

Digital Twin-Enhanced Radar and Joint Communication-Sensing Systems: Application in Accurate Fall Severity Classification and Beyond

by

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Author's Declaration

I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

I understand that my thesis may be made electronically available to the public.

Abstract

The growing population of old seniors presents a significant challenge to healthcare systems worldwide. According to the United Nations Population Fund (UNFPA), the number of people aged 65 and older is 10.3% of the global population and is expected to reach 20.7% by 2074. The World Health Organization (WHO) reports that in the near future, by 2023, one in 6 people will be over the age of 60. This increase in the elderly population poses a serious challenge to healthcare providers at retirement homes because of the need to provide individual care to their residents.

Falls stand out as the predominant cause of injury and death among the elderly. As stated by the National Council on Aging (NCOA), 1 in 4 Americans aged 65 and older fall each year, which equates to 14 million people. The NCOA also reports that the cost of treating injuries resulting from falls is expected to reach \$101 billion by 2030. Moreover, the Center for Disease Control and Prevention (CDC) reports that repeated fall incidents double after falling once. This sets a significant burden on healthcare providers to assess the severity of falls and provide immediate care for those who are in need.

In this study, we present a novel approach for fall detection, leveraging radar-based sensing systems as well as joint communication-sensing systems and advanced digital twin simulations. The choice of radar technology is rooted in its capability for high-resolution detection of micro-movements and its inherent respect for individual privacy, as it does not require visual imaging. Moreover, the choice of joint communication-sensing systems is motivated by the growing potential of 5G technology in enabling real-time sensing along with communication. Both systems have the capability for utilizing more physical resources, enabling greater resolution enhancement and more accurate detection. Both systems offer a non-intrusive and privacy-preserving solution for fall detection, ensuring the safety and dignity of the elderly.

The integration of digital twins, replicating a diverse array of human physiology and fall dynamics, allows for extensive, varied, and ethical training of sophisticated machine learning algorithms without the constraints and ethical concerns of using human subjects. Our proposed methodology has led to significant advancements in the accuracy and sensitivity of detecting and assessing fall severity, especially in diverse populations and scenarios. We observed notable improvements in the system’s ability to discern subtle variations in falls, a critical factor in elderly care where such incidents can have serious health implications. Our approach not only sets a new benchmark in fall detection technology but also demonstrates the vast potential of combining radar and joint communication-sensing technology with digital simulations in medical research. This research paves the way for

innovative patient monitoring solutions, offering a beacon of hope in improving senior care and proactive health management.

In this study, the digital twin environment was created for both systems, radar and 5G, to simulate various fall scenarios under different conditions. For both systems, the simulated data was used to train machine learning models to detect the severity of falls, verifying the proposed methodology for severity of fall classification in an ideal environment. Furthermore, the correlation between the simulation and measurement results is presented. Measurement campaigns were conducted for both systems to validate the simulation results and to demonstrate the feasibility of the proposed methodology in real-world scenarios. Employing convolutional neural networks for the radar system, we obtained an accuracy of 99.45% using simulated data and 81.25% using measured data in detecting the severity of falls. The analysis addressed various parameters distinguishing different scenarios, including fall speed and the participant's body size. On the other hand, for the 5G system, we achieved an accuracy of 92.46% using simulated data and 88.9% using measured data in detecting the severity of falls.

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Thank you all for being part of my journey.

Dedication

I dedicate this work to my family, with heartfelt thanks to my parents. To my father, your unwavering support and guidance have made this journey possible. Your example has been a source of inspiration, and your efforts to help me become a better person mean the world to me. To my mother, thank you for making me who I am, and for your endless care, love, and prayers.

I dedicate not just this work but my future achievements to both of you, and I will always be grateful for your influence. To my brothers and sister, I can't be more grateful for you being in my life and for everything you have done for me.

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List of Abbreviations

ADC Analog to Digital Converter [10](#)

CNN Convolutional Neural Networks [8](#)

CSI Channel State Information [22](#), [25](#), [26](#)

CSI-RS Channel State Information Reference Signal [22](#), [24](#), [25](#), [46](#), [47](#), [73](#)

CW Continuous Wave [6](#), [8](#), [31](#)

DMRS Demodulation Reference Signal [20](#), [24](#), [25](#)

DT digital twin [3](#), [4](#), [26–28](#), [31](#), [33](#), [45](#), [47](#), [48](#), [50](#), [59](#), [69–71](#)

FMCW Frequency Modulated Continuous Wave [7–11](#), [31](#)

JCS Joint Communication Sensing [3](#), [15](#), [17](#), [22](#), [25](#), [30](#), [45](#), [57](#), [69–71](#)

LNA Low Noise Amplifier [10](#)

LPF Low-Pass Filter [10](#), [13](#)

LTC Long-Term Care [1](#), [2](#), [32](#), [44](#)

NR New Radio [4](#), [15](#), [22](#), [45](#), [72](#), [73](#)

PA Power Amplifier [10](#)

PBCH Physical Broadcast Channel [18](#), [20](#)

PRF pulse repetition frequency [7](#)

PSS primary synchronization signal [20](#)

PSWs personal support workers [1](#)

PTRS Phase Tracking Reference Signal [20](#)

RF radio frequency [5](#), [7](#), [9](#)

SAR Synthetic Aperture Radar [6](#)

SSS secondary synchronization signal [20](#)

STFT Short-Time Fourier Transform [8](#), [14](#)

UE user equipment [15](#), [18](#), [20](#), [22](#)

UWB Ultra-Wideband [8](#), [31](#)

VCO Voltage Controlled Oscillator [9](#), [10](#)

Chapter 1

Introduction

1.1 Motivation

As the aging demographic continues to reshape societies across the globe, the challenges within the healthcare system, particularly in [Long-Term Care \(LTC\)](#) facilities, have become increasingly pronounced. Approximately 9.1% of the global population, 701 million individuals, is estimated to consist of seniors aged 65 and above [\[1\]](#). Care homes across North America find themselves struggling with extreme staffing and resource shortages, often resulting in alarming levels, leading to preventable deaths, closures of care homes, surging costs, and a pervasive negative impact on the quality of life for residents [\[2\]](#). This crisis is exacerbated by the lack of preparedness within the healthcare system for the impending surge in the aging population.

The senior care industry is facing an added challenge due to a substantial portion of retirement homes being not up-to-date, making it difficult to modernize and create innovative approaches to meet the rising demand for services. The persistent pressure to accomplish more with limited resources has become unsustainable, leading to burnout among healthcare staff. Startlingly, more [personal support workers \(PSWs\)](#) and front-line caregivers have left the industry in the last year than have joined [\[3\]](#), underscoring the urgent need for comprehensive solutions to address these systemic challenges. Despite the evident signs of the impending demographic shift, both the healthcare system in general and [LTC](#) specifically find themselves ill-prepared to meet the needs of an aging population. This unpreparedness has far-reaching consequences, impacting not only the immediate health outcomes of seniors but also contributing to the closure of care homes and escalating

healthcare costs. The urgency of the situation necessitates a swift and effective response to ensure the well-being of seniors and alleviate the strain on healthcare professionals.

Exacerbating the shortage crisis is the burden of alarm fatigue among healthcare professionals, including staff in LTC facilities [4]. The high volume of alarms and notifications can overwhelm caregivers, contributing to a desensitization known as alarm fatigue. This taxing phenomenon poses a serious threat to the prompt response to critical alerts, jeopardizing the well-being of seniors. One of the sources contributing to alarm fatigue is falls, as they stand as a primary cause of death and injury among seniors [1, 5, 6].

The severity of a fall refers to the extent of impact or potential harm incurred by the individual [7]. In addition to mitigating alarm fatigue, identifying the severity of falls in senior care empowers caregivers to craft personalized care plans, tailor preventative measures to reduce future fall risks, and allocate resources judiciously based on the urgency of each case. Falls can vary widely in their impact on individuals, ranging from minor incidents to potentially life-threatening situations. By discerning the severity of each fall, caregivers can allocate their attention and resources more effectively, focusing on urgent cases while appropriately addressing less critical incidents. Moreover, accurately assessing the severity of falls enables caregivers to provide timely and targeted interventions. Alarm fatigue occurs when caregivers become desensitized to frequent or repetitive alerts, leading to delayed responses or even disregard for alarms.

