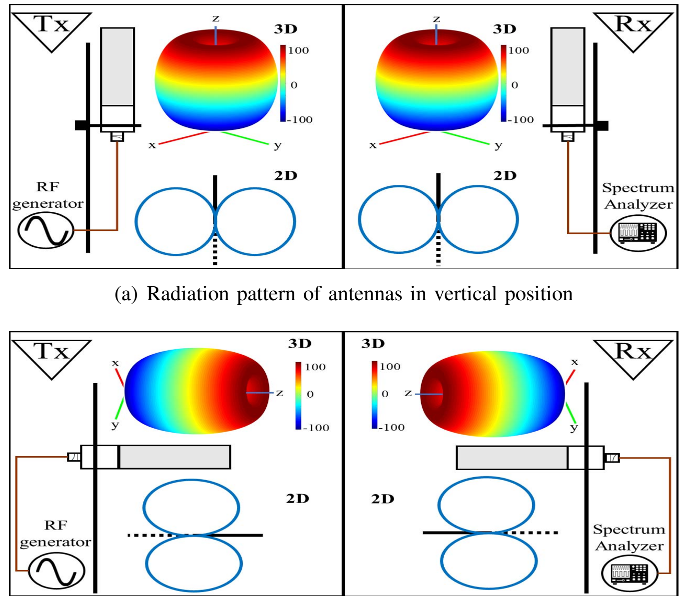
The spectrograms computed during the experiments are processed in the recognition stage to reduce the noise generated by the measurement equipment and extract the principal features. The feature extracted are analyzed by a classification algorithm to determine if they correspond to a falling event or a non-moving state. The accuracy of the recognition stage determines the number of false alarms that can occur in the decision stage. The output of the decision stage is an alert message that is prompted when the event occurs. However, in this work the recognition stage is limited to identifying the differences caused by varying the rotation of the antennas. The experimental process adopted in this paper is summarized in the diagram shown in Fig. 2.

B. Hardware Design

The hardware employed in our experiments includes a RF generator Keysight N9310A, a spectrum analyzer FieldFox N9912A, two 2.4-2.5 GHz omni-directional antennas, one 3.9 GHz Intel(R) i7 CPU 8 GHz RAM computer with Matlab$^{\text{TM}}$ software installed. The positioning of the instruments is shown in the schematic in Fig. 3. The omni-directional antennas were characterized using the FieldFox spectrum analyzer in its cable and antenna test mode. For a 2.42 GHz frequency, the antennas have a 32.4 dB in return losses, an impedance of $50 + j0.70$ Ohms and a voltage standing wave ratio of 1.042. At this frequency the antennas operate with their best performance. Therefore, the RF generator was configured with a center frequency of 2.42 Ghz and a transmission power of 20 dBm for the best performance of the system. Furthermore, during the experiments the spectrum analyzer was configured to capture signals with a sweep time of 271 ms for 1001 points with 1 KHz of span.

C. Experimental Scenarios

The experiments were conducted within an indoor space of the Faculty of Sciences of the Autonomous University of San Luis Potosí. The location corresponds to an office room. The room has a dimension of $7m \times 5m$ and has furniture such as tables, chairs and computer equipment (Fig. 3). The Tx transmitter was installed in the top right corner of the room according to Fig. 3b with one of the omni-directional antennas. The Rx receiver was positioned in the top left corner of the room (Fig. 3c) with the second omni-directional antenna. Both antennas were placed at a height of 2m.



(a) Radiation pattern of antennas in vertical position

(b) Radiation pattern of antennas in horizontal position

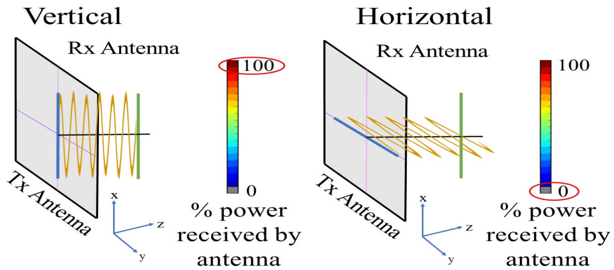
Fig. 4. Radiation pattern of antennas configuration in 2D and 3D view.

