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Device-Free Human Fall Detection Using RF Signals

Detección de Caídas Humanas Libre de Dispositivos Utilizando Señales de RF

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Resumen

La población de adultos mayores que vive de forma independiente tiene el riesgo de caer mientras realizan sus actividades de la vida diaria. Estas caídas pueden tener consecuencias físicas o psicológicas que repercuten en la calidad de vida de estas personas si no son atendidas oportunamente. La percepción y detección inalámbrica de estos eventos a través de señales de radiofrecuencia (RF) es un enfoque que ha ganado popularidad debido a que no requieren la portación de sensores o el monitoreo por video. En este trabajo, se presentan las principales consideraciones para el desarrollo de una plataforma de radio sensado usando señales de RF de características similares al WiFi. Además, nosotros realizamos una prueba de concepto con caídas reales para medir y comparar las dispersiones en frecuencia, también conocidas como firmas Doppler, que son provocadas cuando una persona interfiere con las señales de RF. La plataforma logró alcanzar una exactitud máxima del 92% y una tasa de falsos negativos del 8% utilizando un algoritmo de máquinas de soporte vectorial que es un clasificador en un enfoque basado en características. Los resultados muestran la importancia que tiene la arquitectura con la que se diseñan este tipo de plataformas y las técnicas claves para su funcionamiento.

Palabras clave: Detección de caídas, Firmas Doppler, WiFi, Polarización, Espectrograma.

Abstract

The population of elderly people living independently is at risk of falling while carrying out activities of daily living. These falls can have physical or psychological consequences that affect the quality of life of these people if they are not treated promptly. Wireless perception and detection of these events through radio frequency (RF) signals is an approach that has gained popularity because it does not require the carrying of sensors or video monitoring. In this work, we present the main considerations for the development of a radio sensing platform using RF signals with characteristics similar to WiFi. In addition, we performed a proof of concept with actual falls to measure and compare frequency dispersions, also known as Doppler signatures, caused when a person interferes with RF signals. The platform was able to achieve a maximum accuracy of 92% and a false-negative rate of 8% using a support vector machine algorithm that is a classifier in a feature-based approach. The results show the importance of architecture with which such platforms are designed and the key techniques for their operation.

Key Words: Fall detection, Doppler signatures, WiFi, Polarization, Spectrogram.

1. Introduction

The world faces a transition state in people's longevity due to falling fertility rates and behavioral changes that increase life expectancy. The projected population of elderly people by 2050 will represent a growth of 16% compared to 2019 [1]. For example, in the US, the elderly population increased by 14.4 million people from 2009 to 2020, representing a 36% increase [2]. In Europe, it is expected that by 2070 the proportion of seniors in its population will be the second highest in the world [3]. Although life expectancy is increasing, this does not mean that healthcare is also improving [4].

The need for timely healthcare treatment for elderly people living independently has motivated the development of new technologies for remote health monitoring. One of the most recurrent fatal events around the world is a fall. These events are transient and rare in people's daily lives. However, the consequences for people's health can affect their quality of life. In fact, 37.3 million elderly people require medical attention each year due to falls [5]. These places falls as one of the top detection priorities for health monitoring systems. Therefore, several fall detection systems have been developed based on a wide range of technologies and approaches.

Some of the most promising fall detection systems are those based on pressure sensors, vision, wearable devices, or recently radio frequency (RF) (Table 1). Vision systems with high-resolution images are a practical alternative for detecting falls with high precision. However, it is expensive to implement specialized cameras and place them at every point of the indoor environment to be detected. Furthermore, image processing to model the movements and shape of the human body is highly complex. This is because the captured images vary depending on occlusions or changes in the person's position [6, 11]. Finally, a vision system can compromise the privacy of users.

Table 1. Approaches to fall detection systems.

Approach for sensing	Reference	Features
Vision-Based	Zhang [6] (2020)	Mandatory direct line of sight with the person.
Wearable-Based	Hauth [7] (2021)	Wear or carry the device.
Environment-Based	Liu [8] (2019)	Expensive and complex installation.
RF-Based	Muaaz [9] (2022) Cardenas [10] (2021)	Adapted to AP existing in the indoor environment. Device-free.