The deployment of sensors for such applications necessitates the use of machine learning algorithms for fall detection and severity classification. This is due to the inherent ability of machine learning algorithms to learn the key features of human activities without the need for human intervention to specify any features, as opposed to signal processing techniques [8]. The use of machine learning algorithms requires a large dataset, especially in cases where the similarities between features to be classified are high. Therefore, for certain types of applications like severity of fall classification, there is a need for a large number of participants to conduct measurement campaigns. However, due to the inherent risks associated with falling, physically simulating specific scenarios becomes challenging and can potentially lead to severe injuries, such as bone fractures or traumatic brain injuries [9]. The obstacles for such measurement campaigns can include ethical concerns, the need for additional safety measures, a lengthy recruitment process, and the psychological impacts on participants. Along with the inherent dangers of performing the falls, measurement campaigns can take a very long time to collect a sufficient dataset. These combined issues limit the scope of a fall classification problem.

1.2 Objective

The goal of this thesis is to deploy the emerging technology of [digital twin \(DT\)](#) for two main systems: the radar system and the [Joint Communication Sensing \(JCS\)](#) system. Both systems are used to classify the severity of falls. The main objective of using [DT](#) technology is to generate a dataset of falls in different scenarios. These generated datasets will then be used for training machine learning algorithms independently for both systems. Another goal of this thesis is to conduct measurement campaigns to validate the reliability of using simulated datasets for training in real scenarios. For both systems, machine learning algorithms will be trained on the simulated data and then tested using hardware-measured data. The final step in this work, after validating the reliability of the [DT](#), is to study the different aspects of fall signals and the areas where [DT](#) technology can improve future studies.

1.3 Thesis Outline

The structure of this thesis is as follows:

- Chapter [2](#): Provides background information related to radar systems and [JCS](#) systems, along with a literature review on the use of radar systems and [JCS](#) for human activity recognition.
- Chapter [3](#): Elaborates on our work on the [DT](#) of radar systems for the classification of fall severity. This chapter explains the system architecture of a reliable fall detection system, followed by the simulation, measurements, and results of this part of the work.
- Chapter [4](#): Discusses our work on the [DT](#) of [JCS](#) Systems for the classification of fall severity. The content of this chapter is structured similarly to the previous chapter while contrasting the two systems.
- Chapter [5](#): Presents the conclusions of our work on both systems, highlighting the comparison between them and how [DT](#) is shaping a futuristic approach to developing these systems, followed by future work to be conducted on both systems.

Chapter 2

Background

In this chapter, an overview of the technologies used in this work is provided. These technologies include radar systems, 5G [New Radio \(NR\)](#), and [DT](#) technology. The radar system is employed for fall detection, while 5G [NR](#) is utilized for communication and sensing. [DT](#) technology is used to generate data for training machine learning algorithms. The following sections provide an overview of recent advances in the literature on fall detection, followed by a detailed explanation of radar systems, 5G [NR](#), and [DT](#) technology. For each technology, the basic operation, signal processing, and applications are discussed, along with their use cases in the literature for fall detection.

2.1 Sensors Used for Fall Detection

Various technologies, such as wearable, non-wearable, and hybrid systems, have been developed for fall detection [\[10\]](#). Wearable systems include accelerometers and smartphones [\[10\]](#). Non-wearable devices include acoustic sensors [\[11\]](#), floor pressure sensors, near-field imaging, cameras [\[12, 13\]](#), ultrasonic sensors [\[14–16\]](#), and radars [\[17, 18\]](#). Hybrid systems may involve a combination of different wearable and non-wearable devices [\[19, 20\]](#). The choice of each system depends on the application and the required criteria. For example, wearable devices such as inertial motion capture sensors are more suitable in applications where human posture and motion need to be tracked, while also keeping information about each individual body part. These kinds of applications are used in sports, rehabilitation, and virtual reality [\[21\]](#). However, these devices may not provide the comfort needed for elderly people or individuals with disabilities, as they must wear the device continuously.

Another example is the use of acoustic sensors for fall detection. In [22], researchers used acoustic sensors to detect falls in a smart home environment. They utilized the ultrasonic band by leveraging existing devices in the home environment. Although the system’s performance was acceptable in a controlled environment, it suffered from multiple issues. Human voices and music affected the device’s performance, even though theoretically, this should not have been the case. Additionally, the system’s performance was impacted in scenarios where falls occurred out of the line of sight. The table in Fig. 2.1 shows a comparison between the characteristics of various types of sensors. The following sections elaborate on the reasons for choosing radar and communication systems, followed by a discussion of the basic operation of both.

	Camera	Inertial measurement unit (IMU)	Acoustic	Radar	WIFI Sensing	5G Sensing
Privacy	✗	✓	✓	✓	✓	✓
Not Wearable	✓	✗	✓	✓	✓	✓
No Battery	✓	✗	✓	✓	✓	✓
No Interference	✓	✓	✗	✓	✗	✓
Doesn't Require Separate Hardware installation	✗	✗	✗	✗	✓	✓

Figure 2.1: Comparison of the characteristics of different types of sensors

2.2 Radar Systems

Radar sensors are [radio frequency \(RF\)](#) based sensors that are used for detecting objects in environments where visibility is limited. The main functionality of a radar system is to determine the range, angle, and velocity of objects within coverage area.

Radar sensors emerge as a promising solution [23] due to their efficacy in preserving privacy, ensuring accuracy, operating independently of illumination levels, and detecting even slow falls that might be missed by wearables [1, 5, 17, 18, 24–29].

The basic concept of radar is to transmit an electromagnetic wave towards a target and receive the reflected wave. The time delay between the transmitted and received signals is estimated to determine the range of the target based on the speed of light. The velocity of the target is determined by the Doppler shift introduced in the received signal due to the relative motion between the object and the radar. The range and velocity information can be estimated using one transmitter and one receiver channel in the radar system. However, to estimate the angle of the target, multiple receiver channels are required in the case of a static radar. Otherwise, the radar needs to be moving either in rotational or translational motion while deploying different angle detection algorithms. The target's angle is estimated by analyzing the phase differences between signals received at multiple antennas.

Radar systems can utilize various waveforms, often named after the specific waveform type, depending on the application. Common radar waveforms include:

- **Continuous Wave (CW) Doppler radar:** CW Doppler radar transmits a continuous wave at a constant frequency, designed to measure the velocity of moving targets using the Doppler effect. It is highly effective at detecting object speed by analyzing the frequency shift between transmitted and received signals, caused by target movement. Beyond velocity measurement, CW Doppler radar is widely used in law enforcement for speed detection, traffic monitoring [30], automatic door systems, security systems, and industrial automation. This makes it a versatile tool in various fields, including traffic management, security, and automated processes.
- **Phase-Coded Radar:** In phase-coded radar, the transmitted signal is modulated with a specific phase code. By correlating the received signal with the transmitted code, the radar can accurately estimate the target's range and velocity. This approach is particularly effective in environments with high interference, offering improved target detection and resolution. However, these benefits come with the trade-off of increased computational complexity for both the transmitter and receiver. Phase-coded radar is widely used in various applications. In military systems, it enhances target detection and tracking capabilities even in cluttered or jamming-prone environments [31]. In weather radar [32], it improves the resolution and accuracy of detecting and analyzing precipitation and atmospheric conditions. Additionally, in Synthetic Aperture Radar (SAR) [33], phase-coded signals are key to achieving high-resolution imaging, making it valuable for reconnaissance, mapping, and environmental monitoring [34]. The versatility and robustness of phase-coded radar make it an essential technology across these and other advanced radar applications.

- **Pulse Radar:** Pulse radar is a type of radar system that transmits short, powerful bursts of RF signals and calculates the time delay between the transmitted pulse and the received echo to determine the range of a target. The longer the delay, the farther the target is. One of its key advantages is its ability to use the same antenna for both transmitting and receiving signals, thanks to a device called a duplexer, which switches the antenna between the transmitter and receiver. The pulse repetition frequency (PRF) is crucial in determining the radar’s maximum range and its ability to detect fast-moving targets. Additionally, the range resolution, which depends on the duration of the pulse, allows the radar to distinguish between closely spaced targets [35]. Pulse radar is widely used in various applications, including air traffic control for tracking aircraft [36], military surveillance for detecting targets [37], weather monitoring for storm detection, marine navigation for collision avoidance, and ground-penetrating radar for locating buried objects .
- **Frequency Modulated Continuous Wave (FMCW) Radar:** FMCW has been widely used in civilian applications due to its inherent processing simplicity and low operation and manufacturing costs. It has been used for automotive sensing applications [38], activity classification and localization of UAVs [39], hand gesture recognition [40], short-range surveillance [41], and industrial automation [42]. FMCW radar transmits a continuous signal that is linearly modulated in frequency, meaning the frequency of the signal changes gradually over time, typically in a sawtooth or triangular pattern. This modulation allows the radar to measure the range of a target by analyzing the difference in frequency between the transmitted and received signals, known as the "beat frequency" [43].