The antennas are omnidirectional monopole used by commercial WiFi systems. The experimental platform allows changing the position and orientation of the antennas. Nevertheless, when the orientation is changed, certain transmission features are affected in the antennas. Therefore, when fixing any position of the sensing equipment in the environment, it is necessary to carry out a study of two principal features given an orientation.

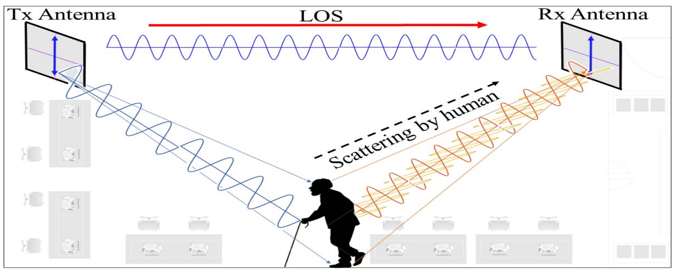
The first feature is the radiation pattern, where the power density is represented. The radiation pattern of the antennas is shown in Figure 4. A vertical scenario is defined as the orientation commonly used in antennas at access points (Figure 4a). In the vertical position, the maximum radiation points can be determined. An important feature of this class of antennas is that their radiation pattern creates zones where the power density is very low. A signal capture in a low radiation area presents disturbances. Therefore, it is important to know how our sensing channel operates.

On the other hand, in the horizontal scenario the antennas are oriented in direction of the LOS (Figure 4b). In this scenario, the direction of the radiation pattern is changed. The horizontal and vertical scenarios allow us to register the effect in the classification stage of the signals.

It is true that a large number of orientations can be defined to vary this feature. However, this work focuses only on the



(a) Effects of polarization on the power received by the antennas



(b) Change of polarization caused by the multipath effect and reflection

Fig. 5. Characteristics of the polarization in antennas.

two cases defined as vertical and horizontal scenarios. The configuration of these two scenarios is followed below.

1) Vertical positioning scenario: According to Fig. 4a, both antennas were positioned 5m apart from each other. The ladder was positioned near the middle of the room, from that position the falls were performed.

2) Horizontal positioning scenario: In this case the antennas were configured as in Fig. 4b at 5m distance from each other. As in the case of vertical positioning, the falls were performed on a ladder approximately 3m away from the platform.

The second feature is the linear polarization of the antennas. In this case, the electric fields of the monopole antennas oscillate in only one direction depending on their orientation. In Figure 5a, the power received by an Rx antenna is shown depending on the polarization of the transmitted signal. This means that the signals captured with a perpendicular polarization is null. This is a very important concept in fall detection systems. Even though the antennas are positioned with the same polarization in the LOS, they are affected by the multipath effect. This effect causes a signal to propagate through different paths. The result is a signal formed by the interaction of the different signals that have traveled to different paths (Figure 5b).

The signals propagated by the transmitting antenna impinges the surfaces in the indoor space, including the human body. The signals that are reflected undergo a change in their polarization perpendicular to the plane of incidence. Therefore, if a signal cannot be detected during a fall event, it can generate false alarms (Figure 5a). This is the importance of the polarization state of antennas in detection systems.

Our fall detection platform allows to register the effect of the horizontal and vertical scenarios. In these scenarios it is possible to measure the variation of different angles of fall observation and determine the antenna orientation that reduces false alarms.

TABLE I
PHYSICAL CHARACTERISTICS OF TEST SUBJECTS

Subject	Age	Gender	Height (m)	Weight (Kg)
1	23	Female	1.61	60
2	24	Male	1.75	77
3	27	Male	1.72	73
4	38	Female	1.55	58
5	47	Female	1.55	65
6	48	Male	1.71	85

D. Experimental Protocol

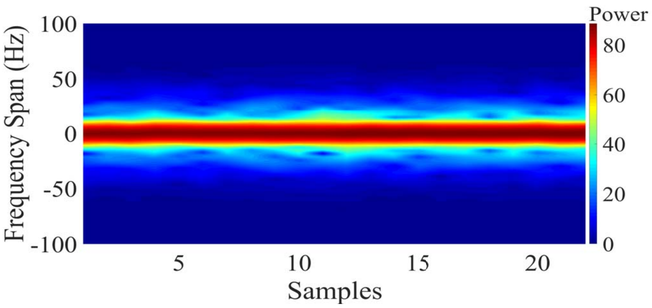
With the sensing platform implemented in the indoor environment, 6 test subjects were selected to perform the experiments. This group of people developed a sequence of falls to a fixed height of 59cm. This is the average height of the third step of a ladder.