On the other hand, wearable device systems use sensors attached to people for constant monitoring. Several of these sensors are embedded in most smartphones, smartwatches, or smart wristbands. However, one of the drawbacks of this approach is that placement affects the accuracy with which events can be detected [7, 12, 13]. Furthermore, if the person does not wear the sensor, the system will not be able to monitor the person or detect if they have a fall. Therefore, it is a solution that can become invasive.

Another type of detection is environment-based systems, where sensors are embedded within the site [8]. These systems can be based on two types of signals: acoustic waves or mechanical vibrations. However, acoustic waves tend to degrade greatly due to the multipath effect and a large number of sensors must be installed. Rack-mounted sensors in the indoor environment are very accurate, but costly to implement. Furthermore, installing the sensors on the floor can require a complex process.

Event detection through RF signals is a recent approach that aims to reduce some gaps in already established sensing systems. In this case, a transmitted RF signal is deflected by static and moving objects in the indoor environment. When the signal is received, some of its features that were altered during its trajectory can be characterized to determine which movement caused them. This technique has several advantages such as being non-invasive for people since there is no need to carry any device or sensor. Furthermore, the user's privacy can be preserved by not involving images of the persons or their personal space. There are two alternatives in its implementation, the use of Doppler radars or capitalizing on commercial Wi-Fi systems. The first alternative requires specialized equipment, i.e., the radar, and makes it an expensive solution. In addition, this requires the incorporation of a greater number of sensors to improve its precision rate [14]. The alternative based on WiFi RF signals does not require additional hardware and can take advantage of the transmitting and receiving technology already present in access points (AP). In this approach, certain signal features, such as the received signal strength indicator (RSSI), the channel state information (CSI), or the Doppler signatures can be considered. However, these or other features must prove their capabilities to be applied in specific fall detection tasks. Due to the significant number of techniques and approaches, introducing researchers to this topic has become a challenge. Therefore, a review of current detection models and their main characteristics is necessary.

One of the essential stages of fall detection and monitoring systems is the classification of the features extracted from the WiFi RF signals. This stage represents the largest area of research, and multiple contributions have been made in implementing increasingly robust detection algorithms with high accuracy rates [9,15]. However, little research has been carried out on the physical layer of WiFi RF systems [16], specifically on the factors that affect the transmission of signals in the environment. Some of these factors are the spatial orientation of the transmitting and receiving antennas or their

location. The physical variations of the antennas are strongly related to the radiation pattern and polarization that cause mismatched couplings that influence the detection of events [17]. Therefore, they are determining factors to be taken into consideration when starting the design of a radio-sensor platform.

In this work, we offer an introduction to device-free event detection based on WiFi signals. We discuss the advantages, challenges, and alternatives in fall detection systems to assemble our sensing platform using general-purpose equipment. The platform uses a continuous wave (CW) RF signal to measure its frequency dispersions when interfered with by a human body during a fall. The experiments were conducted with a group of volunteers with different physical characteristics. To determine the sensing capabilities of a platform based on RF signals with characteristics similar to those of WiFi, a support vector machine (SVM) classification algorithm was used. The results of up to 92% accuracy are presented to demonstrate that it is necessary to establish the appropriate methodologies for each type of application. In our case, the key points in the design and construction of our platform are shown in the following sections.

2. Architecture of a WiFi-Based Event Detection System

In general, a fall detection platform based on WiFi RF signals comprises three phases: sensing, recognition, and decision. Figure 1 exemplifies the use of these three phases in a fall detection system that uses Doppler signatures for recognition. In this case, the RF waves perceive human movements and are used to recognize falls. In the sensing phase, the transmitting antenna emits a probe signal that spreads throughout the indoor environment. The probe signal is used to create waves of electromagnetic reflections with all objects in the vicinity of its range, these objects include people. When the probe signal impinged on an accelerating body, the signal is reflected and undergoes an apparent frequency shift caused by the Doppler effect [18]. The acceleration of a person during a fall causes considerable changes in frequency. The registration of these changes is known as the Doppler signature of the event and can be used to detect falls. One of the most commonly used techniques to analyze Doppler signatures is through spectrograms [19]. However, the concepts of the sensing phase can be extrapolated to other event detection applications.