2.2.1 Radar-based Fall Detection

Various fall detection systems have been developed by researchers using different types of radar technology. In this section, the deployment of radar systems within an environment will be explored, along with the data processing methods and classifiers that have been employed. A fall detection system is typically composed of three main components: the radar system, the post-processing unit, and the classification unit. The radar system refers to the hardware responsible for transmitting and receiving electromagnetic waves, performing the RF front-end tasks according to the specific system used. The data from this phase is digitized using an Analog to Digital Converter and then fed into the processing unit. In the processing unit, essential parameters such as range, velocity, and angles are calculated from the raw data based on the system’s requirements. Finally, the processed

data is analyzed in the classification unit, where machine learning techniques have been widely investigated in the literature for accurate fall detection.

For example, in [1], the researchers used an ultra-wideband radar system to detect falls. **Ultra-Wideband (UWB)** radar systems are one form of pulsed radar where the transmitted signal is a very short-duration pulse with a relatively large bandwidth, enabling **UWB** radars to achieve high range resolution. The system employed various processing techniques, such as singular value decomposition, to filter out clutter and extract fall features, followed by a detection stage based on **Convolutional Neural Networks (CNN)**. The data in this work was represented in a matrix form corresponding to range over time. Researchers in [27] used **UWB** radar as well, yet they used a Kalman filter, DC removal, and bandpass filtering to process the data and suppress noise effects. This work used transformers as the classification unit as they exploit the attention mechanism in the transformers to extract fall features from the data.

In [17], a **CW** Doppler radar system along with an **FMCW** radar was used to detect falls. **Short-Time Fourier Transform (STFT)** was used to analyze micro-Doppler signatures of human activities carried out in the vicinity of the radar system. The data was represented in a stream form corresponding to detected peak power over time. The researchers used this format for real-time detection of falls. The least squares support vector machine (LS-SVM) was used as a classifier in this work.

On the other hand, **FMCW** radar systems were used in [24], [26], [28], and [29]. In [24], there was a separation of fall types based on the underlying cause. The criteria for soft falls in [24] involved instances of smooth and slow movements, such as those resulting from a heart attack. Accidental falls, on the other hand, were characterized by abrupt changes in the Doppler domain, and machine learning algorithms such as SVM, k-nearest neighbors, and ensemble learning were used for classification. In [26], a 2D **CNN** was used to detect falls. The processing done to the data in this work included the generation of 4 representations of the data: range-time, velocity-time, angle-time, and motion-state. Then all of them were combined as input to the 2D **CNN**. In [29], life-threatening falls were detected according to two symptoms: a sudden detected height drop of the human followed by lying on the ground for a certain amount of time. Yet, monitoring height changes might not be a sufficient criterion as there are situations where participants are raising their hands in the air. Researchers in this work generated 4D point cloud data from the radar data.

There has been extensive work on various aspects of fall detection and identification, yet fall scenarios performed to assess the efficiency and extract features of falls are limited, which may not be generalized in most cases. For example, in [26] five different behaviors

are performed (falling, scooting, stopping, squatting, sitting, and arising), each behavior is performed 100 times by each of four participants. In [27], 11 participants contributed to measurements with each participant doing 30 tests, 15 falls, and 15 non-fall events. In [28], 97 tests were done in total, including 10 scenarios. Each of those studies included data that used the same radar configuration and setup, which may not cover all edge cases needed for generalization.

Throughout this part of the literature review, the combination of using different types of radar systems with different processing techniques and classifiers has been explored. Yet, the study of radar systems involves different key challenges that are common with respect to the fall detection task. These challenges include the limited size of the dataset, the challenge of performing fall tasks, and the time consumed for data collection. These challenges are addressed towards the end of this chapter.

2.2.2 FMCW Radar Overview

As mentioned earlier, FMCW radar is a desirable choice for civilian applications. FMCW radar can provide customized range and velocity resolution based on the application requirements. It is also noted that the FMCW radar system radiates less power as it operates at 100% duty cycle as opposed to pulsed radars. This is an important factor in applications where health concerns are raised due to electromagnetic power. This comes at the cost of having a lower maximum range compared to pulsed radars, which is acceptable in this application at the home environment.

Fig. 2.2 shows the block diagram of the basic architecture of an FMCW radar system. The main components in the FMCW radar system are [44]:

- **Chirp Waveform Generator:** This component is responsible for driving the transmitted frequency in a linear trend over time with a cyclic behavior.
- **Voltage Controlled Oscillator (VCO):** This component is used to generate the waveform that is transmitted by the radar. The VCO is controlled by the chirp waveform generator to generate the desired frequency sweep over time.
- **Power Divider:** This component is used to divide the RF signal generated by the VCO into two paths. One path is used to feed the Power Amplifier to prepare the signal for transmission. The other path is used to feed the mixer where it is used by the receiver part as a reference signal.

- **Power Amplifier (PA):** This component is used to amplify the RF signal generated by the **VCO** to the required power level needed for transmission.
- **Antenna:** This component is used to transmit the RF signal generated by the **PA** and receive the reflected signal from the targets in the environment. Antennas can be designed to have different beam patterns based on the application requirements. Antennas also can be designed to have multiple elements to provide angle information of the targets or steer the beam to different angles for systems such as MIMO and Phased Array radars.
- **Low Noise Amplifier (LNA):** This component is used to amplify the received signal at the antenna to the required level for processing. The main difference between the **LNA** and the **PA** is that the **LNA** is designed to have a low noise figure to maintain the signal-to-noise ratio of the received signal. The output of the **LNA** is fed to the mixer to generate the beat frequency.
- **Mixer:** This component is used to multiply the received signal by the reference signal generated by the coupler. The output of the mixer is the beat frequency as will be illustrated in the next section.
- **Low-Pass Filter (LPF):** This component is used to filter out the high-frequency components resulting from the multiplication process in the mixer. The output of the **LPF** is the beat frequency that is used to estimate the range of the target.
- **Analog to Digital Converter (ADC):** This component converts the analog signal from the **LPF** into a digital signal for subsequent processing and target detection. A critical factor affecting radar performance is the **ADC**'s sampling rate, which must adhere to the Nyquist rate to ensure accurate representation of the analog signal.

2.2.3 FMCW Radar Signal Analysis

The development of the Frequency Modulated Continuous Wave (FMCW) waveform addresses a key limitation of pulsed radars: the trade-off between range resolution and pulse width. To achieve higher resolution with pulsed radars, the pulse width must be reduced, which increases both the bandwidth and the peak transmitted power. The **FMCW** radar system was designed to overcome this limitation. By employing a linear frequency modulation technique, **FMCW** radars can achieve higher range resolution without needing to reduce the pulse width, thus maintaining the same bandwidth. The theoretical analysis of

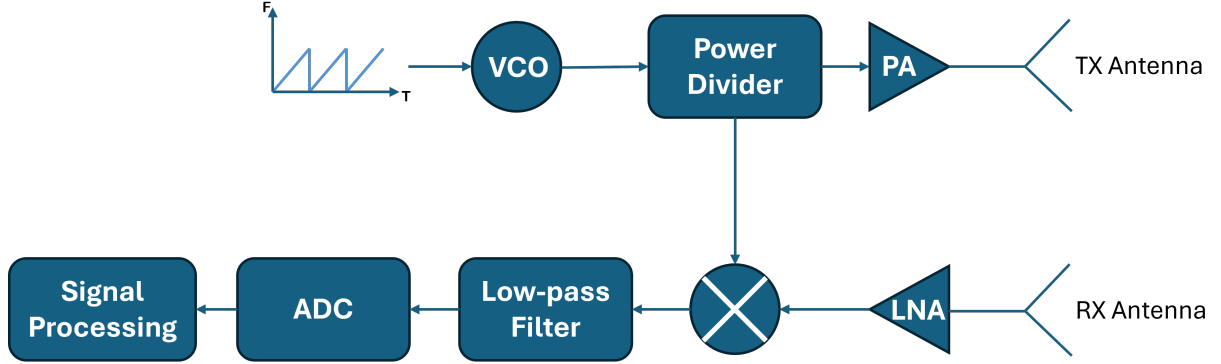


Figure 2.2: High-level block diagram of the FMCW radar

range and velocity resolution for FMCW radars is detailed through the ambiguity function, as discussed in [43]. Following this, the transmitted and received FMCW signals will be analyzed, focusing on the methods for calculating the range and velocity of targets.