The protocol that the participants followed was to place themselves on the corresponding step and remain still. Then, they received a visual and audible signal sent by the control computer to indicate the start of the test. The next instruction was to perform a falling motion from their starting position toward a padded surface to cushion the impact against the ground. Once the participants were on the ground, they had to remain in that position until a new audio signal indicated the end of the test. This allowed the platform to only record the movement of the fall. In total, a sequence of 10 falls was carried out in each of the experimental scenarios designed.

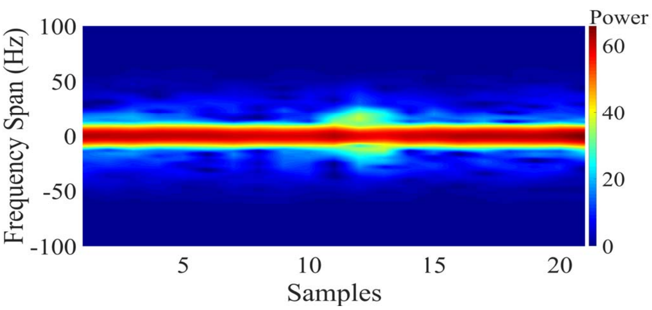
The selected participants were people between 23 and 48 years of age in good physical condition. We consider that an older age could put the integrity of the participants at risk. However, the variation of ages provides a record of how a person falls over the years. In addition, the group has another series of physical characteristics to be studied. Some of these are shown in the Table I. Finally, all the experiments were recorded by the platform and a video recording system. The video recording had the purpose of providing visual evidence and also a timestamp during the development of the experiments.

IV. Results

In this paper we developed an analysis of the variations in a fall detection systems caused by the multiple observation angles of the sensing equipment. For this purpose, a database with 60 falls from 6 different people was used. The database was generated by experimentation in two different scenarios using our sensing platform based on RF-WiFi signals. The result of this was a database containing the spectrums captured throughout the time of experimentation. The spectrograms were separated into two groups. The first group contains the spectrums captured using the vertical positioning on the WiFi antennas. The second group is that of horizontal positioning. Both groups were subjected to a pre-processing stage. At this stage, a Gaussian-type high-pass filter was applied to



(a) Vertical orientation antennas with the fall recorded in sample 12.



(b) Horizontal orientation antennas with the fall recorded in sample 12.

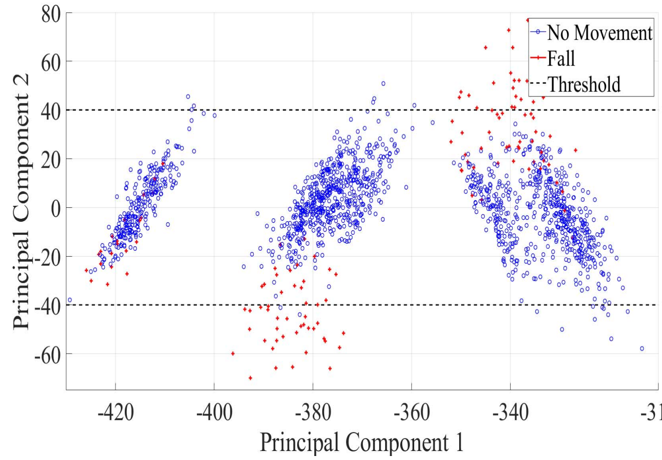
Fig. 6. Spectrograms collected by the fall detection platform: a) Vertical scenario, b) Horizontal scenario.

the spectrograms. Furthermore, a bandwidth of 200 Hz was defined. The result of this is shown in the Figure 6.