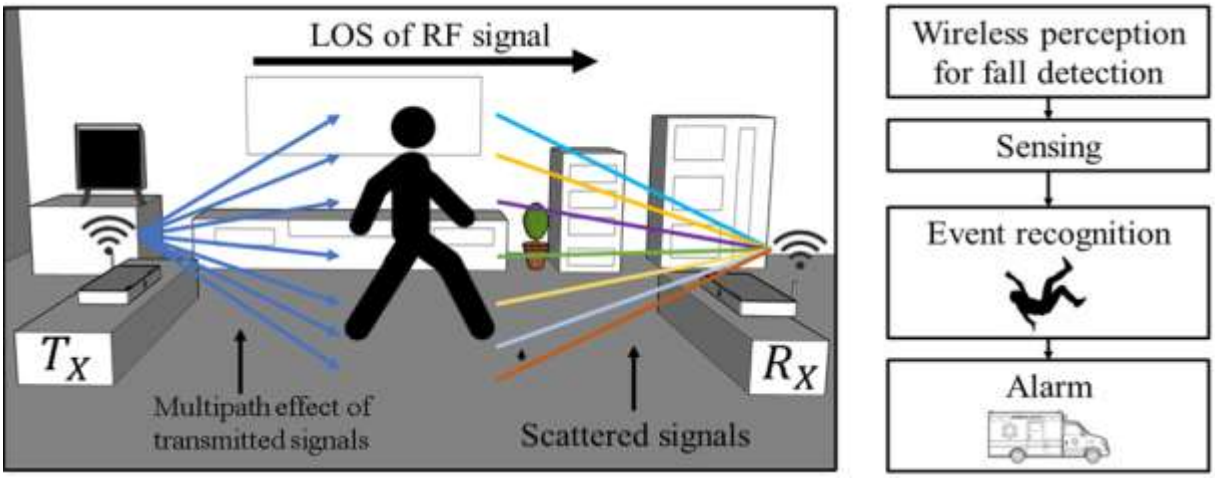


Figure 1. Overview of the fall detection system using Doppler signatures of RF-WiFi signals.

The second phase of the detection process is the classification stage. In this phase, the features extracted from the signals captured during sensing are analyzed to determine if changes have occurred. Nevertheless, there are several algorithms and approaches to data classification. These methodologies can be categorized into two: feature-based and model-based. Determining the trade-off between advantages and disadvantages of each approach is a demanding task. Therefore, we present both approaches in detail in Section 4.

The last phase is known as the decision stage since it is intended to alert in real-time when a fall has occurred. A signal is sent to the medical care systems and the emergency is attended to. However, this phase requires extensive cooperation between emergency medical management systems, information systems, geographic information systems, and informatics technologies. Therefore, this stage is outside the scope of our research and will not be addressed.

3. Event detection using RF signals

In human activity recognition (HAR) within an indoor environment, several sensors can be used to characterize movements [6-10]. Currently, systems based on RF signal sensing have facilitated the development of applications for this purpose. This is because they have a device-free approach and are highly attractive for health monitoring, internet of things, or security applications. Furthermore, they are low-cost and have a wide spectrum of features that can be extracted from the signals. However, due to the random nature of activities, RF signal processing, and feature extraction techniques directly affect detection accuracy. This indicates that using the same methodology to identify different activities does not always give the best results. Therefore, it is challenging to get into HAR if the field of application or the detection parameters are not extensively known.

On the other hand, HAR generally comprises any activity that can be identified derived from human movement. Nevertheless, the main attention must be paid to those activities that are transitory and that can endanger the life or health of people. An example of this might be when monitoring a person's walking. This is a recurring activity of daily living (ADL) that is performed with almost constant rhythm, posture, and speed. However, if an abrupt change or anomaly is detected at some point in the walk, may be due to a fall. A fall is then considered the transient event to which the detection system must respond. Differentiating between activities and transient events can justify the basis of any movement detection platform. But the relationship between both concepts is not always something that is presented in a practical way.