Fig. 2.3 illustrates how the transmitted and received signals are modeled in frequency VS time showing the effect of the round trip time due to a reflected wave from a moving target. The waveform of the transmitted signal can be modeled as follows:

$$s(t) = A \cos[\omega_0 t + \theta(t) + \phi_0] \quad (2.1)$$

where A is the amplitude of the transmitted signal, ω_0 is the carrier frequency, θ is the shift in frequency defined by the sawtooth waveform, and ϕ_0 is the phase shift. The instantaneous frequency of this signal is given by:

$$f(t) = \frac{1}{2\pi} \left[\omega_0 + \frac{d}{dt}\theta(t) \right] \quad (2.2)$$

where $\theta(t)$ has a linear slope, i.e., BW/T , indicating the bandwidth divided by the sweep time.

The received signal can be expressed as:

$$s_r(t) = \alpha A \cos [(\omega_0 + \omega_D) (t - t_d) + \theta (t - t_d) + \phi_0] \quad (2.3)$$

Here, α represents the attenuation factor, $t_d = \frac{2R}{c}$ is the round-trip time between the radar and the target, $\omega_D = 2\pi f_D = \frac{2V \cos \theta}{\lambda}$ represents the Doppler shift, where $V \cos \theta$

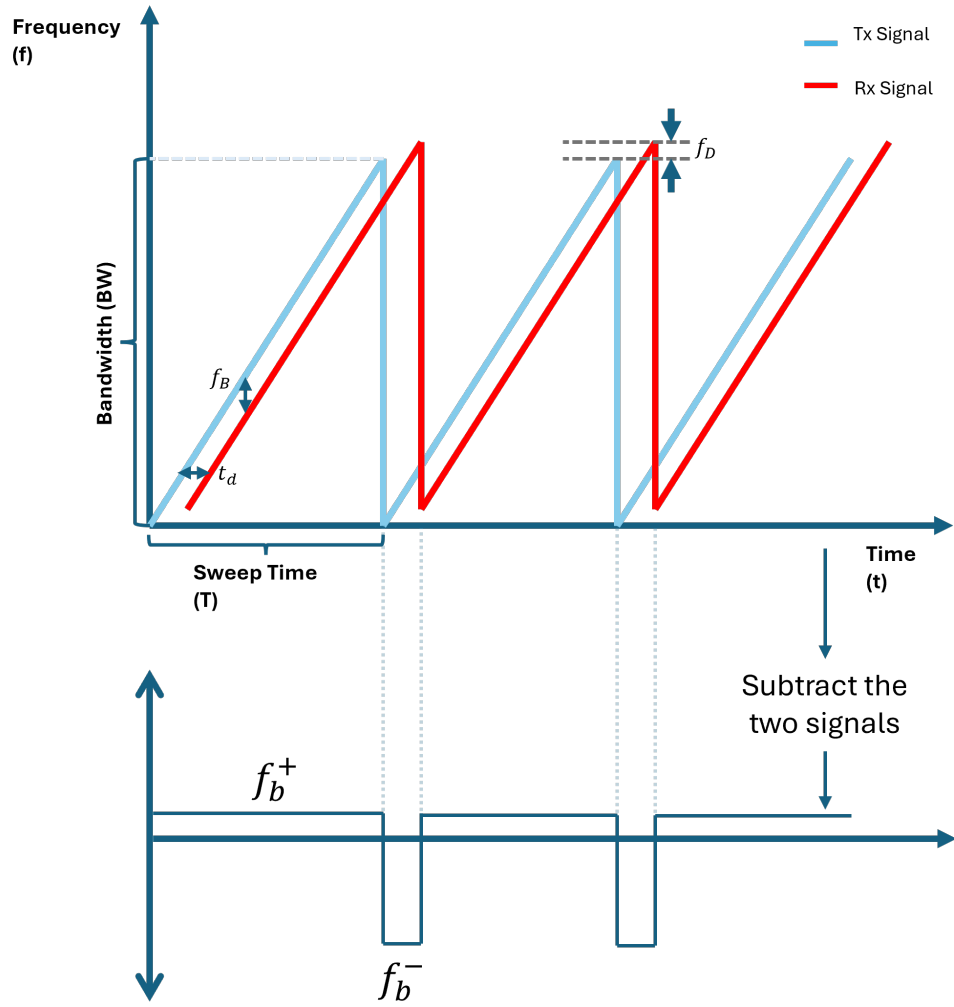


Figure 2.3: Transmitted and received sawtooth signals of the FMCW radar. Subtracting these two signals results in the positive and negative beat frequency components.

is the radial velocity, and λ is the wavelength. The frequency of the received signal is described by:

$$f_r(t) = f_0 + f_D + \frac{1}{2\pi} \left[\frac{d}{dt} \theta(t - t_d) \right] \quad (2.4)$$

The beat frequency, which is the difference between the transmitted and received frequencies, is given by:

$$f_b(t) = f(t) - f_r(t) = \frac{1}{2\pi} \left[\frac{d}{dt} \theta(t) \right] - \frac{1}{2\pi} \left[\frac{d}{dt} \theta(t - t_d) \right] - f_D \quad (2.5)$$

Given that both the transmitted (2.1) and received (2.3) signals are cosine functions, the output of the mixer (which multiplies these two signals) is governed by the product-to-sum identity:

$$\cos(A) \cos(B) = \frac{1}{2} [\cos(A - B) + \cos(A + B)] \quad (2.6)$$

Thus, the output signal of the mixer is:

$$\begin{aligned} s_r(t) &= \frac{1}{2} \alpha A^2 \cos [\omega_0 t_d - \omega_D (t - t_d) + \theta(t) - \theta(t - t_d)] \\ &+ \frac{1}{2} \alpha A^2 \cos [\omega_0 t + (\omega_0 + \omega_D) (t - t_d) + \theta(t) + \theta(t - t_d)] \end{aligned} \quad (2.7)$$

Since the output of the mixer passes through an **LPF**, the high-frequency component $\cos(A + B)$ is eliminated, leaving the output of the **LPF** as:

$$s_r(t) = \frac{1}{2} \alpha A^2 \cos [\omega_0 t_d - \omega_D (t - t_d) + \theta(t) - \theta(t - t_d)] \quad (2.8)$$

This output from the Mixer and **LPF** is equivalent to subtracting the transmitted and received signals, resulting in the beat frequencies f_b^+ and f_b^- as shown in fig. 2.3. There are two methods to solve for range and velocity using these signals. The first method is detailed in [44] and builds on equation (2.7). The second method derives from equations (2.2) and (2.4), leading to the following equations:

$$f_b^+ = \frac{\text{BW}}{T} t_d - f_D = \frac{2\text{BW}}{cT} R - f_D \quad (2.9)$$

$$f_b^- = -\frac{\text{BW}}{T} t_d - f_D = -\frac{2\text{BW}}{cT} R - f_D \quad (2.10)$$

Once f_b^+ and f_b^- are extracted using Fast Fourier Transform (FFT), the range and velocity can be determined using equations (2.9) and (2.10) as follows:

$$R = \frac{cT}{4BW} \cdot \frac{(f_b^+ - f_b^-)}{2} \quad (2.11)$$

$$f_D = -\frac{f_b^+ + f_b^-}{2} \quad (2.12)$$

2.2.4 Micro-Doppler Analysis

The micro-Doppler effect can be defined as the additional modulation sidebands introduced by smaller parts that are in relative motion to a main rigid body of a certain target. This effect appears in radar signals as an echo around the Doppler frequency of the main bulk of the target [45]. For example, when a bird is flying, the wings flap, which appears as a modulation in the radar signal around the Doppler frequency of the flying bird. The same occurs for UAVs when the propellers rotate. In the case of humans, the micro-Doppler effect can be introduced by the movement of the limbs. This happens because the limbs swing in a periodic manner while walking, for example. Also, for non-periodic motions such as falls, the micro-Doppler effect can appear as distributed velocity components around the main body's velocity component, which changes over time [23]. This effect can be used to classify the micro-Doppler signature of human activities since each activity involves unique limb motions, which in turn result in a unique micro-Doppler signature. This has been utilized in the literature as a method to classify human activities using radar signals, as will be shown next.

The micro-Doppler effect can be analyzed using STFT through the following equations:

$$\chi(\tau, f) = |\text{STFT}(s)|^2 = \left| \int_{-\infty}^{+\infty} s(t)h(t - \tau)e^{-2\pi ft} dt \right|^2 \quad (2.13)$$

where $h(\cdot)$ represents the window function. In practice, the STFT is typically computed using the FFT, meaning both the signal and window function are discrete and quantized. Essentially, the STFT can be understood as the Fourier transform of the "windowed" signal $s(t)h(t - \tau)$. The resolution of the STFT is influenced by the window size, resulting in a trade-off between time and frequency resolution: a larger window improves frequency resolution but reduces time resolution [46].