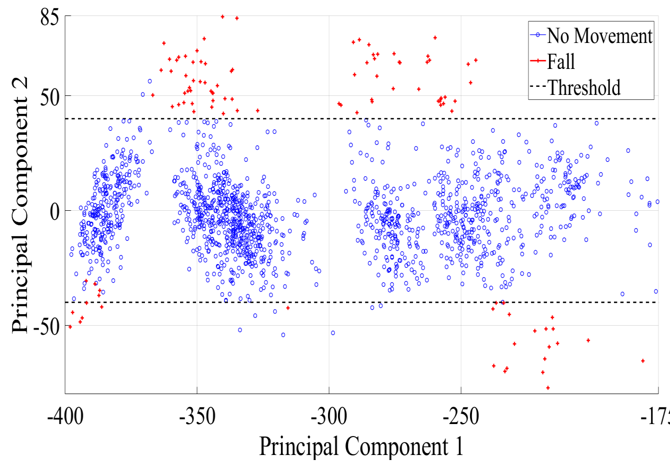
Figure 6 shows a comparison between the spectrograms of the sensing group using antennas with vertical orientation (Figure 6a) and the group of antennas with horizontal orientation (Figure 6b). In the vertical case, the fall was recorded in sample 12. This was determined according to the timestamp provided by the video recording equipment. This spectrogram shows how the signal power suffered a slight disturbance caused by the acceleration of the falling body. However, within the spectrograms of the horizontal case the dispersion registered in the Doppler signatures is more prominent. In Figure 6b, the fall was also recorded in sample 12. A noticeable difference is recorded in the experiments, both scenarios have the same angle of observation of the event but different antenna orientation. The dispersion register in the spectrum during the fall is larger in the horizontal scenario. Therefore, the classification stage provides a better differentiation due to the larger effect recorded in the spectrums.

To validate these results, we use PCA. This technique was applied to each of the spectrums captured in both scenarios. In our case we use the numerical results of the first two components. These components contain most of the energy of the signal and can be used to project the differences between all the spectrums.

Figure 7 shows the comparative graphs for the experiments in the vertical and horizontal case. These graphs show the numerical values of the first and second principal components. The dots correspond to the values obtained for the spectrums



(a) Vertical antenna



(b) Horizontal antenna

Fig. 7. Projection of the first and second principal components.

where no movement was recorded. The falls are identified by crosses.

In both cases, the data for each of these two classes tend to cluster. However, in the horizontal case a threshold can be easily determined between these two classes. The vertical case does not show a clear separation of the classes. The horizontal scenario recorded a greater dispersion in the Doppler signatures of the spectrograms, and these dispersions allows a clear distinction between falls and no movement classes.

The orientation of the antennas has a great impact on Doppler signature dispersion. The horizontal orientation of the antenna positively impacts the distinction of the two characterized classes: falls and no movement. This evident separation reduces the possibility of false alarms. Taking this into account, it is possible to design or improve a fall detection systems based on RF-WiFi signals. This platform allows to reduce the errors caused by the observation angle without increasing the number of sensors in the same indoor environment. Furthermore, the results were obtained using a platform designed with general-purpose measurement equipment. For this reason our platform is affordable and easy to replicate.

On the other hand, it is necessary to add new activities in the experimental protocol such as: walking, sitting or going up and down stairs. In this way the proposed sensing platform can be compared with other similar works, such as those in [8] and [9]. For that purpose, it is necessary to consider classification algorithms that allow to compute the precision of detection in terms of probability. Our platform is designed in blocks. Therefore, it is possible to incorporate additional elements without modifying the other parts of the system. These are key elements in the continuous evaluation of the performance of the platform.

V. Conclusion

In this paper, we develop a fall detection platform based on sensing RF-WiFi signals. The platform is used to study the effects of the antennas orientation and improve the performance of the fall detection systems. Spectrograms were captured during experiments involving a series of falls that capture the dispersion in the Doppler signatures created by the event. The recorded spectrograms were analyzed to establish how antenna orientation affected the dispersion. In this case, the orientation in the horizontal scenario allowed us to observe a larger dispersion at the moment of the fall event. Furthermore, the principal component analysis was used to extract the features of the spectrograms. The principal features were used to analyze the differences between the spectrums that record a fall and those that did not. The PCA results shows that horizontal scenario provides a clear separation between no movement and falls. Therefore, the effects caused by the orientation of the antennas impact the performance of the classification stage of the fall detection systems.

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