Figure 2 shows a classification of event detection applications using systems based on RF signals. The diagram distinguishes three important concepts: events, activities, and detection parameters. The events comprise surveillance applications and some of the most common health problems in the elderly population. The activities that are included belong to recurrent ADL that can be used as a basis for the monitoring and detection of anomalies. However, it should be noted that activities can be divided into two categories: (1) micro-activities and (2) macro-activities. Micro-activities are those that are not perceived by simple view or that people perform unconsciously. Nevertheless, these are equally recurrent in daily life, like breathing or the constant rhythm of the heartbeat. Macro-activities, on the other hand, are activities that require mobility of the body. These actions can be, e.g., walking, running, jumping or moving the limbs. Therefore, at this point, the range of activities

to be monitored can be limited depending on the event to be detected. This simplifies the design of the platforms and improves the state-of-the-art study process. Finally, the detection parameters used for feature extraction and classification of the RF signals are included in the diagram. These parameters are used to characterize changes in the signals, caused by human movements. In this way, through classification algorithms, the behavior of the signal can be associated with a particular activity. Nonetheless, some of these parameters extract finer granularity data capable of distinguishing micro- activities, such as Fresnel zones. Other parameters do not extract coarse granularity details and can be used to extract macro-activity changes. The angle of arrival, amplitude, phase, and Doppler signatures are commonly used in applications where body movements are considered important.

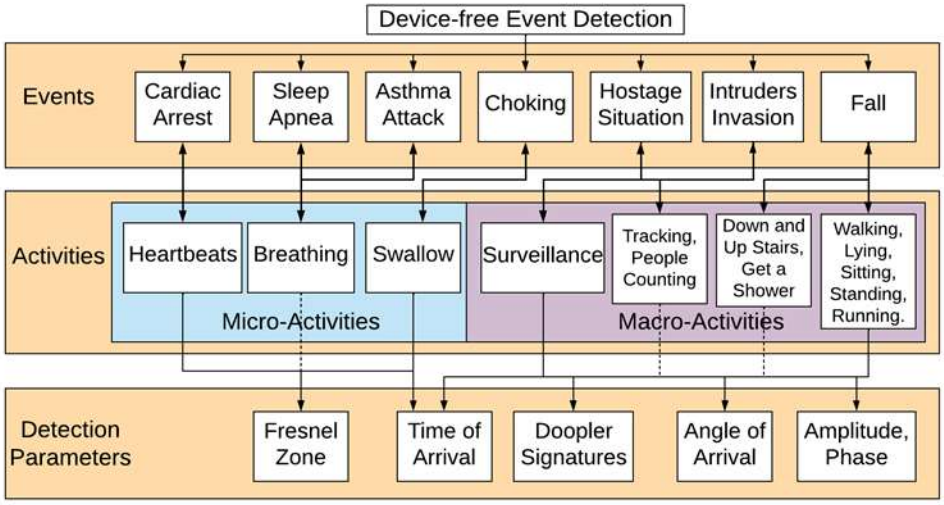


Figure 2. Event classification diagram for a device-free approach.

Following the methodology outlined in Figure 1, a sensing platform can be designed and developed using RF signals. For example, the development of a platform for fall detection must be designed following the next steps. A fall can be induced by several circumstances, but the action of falling always comprises the movement of the body. Therefore, falls belong to the macro activities category and can be differentiated from activities such as walking, running, or sitting. The starting point of the system should consider the behavior of signals in the presence of these activities, as in the works presented in [20] and [21]. Afterwards, anomalies can be identified through detection parameters such as Doppler signatures or others. In this way, a complete fall detection system like the one shown in [22] and [23] will not need an exhaustive study of other methodologies, techniques, or the characterization of other activities. However, the selection of techniques to perform the event recognition can also affect accuracy rate. It is then necessary, to know the alternatives that best adapt to the computation requirements and detection time.

4. Approaches to event recognition

For detection systems in indoor environments, the detection parameters can be analyzed and classified by different techniques. These techniques are divided into two categories: feature-based approach and model-based approach. Each approach provides advantages and can be exploited to

increase the accuracy of the system. However, the data set integrated by the detection parameters must satisfy certain features to be used by each technique. Likewise, hardware plays an important role in the classification process. Therefore, we introduce the basic concepts for the development of this stage in device-free detection systems.