2.3 5G New Radio

5G is an emerging technology that is widely deployed for communication. It provides proper indoor and outdoor coverage and performs well with mobility. 5G is built on three key components for its applications: massive machine-type communications (mMTC), enhanced mobile broadband (eMBB), and ultra-reliable low latency communications (uRLLC). These three areas allow for the transmission of various waveform configurations [47], [48], [49]. Additionally, the waveforms that are transmitted can also be utilized for sensing applications.

Fig. 2.4 shows a 5G network with various types of communications, including those between base stations and users, UAV swarms, vehicles, and other base stations. The network can be deployed indoors and outdoors and work on a variety of frequency bands, as illustrated in the subsections below. The integrated sensing and communication (ISAC) in the figure encompasses the broader scope of JCS. The ISAC specifies that communication and sensing applications can use different and integrated waveforms; however, in the literature, JCS typically refers to using the same waveform for both communications and sensing applications, though some researchers use the terms interchangeably.

This section explains how 5G NR can be used for both communications and sensing. The following subsection describes the basic structure of 5G NR next-generation Node Base station (gNB), the gNB is responsible for connecting users to the network. Following that, Orthogonal Frequency Division Multiplexing (OFDM), which is the key modulation technique used in 5G and other communication standards such as 4G, 6G, and Wi-Fi, is introduced. The following subsection explains channel estimation, which is an important aspect of sensing in communication systems. The rest of this section discusses how these 5G concepts are applied in JCS applications, including a literature review of the most recent research on the use of JCS systems for fall detection purposes.

2.3.1 5G Downlink

A 5G system architecture consists of three main components: user equipment (UE), radio access network (RAN), and core network (CN). The term "UE" refers to any user-end device that can connect to the network, such as mobile phones or IoT devices. The RAN is the part of the system that connects UEs to the core network. The core network serves as the 5G architecture's backbone, ensuring UE connectivity, policy management, mobility management, and other functions. The 5G core is comprised of several subsystems that handle different functions, including the Access and Mobility Management Function

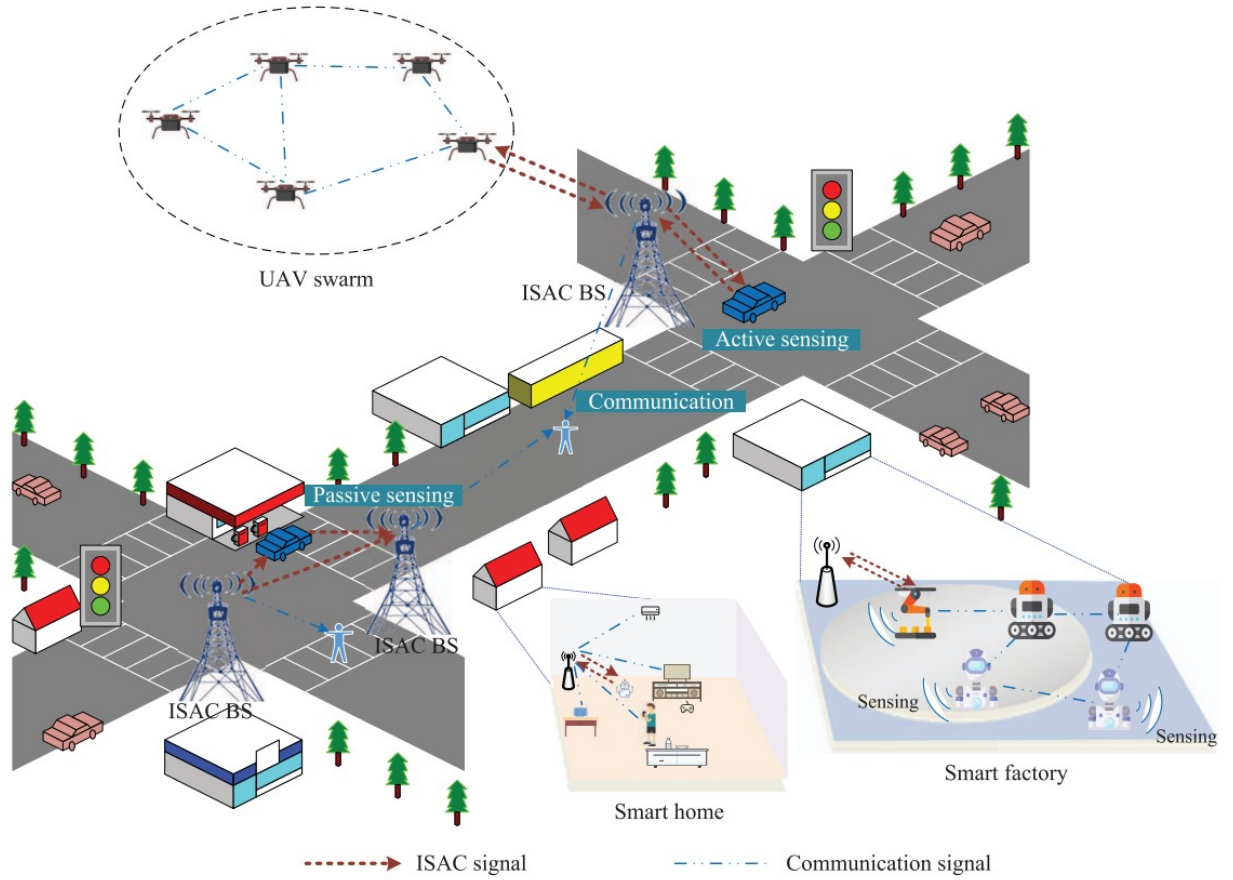


Figure 2.4: An illustration a 5G network integrating communication and sensing. The ISAC base stations support both active and passive sensing for applications such as vehicle detection and environmental monitoring. UAV swarms communicate and coordinate via ISAC signals, while smart homes and factories leverage 5G for automation and efficient operations. Communication signals (blue dashed lines) ensure connectivity across various environments, highlighting the versatility of 5G in supporting diverse applications [50].

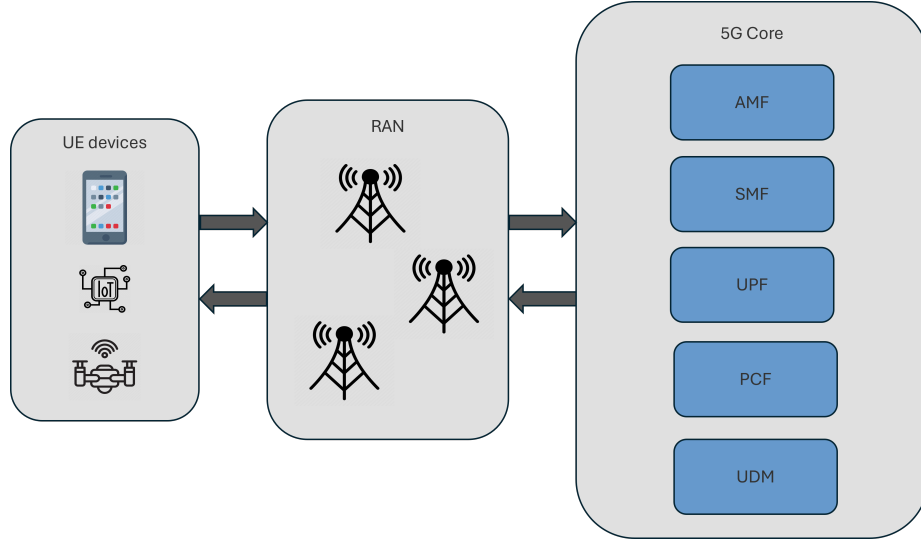


Figure 2.5: The main components in 5G system architecture: UE, RAN, and 5G Core.

(AMF), the Session Management Function (SMF), the User Plane Function (UPF), the Policy Control Function (PCF), and Unified Data Management (UDM). However, these subsystems are beyond the scope of this work. The RAN component of the 5G network implements the main functionality of JCS. Fig. 2.5 shows the 5G network's components and their connections.

3GPP standards support a wide spectrum; Frequency Range 1 (FR1) for 450 MHz to 7.125 GHz and FR2 for millimeter wave (mmWave) from 24.25 GHz to 71 GHz [51], [52]. The lower band of the FR1 (below 1 GHz) is better suited for long-distance communications in rural areas with low data rates. On the other hand, frequencies between 1 GHz and 7 GHz provide a good balance of data rate speed and coverage area. The FR2 band is better suited for indoor communications because losses increase significantly with distance.

The structure of 5G standards specifies that a 5G frame is composed of 10 subframes, each of which contains a number of slots determined by the subcarrier spacing. Each slot contains 14 OFDM symbols. The frame duration is 10 milliseconds, with each subframe lasting 1 millisecond. The 5G standards allow subcarrier spacing of 15, 30, and 60 kHz in the FR1 band and 60, 120, 240, 480, 960 kHz in the FR2 band [53]. When the subcarrier spacing is doubled, the number of slots per frame doubles as the length of each OFDM symbol is shortened in half. A 5G frame can be represented as a grid of resources in both time and frequency, with the subcarrier number representing the frequency axis and the OFDM symbol number representing the time axis. A resource element is the smallest

physical resource unit, consisting of one subcarrier and one OFDM symbol, whereas a resource block is a group of twelve subcarriers spread across a variable number of OFDM symbols. Fig. 2.6 shows the details of a 5G frame, whereas Fig. 2.7 shows how the number of slots corresponds to the subcarrier spacing within the frame. The 5G standards define the waveform as OFDM with Cyclic Prefix (CP-OFDM). LTE and Wi-Fi use the same basic concepts and waveforms; however, 5G has some differences from LTE that allow it to achieve higher spectral efficiency.

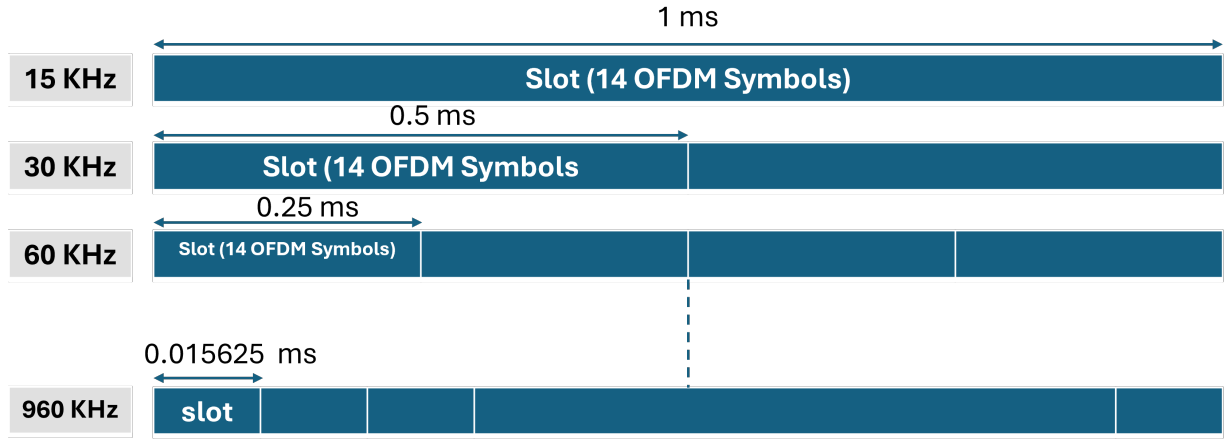


Figure 2.7: Illustration of slot duration variation in 5G NR based on different subcarrier spacing.

2.3.2 5G Physical Channels

Carrier configuration in a 5G network can be either downlink (DL) for gNBs or uplink (UL) for UEs [54], [55]. Each carrier has multiple physical channels that serve different purposes. Each of these channels transmits a specific type of information between the gNB and the UE. In this work, the gNBs will be used for the sensing application. The primary channels defined on the DL side are:

- **Physical Broadcast Channel (PBCH):** used to carry the Master Information Block (MIB), which contains the basic information needed by the UE to connect to the network. The PBCH is responsible for broadcasting this basic information to all UEs within the coverage area, ensuring that all UEs in the area have access to the network configuration.

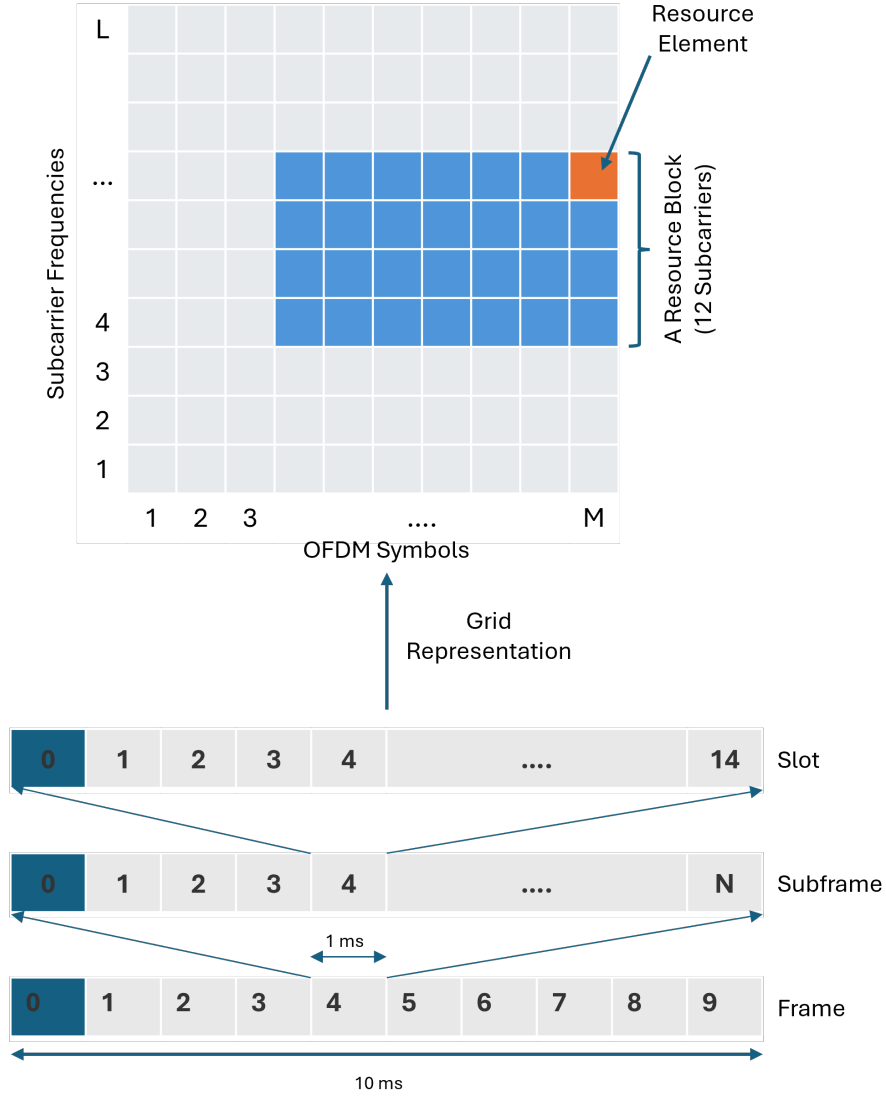


Figure 2.6: Illustration of the 5G NR frame structure according to 3GPP standards. The top grid represents the resource grid, where the x-axis corresponds to OFDM symbols and the y-axis to subcarrier frequencies. Each small square in the grid represents a resource element, the smallest unit in the grid, consisting of 1 subcarrier and 1 OFDM symbol. A group of 12 consecutive subcarriers across one or more OFDM symbols forms a resource block, highlighted in orange. Below the grid, the figure shows the hierarchical structure of a 5G frame, which consists of 10 subframes, each lasting 1 ms. Each subframe is divided into a number of slots, each composed of 14 OFDM symbols.

- **Physical Downlink Control Channel (PDCCH):** transmits Downlink Control Information (DCI) for resource allocation and scheduling. This signal contains control commands for all UEs within coverage, as well as resources for uplink and downlink.
- **Physical Downlink Shared Channel (PDSCH):** used for carrying the actual data from the base station to the UE.