1.1 Feature-based approach

The main challenge in event detection is to select the parameters that can provide a unique pattern that distinguishes the captured events and activities. Therefore, it is necessary to find a unique and consistent connection between the event and the features provided by the RF signals. Afterward, these features will represent the detection parameters necessary for the signal classification process. Figure 3, shows a schematic diagram of a feature-based system, starting with the input data and ending with the classification result. This process consists of three principal stages: feature extraction, training, and validation.

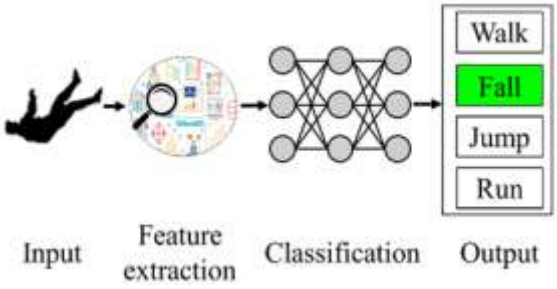


Figure 3. Feature-based event recognition.

Feature extraction consists of finding a set of finite measures that quantitatively capture the changes recorded in the detection parameters. For example, Wang et al. [22] used CSI amplitude as a detection parameter to extract seven features (normalized standard deviation, offset of signal strength, period of motion, median absolute deviation, interquartile range, signal entropy, and velocity of signal change) that allow detecting fall events. Hu et al. [24] extracted the eigenvalues of the respective covariance coefficient of the CSI phase matrix to detect intruder invasion events. Therefore, feature selection is a complex process, but it can significantly increase the accuracy rate of the system [25].

During the training of the data, the RF signals are labeled by classes according to the event or activity to which they belong. Furthermore, each class is assigned a profile of features extracted from the detection parameters. Afterwards, in the validation stage, a separate set of unlabeled signals is added to the system. The new feature profile generated by the unlabeled signals is compared with the training profiles and the class to which it should belong is determined. Correctly labeled signals´ scores determine the accuracy of the system.

Therefore, different statistical computational algorithms appropriate for recognition can be established in this approach. Machine learning algorithms are the most common algorithms to implement in this type of approach. For example, Wang et al. [22] used support vector machines and random forests for fall detection. However, there are several other algorithms such as K-near neighborhoods, and decision trees, among others. The performance of these will depend on how simple or sophisticated the extracted features are. Fine granularity features are demanded in macro activities applications, Moreover, the selection of algorithms is highly influenced by computational time and cost.

1.2 Model-based approach

On the other hand, in a model-based approach to HAR, the relationships between human movements and mathematical abstractions of the signals are studied. These abstractions are

represented through multiple layers to develop the model. Model-based approach requires longer training time than the feature-based approach. However, in the validation stage, the time is considerably less. Furthermore, the principal difference between these two approaches lies in the feature extraction stage. In the model-based approach, the extraction process is executed automatically [26]. As shown in Figure 4, feature extraction and classification are part of the same process block. Therefore, large databases are needed for accurate model building. This entails a high computational cost, thus optimized hardware is needed for the development of these tasks (such as graphics processing units, GPU).

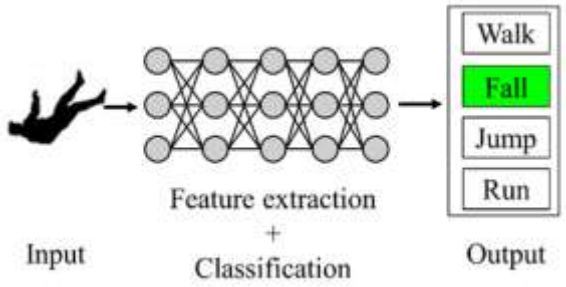


Figure 4. Model-based event recognition.

Model-based approaches are intelligent systems commonly used in real-world applications. Neural networks are the algorithms used for the development of these applications. There are four types of learning that can be performed with these algorithms: supervised, unsupervised, semi-supervised, and reinforcement learning. In supervised learning, features are separated by labels, and it works as the preparation of the data for training. Some architectures used for these tasks are convolutional neural networks, recurrent neural networks, among others.