2.3.3 5G Physical Signals

The standard defines multiple signals that are used in the DL such as:

- **Physical Synchronization Signal:** this type of signal is divided into two parts: **primary synchronization signal (PSS)** and **secondary synchronization signal (SSS)**. This signal facilitates initial synchronization and cell search. The PSS has only three possible sequences that are used to determine frame timing. It appears at the start of the frame. To detect the PSS, the receiver runs three correlators in parallel. After the PSS is detected, the SSS is used to determine the cell ID. The SSS contains 336 possible sequences, which are combined with the PSS to determine the cell ID. The SSS appears two OFDM symbols after the PSS. Together, the PSS and SSS generate 1008 unique cell IDs.
- **Demodulation Reference Signal (DMRS):** used to estimate and equalize channels during the data reception process. The DMRS is only utilized in the PDSCH resource blocks. It is an essential component for ensuring high-quality data transmission. It is also a pseudo-random sequence known to both the transmitter and the receiver. The DMRS is highly configurable, with two types and additional attributes such as the number of DMRS ports, DMRS symbols, and repetition factor. However, it is beyond the scope of this work. The PSS, SSS, DMRS, and PBCH form the Synchronization Signal Block (SSB). The SSB is defined by 3GPP standard TS 38.211 [53], which states that the block size should be 240 subcarriers in 4 OFDM symbols. Fig. 2.8 shows the details of an SSB generated by the MATLAB 5G toolbox.
- **Phase Tracking Reference Signal (PTRS):** this signal is a specialized reference signal used in phase tracking. The PTRS is used to resolve phase noise issues in the receiver. Phase noise is a critical issue in the demodulation process, particularly in the high frequency bands, so the PTRS can serve as a reference for the receiver to track the phase noise. The PTRS should be used before estimating the channel to ensure that the phase noise is removed.

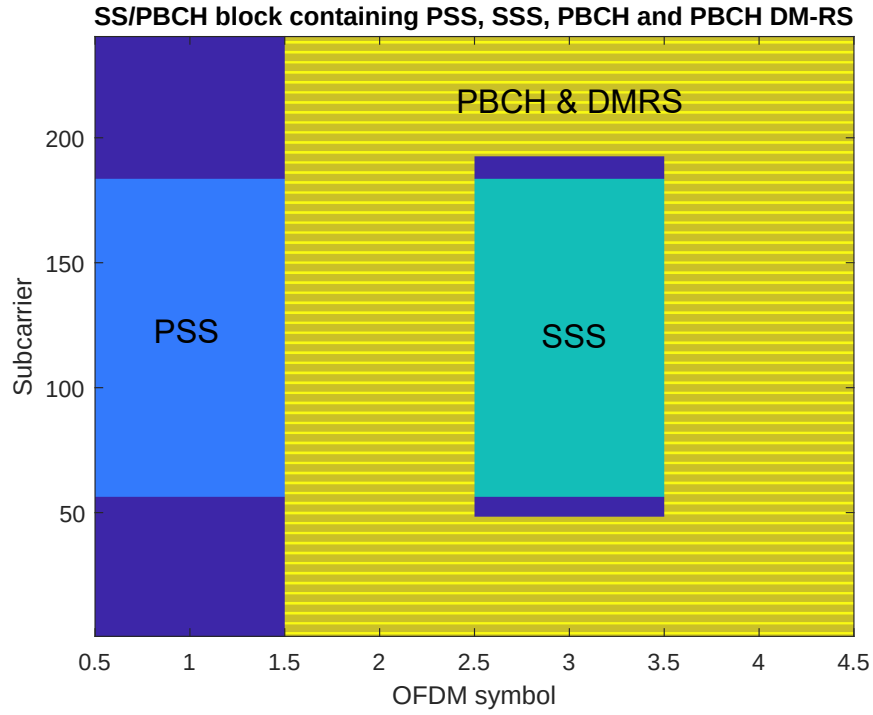


Figure 2.8: Demonstration of the synchronization signal block (SSB), where the Primary Synchronization Signal (PSS) is the first to appear for frame detection and initial time synchronization, followed by the Secondary Synchronization Signal (SSS) to determine the cell ID. The other parts of the block include the Master Information Block (MIB) and Demodulation Reference Signal (DMRS) for channel estimation. This figure was generated using matlab 5G toolbox [56]

- **Channel State Information Reference Signal (CSI-RS)**: this signal has a significant impact on the overall performance and efficiency of 5G networks. The **CSI-RS**, like other reference signals, follows a known sequence shared by both the transmitter (gNB) and the receiver (UE), making it useful for channel estimation and feedback processes. According to 3GPP, the **CSI-RS** is specifically designed to help the UE report accurate **Channel State Information (CSI)** [54]. This **CSI** report is essential for enabling several advanced features in 5G, such as beam management, which is crucial for optimizing beamforming techniques, power control, which aids in maintaining optimal signal quality and reducing interference, and scheduling, which ensures efficient resource allocation based on channel conditions.

The **CSI-RS** is transmitted from the gNB to the UE and serves multiple purposes, depending on the deployment scenario and the network's configuration. One of its primary functions is to aid in time-frequency tracking, which is vital for maintaining synchronization between the gNB and UE, especially in environments with high mobility or rapidly changing channel conditions. Additionally, the **CSI-RS** is integral to the computation of **CSI** in the uplink, where the UE analyzes the received **CSI-RS** to assess the quality of the downlink channel and then reports this information back to the gNB.

The **CSI-RS** feedback enables the gNB to make informed decisions about beam selection, transmission power adjustments, and resource block allocation, all of which help to optimize network performance. **CSI-RS**'s adaptable design enables it to be configured for various scenarios, such as supporting multiple antennas and MIMO (Multiple Input Multiple Output) configurations, making it a useful tool in both traditional and advanced 5G deployments. In conclusion, the **CSI-RS** is an important reference signal in 5G **NR** because it provides the data required for dynamic network adaptation to changing conditions, improving reliability, efficiency, and overall user experience in 5G networks.

The 3GPP [53] defines two types of **CSI-RS** configurations: Zero-Power (ZP) and Non-Zero-Power (NZP). Both serve different functions and are used in various scenarios. In this work, we use the NZP **CSI-RS** for sensing applications as part of the **JCS** framework, which has been extensively studied in the literature, as shown in the following section. Fig. 2.9 shows an example of a 5G downlink frame with all signals and channels.

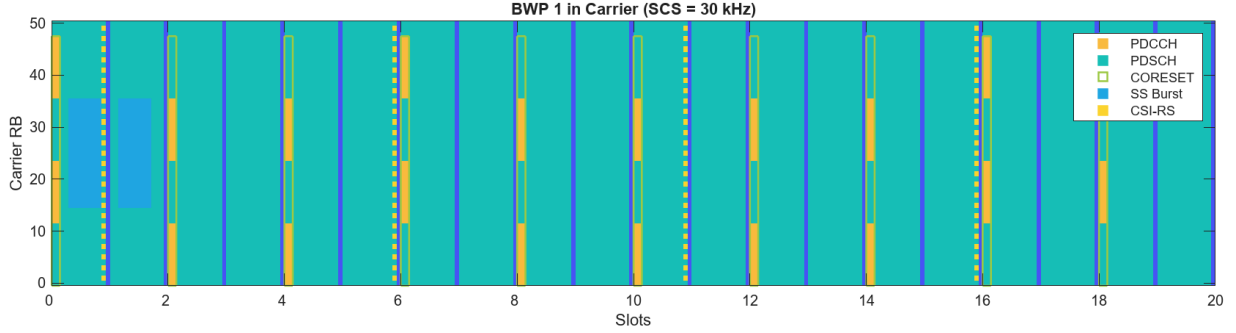


Figure 2.9: Example of a 5G NR downlink resource grid generated by the 5G Waveform Generator toolbox in MATLAB. This example was generated for a signal with a 20 MHz bandwidth and subcarrier spacing of 30 kHz, resulting in 51 resource blocks, 20 subframes, and each frame having 2 slots. This example contains both the PDCCH and PDSCH channels, with each containing information and signals as advised by 3GPP standards.

2.3.4 5G Channel Estimation

In communication systems, the channel is the medium through which signals are transmitted from transmitter to receiver. Noise, interference, and fading can all have an impact on the channel's performance. In a communication system, the waveform is sent from the transmitter to any receiver within its coverage area. On the other hand, this waveform is reflected by the environment and surrounding objects. The reflected waveform can be received by the same device used in the transmission process. The Doppler effect causes each reflected wave to have a different round trip time and frequency shift. The receiver receives all of these waves simultaneously. The following equations mathematically illustrate the wireless channel model.

According to [57], the transmitted signal $x(t)$ can be formulated according to equation 2.14

$$x(t) = \sum_{m=0}^{M-1} \sum_{k=0}^{N-1} s(k, m) e^{j2\pi f_k t} \text{rect} \left(\frac{t - mT_s}{T_s} \right) \quad , \quad (2.14)$$

where M and N are the number of OFDM symbols and subcarriers, respectively, s is the modulated reference symbol, T_s is the total duration of the OFDM symbol, and f_k is the k -th subcarrier of the reference signal. For simplicity, assume the transmitted wave is X_{tx} . Equation 2.15 can be used to formulate the received signal $y(t)$, assuming H reflected signals [58].

$$y(t) = \sum_{h=0}^{H-1} b_h X_{tx}(t - \tau_h) e^{j2\pi f_{D,h} t} e^{j\tilde{\varphi}_h} + \tilde{z}(t) \quad (2.15)$$

This equation includes a representation of the following effects: the attenuation of every reflected signal amplitude b_h , signal delay τ_h , Doppler shift $f_{D,h}$, random phase shift $\tilde{\varphi}_h$, and noise $\tilde{z}(t)$.