The task of unsupervised learning is to learn the features embedded in the data and correlate them with the classes to which they belong. In this case, generative adversarial networks, autoencoder, or deep belief networks are used. In the case of hybrid learning, the benefits of both supervised and unsupervised learning are exploited. Thus, complex hybrid models can be created from the bases of each basic model. For example, it is possible to mix supervised models, unsupervised models, or a combination of both [26].

Finally, reinforcement learning is an approach that takes decisions sequentially by rewarding good sequences of actions. This reinforcement is carried out through basic learning models by introducing agents that alter the environment to obtain feedback. This way, systems become more robust and improve their performance by learning from changing agents. This is a key point in the development of intelligent systems that can learn from changes.

As this section has shown, there are several advantages to implementing a model-based approach. Nevertheless, the requirements of these systems must be taken into consideration. Herein lies the importance in the correct selection of the approach to be used in event detection platforms. If the data selection is small and/or the computational cost needs to be minimized, the feature-based approach will improve performance. Otherwise, the model-based approach will give an improvement in accuracy as long as the necessary requirements are fulfilled. Therefore, the performance of the algorithms is directly related to the exponential growth of the data (Figure 5).

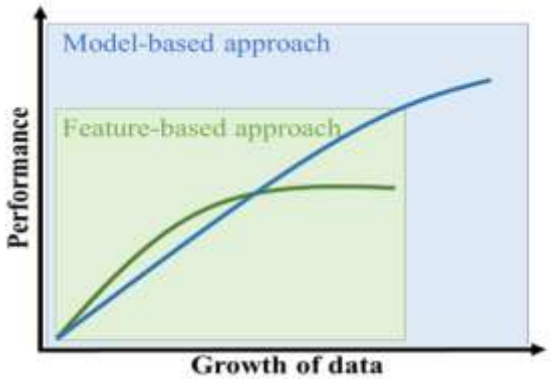


Figure 5. Performance growth between the feature-based and model-based approach.

5. Case Study: Fall detection platform using WiFi RF signals

In this case study, the methodology addressed for the deployment of a radio sensing platform based on the analysis of the Doppler signatures of a transmitted RF signal is followed. We consider a CW RF probe signal during the sensing stage because it has characteristics similar to those transmitted by WiFi physical layer protocol data units (PPDU) [27] but can be analyzed with general-purpose equipment. We used a T_X transmission module that contains an RF generator and configured as shown in Table 2. These configurations were obtained by characterizing a pair of monopole omnidirectional antennas with which the transmission and reception process was carried out. On the other hand, the R_X capture module comprises an RF spectrum analyzer necessary to receive the signals. Table 3 contains the spectrum analyzer configurations with which we obtained the best capture resolution and low sweep time. The spatial positioning of our measurement equipment is based on the proofs of concept presented in [10] and [28]. This is because it has been proven that the orientation of the antennas and their positioning influence the quality of the features that can be extracted from dispersed signals in an indoor environment.

Table 2. Transmission (T_X) parameters.

Parameter	Value
Frequency	2.42 GHz
Return losses	32.4 dB
Impedance	50 + j0.70
Voltage standing wave ratio	1.042
Supplier	Keysight N9310A

Table 3. Reception (R_X) module configuration.

Parameter	Value
Central frequency	2.42 GHz
Sweep time	271 ms
Sample points	1001
Frequency span	1 kHz
Supplier	Keysight FieldFox N9912A

The experiments were performed in a controlled indoor environment. The scenario corresponds to an office room, equipped with fixed furniture such as chairs, tables, desks, lockers, computers, etc. Figure 6 shows a perspective view of the actual test area. The falls were developed using a ladder placed in the center of the room. To avoid causing injuries to the participants there is a padded surface in front of the ladder. The database includes the experiments with 6 participants for each of the proposed antenna orientation scenarios. However, due to the nature and risk of falls in elderly people, the selected participants have to belong to a smaller age range. Therefore, the age range should be between 20 and 50 years. The participants must declare that they are in good physical condition and that they do not suffer from any health problems that could put their integrity at risk. Furthermore, the composition of the group was balanced with the participation of three women and three men.

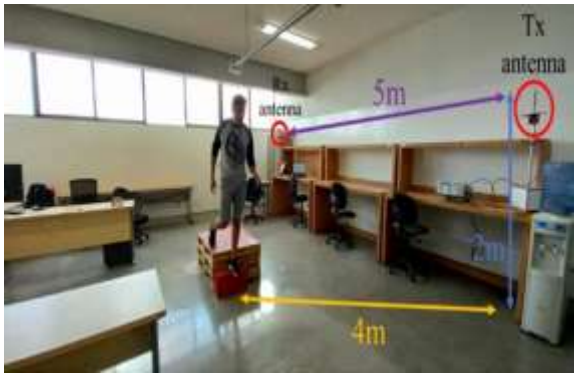


Figure 6. Indoor environment for the test experimentation.

5.1 Results and discussion

Figure 7 and 8 show two examples of spectrograms obtained during a falling event. The processing and analysis of the RF signals and Doppler signatures were carried out using Matlab™ software. Furthermore, the frequency dispersions that were generated in the central carrier signal due to the multipath effect and its interaction with static objects in the environment and the movement of a falling person are shown. During the times marked times t_1 and t_3, no movement was executed, and the central carrier signal remained almost constant. However, during the time t_2 corresponding to the performed falling movement, the recorded frequency dispersion is much larger and can be distinguished from the rest in both spectrograms. During the design of this sensing stage, it is essential to know which parameters allow these Doppler signatures to be analyzed with the best resolution without affecting the number of samples per second since fallings are events that occur in a short period. Therefore, considering the case of falls as macro-activities, our platform has an acceptable resolution of the generated micro-Doppler and an acquisition time of at least two samples per second.

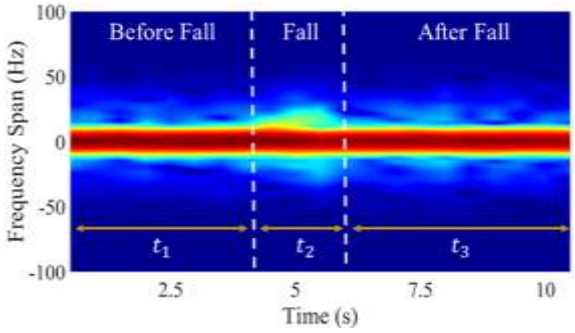


Figure 7. Doppler signatures captured in the spectrograms at a time t_1 (before fall), t_2 (fall) and t_3 (after fall) for subject number one.

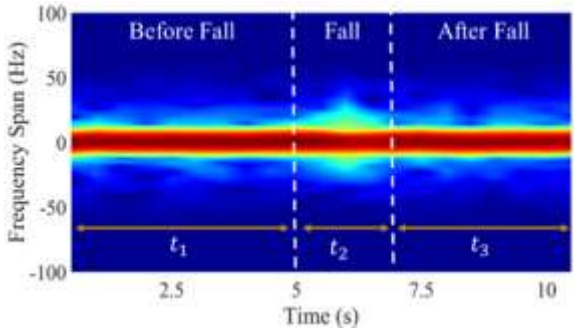


Figure 8. Doppler signatures captured in the spectrograms at a time t_1 (before fall), t_2 (fall) and t_3 (after fall) for subject number two.

We present a graph in Figure 9 that shows the sequence of RF spectra captured during a falling event and when the person was standing statically. As can be seen, the solid blue lines represent the static state of the person, whose power and frequency dispersion have similar and constant values. However, during a fall, the signal frequency is dispersed by the Doppler effect caused by the acceleration of the body. These power, frequency, or energy values can be extracted as particular spectra features and subjected to an intelligent classification process under either of the two approaches previously discussed. Therefore, RF-based fall detection systems must have a preprocessing stage that allows them to evaluate the quality of their features and determine if they contain the information necessary to distinguish events.

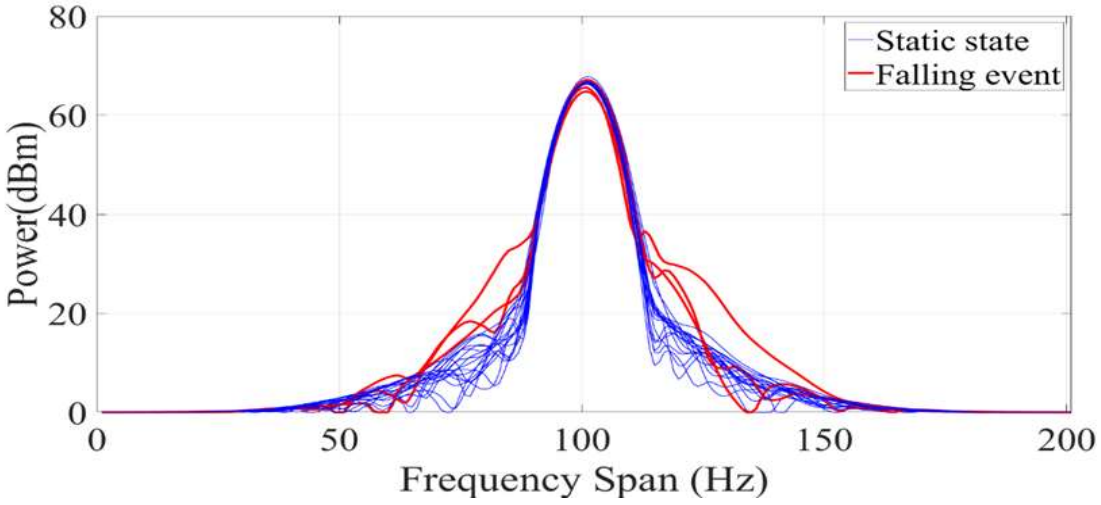


Figure 9. Sequence of Doppler spectrums with falls in thick red lines and static states in thin blue lines.

For this case study, it was determined that the dimensionality of the data makes a graphical or manual analysis of the features unfeasible. Therefore, the Principal Component Analysis (PCA) algorithm was selected because it is a tool that allows for reducing the dimensionality of the data and extracting the most relevant information from each data set [10]. We extracted the first three principal components since they contain about 98% of the input signal energy. Once these components have been extracted and labeled, they can be used for the next stage of the methodology, the recognition of fall events.

For the recognition stage, we use an SVM algorithm that has a feature-based approach. One of the main reasons why we considered this approach appropriate is that our experiments with human falls had a limited number of samples. Therefore, an approach that depends on the quality of features and not the number of data is more suitable for our platform.

The training and testing of the SVM classification algorithm were performed with two data sets corresponding to 80% and 20% of the captured signals, respectively. In this work, the precision results of the classification algorithm are used to show the effectiveness that a platform that considers all the stages of the sensing radio and considers the detection parameters according to the activity that is sought to be identified can have. The precision obtained was 92% of correctly identified falling spectra with a false negative rate of 8%. The extension in the systematic analysis of these results can be consulted in [10]. Therefore, this class of platforms with general-purpose equipment can be presented as a simple way to bring researchers closer to the field of radio sensing with promising results and apply the results to current problems such as fall detection.

6. Conclusions

In this work, we have presented a comprehensive study of the techniques and methodologies used for sensing human activities with a device-free approach. Furthermore, a systematic diagram for the development of event detection systems was proposed. This article proved to be an introduction for researchers starting in the field of wireless perception. Finally, these concepts were tested in the construction of a fall detection system. Splitting the system architecture into stages, allows us to determine the techniques and approaches that best suit the needs of the application. Our results show the importance of the

configurations of the physical layer in the sensing stage. Furthermore, we present an introduction to the principal detection parameters used in different applications of the WiFi signal-based approach. The extracted Doppler signatures proved to be a satisfactory set of separable features to be used as differentiators of falling events. Finally, the classification approaches, that best fit the platform, were presented. In our case, the accuracy percentages confirm that the platform has the capability to detect falling events. Nonetheless, this type of simple classification needs to be tested with the inclusion of new activities. The case of activities such as walking or going up and down stairs can be considered as periodic activities with a constant space-time evolution. So, it is an area of future work that will be explored. Following the concepts shown in this work, the most appropriate option will be the model-based approach, due to data growth.

7. Acknowledgments

The authors declare that this paper's content, figures, and tables are original and their authorship.

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