Each reflected signal from a different object has a different Radar Cross Section (RCS), so the attenuation amplitude can be given by equation 2.16.

$$b_h = \sqrt{\frac{c_0 \sigma_{\text{RCS},h}}{(4\pi)^3 d_h^4 f_C^2}} \quad (2.16)$$

Where c_0 is the speed of light, d_h is the distance between the transmitter and the object, and f_C is the carrier frequency.

The round trip time delay can be given by equation 2.17.

$$\tau_h = 2 \frac{d_h}{c_0} \quad (2.17)$$

The Doppler shift due to the object's relative velocity can be given by equation 2.18.

$$f_{D,h} = 2 \frac{v_{\text{rel},h}}{c_0} f_C \quad (2.18)$$

The multipath reflections in the channel greatly hinder the receiver system's ability to demodulate the signal. The channel estimation process is used to calculate the channel coefficients and impulse response. This estimated channel can be used in an equalization process in which the channel effect is reversed. As previously stated in the context of 5G signals, the [DMRS](#) and [CSI-RS](#) can be used for channel estimation. The [DMRS](#) is used for channel estimation in the PDSCH resource blocks, whereas the [CSI-RS](#) is used for more general tasks like beamforming, power control, and scheduling. Channel estimation can be used in sensing applications to determine target characteristics such as distance, velocity, and position, as described in the previous equations.

Channel estimation techniques fall into three categories: pilot-assisted, blind, and semi-blind [59]. The pilot-assisted channel estimation technique is the most widely used in communication systems. This category contains a variety of techniques, including Least

Squares (LS), Minimum Mean Square Error (MMSE), and Maximum Likelihood. In pilot-assisted channel estimation, the transmitter sends a predetermined sequence of symbols known as pilots. The receiver estimates the channel coefficients based on the pilots it receives. The LS technique is the simplest and most widely used method for channel estimation. However, the blind channel estimation technique does not require the transmitter to send pilots. The receiver estimates channel coefficients using statistical models and known transmitted signal configurations. Semi-blind channel estimation combines both pilot-assisted and blind channel estimation techniques. Because the DMRS and CSI-RS are defined in the 5G standards, this work employs the pilot-assisted channel estimation technique for the sensing application. However, in future work, the blind and semi-blind channel estimation techniques can be used as long as the channel is estimated correctly.

2.3.5 JCS Fall Detection

The use of wireless communication technologies for sensing applications has been a growing trend in recent years. This technology has been investigated for a wide range of civilian applications, such as localization for vehicular networks, human activity recognition, and indoor localization. It can also be used for military applications, such as UAV communication and sensing [60], [61]. The application of JCS for fall detection has been studied in the context of 5G and WiFi systems because they both share the usage of the OFDM waveform for communications. However, there are differences in the standards for defining the waveform configuration and the frequency bands used for both systems. WiFi systems have been more widely studied for fall detection than 5G-based systems due to the availability of the technology and the ease of access to the hardware. The rest of this section will focus on demonstrating the use of 5G and WiFi systems for fall detection in the literature.

In [62], a 5G-based system was proposed for presence and activity detection. The proposed system utilizes the CSI data from the 5G system with the help of machine learning algorithms to perform the required detection. In this work, the researchers collected the CSI data from 51 subcarriers and then averaged those subcarriers to obtain the final CSI data, where each CSI point represents a received packet. Other data processing steps were performed to prepare the final data for the machine learning algorithm. The collected CSI data shown in the work indicates that different subcarriers have different CSI values, which opens the door for further investigation of the change in magnitude and phase between the subcarriers. In our work, we present a more comprehensive study of the CSI data, both in simulations and measurements.

While 5G technologies show significant potential in these domains, WiFi has also been extensively explored for similar applications, particularly in the area of human activity

recognition. WiFi has been used in various scenarios, such as room occupancy monitoring [63], [64], indoor localization and tracking [65], [66], and vital signs monitoring [67], [68].

Building on this, in [69], the researchers propose the SafeDrive-Fi framework for in-vehicle sensing, demonstrating that WiFi CSI can be effectively utilized to differentiate between normal and dangerous driving states with an accuracy of 98.04%. They introduce a novel DETECT algorithm to identify abnormal driver states in noisy in-vehicle settings. Unlike traditional edge-based algorithms, which struggle with noisy CSI, DETECT incorporates median filtering and energy calculation over the variance of aggregated subcarriers to detect abnormalities. Their system design, using CSI and multi-domain features, enhances driver state recognition by almost 19.8% compared to similar RSS-based systems reported in earlier studies.

Several systems and algorithms have been studied in the context of using WiFi for fall detection, such as in [70], [71]. In [72], the DeFall WiFi-based fall detection system, which is environment-independent, is discussed. This system leverages speed and acceleration patterns as inherent features of human falls. The system is composed of two stages: offline template generation and online decision-making. During the offline stage, the speed of human falls is estimated using statistical modeling of CSI. Dynamic Time Warping (DTW) algorithms are then used to create a representative template for typical human falls. In the online stage, fall events are detected by comparing real-time speed and acceleration patterns with this template. Experimental results show that using a single pair of WiFi transceivers, the system achieves a 96% detection rate and a false alarm rate below 1.5% in both line-of-sight (LOS) and non-LOS (NLOS) scenarios.

2.4 Digital Twin

DT technology is a transformative approach that enables the creation of virtual replicas of physical entities, systems, and processes. DT is being developed in various fields, including manufacturing [73], healthcare, and UAV detection [74], [75]. The framework for a DT can be developed with different objectives in mind. DT can be designed for real-time data generation, real-time operation in parallel with the physical entity, or offline data generation for training machine learning algorithms. The following literature provides examples of various proposed implementations of these frameworks.

An early work suggested a framework for a DT in healthcare based on cloud computing and IoT technologies [76]. This framework aimed to assist elderly people in various aspects of healthcare by utilizing data from multiple sensors and devices. It creates a virtual model

of an elderly person’s health, continuously updated with real-time data. Operating on a cloud platform, the system ensures scalability, flexibility, and accessibility, enabling healthcare providers and caregivers to monitor health conditions remotely and in real-time. The framework supports essential healthcare services, such as real-time monitoring, predictive analysis, and the development of personalized care plans. By detecting health abnormalities early, the system can promptly alert healthcare providers, leading to more proactive and personalized care. The study highlights the significant potential of this approach to improve the quality of care for the elderly, reduce strain on healthcare systems, and provide more tailored healthcare solutions. However, the research also identifies challenges, including data privacy, security concerns, and the need for reliable data sources, which must be addressed for widespread adoption of this technology. This work provides a comprehensive framework for developing digital twin in healthcare, which intersects with the proposed system in this work. However, the system proposed in this work focuses more on generating data for training machine learning algorithms with two different systems for a specific application, without the need for real-time data generation or integration with other sensors and devices.

In [77], a DT was developed for generating data to train deep reinforcement learning (DRL) algorithms. The aim of this work was to generate a realization of the flocking behavior of UAVs. The researchers utilized a DT-enabled DRL framework, which provided high-fidelity state information during the training process, leading to more accurate and effective model development. This approach resulted in better performance in achieving the flocking motion of UAVs. Additionally, the trained model could be rapidly deployed in real-world UAVs, with continuous updates and performance evaluations enabled through the connection between the physical UAVs and their digital counterparts.

Following the applications of DT in UAVs, a study was conducted to develop a DT for enhancing wireless channel modeling for UAVs in mobile networks [78]. The approach involved creating an accurate DT of UAVs, integrating 3D mmWave radar imaging to capture essential aspects of UAVs, such as shape, material properties, and movement. These characteristics were used for precise RF channel modeling. This DT, a virtual representation of the physical UAV, is continuously updated with real-time data, allowing for dynamic simulations and a better understanding of the UAV’s interaction with the wireless environment. The study demonstrates that this approach can significantly improve the reliability of communication between UAVs and mobile networks, particularly in complex environments where signal propagation is challenging. The findings have important implications for various UAV applications, including surveillance, delivery services, and emergency response, where robust and efficient communication is vital. A crucial difference in this approach to DT is the integration of hardware and simulations in creating the DT. This

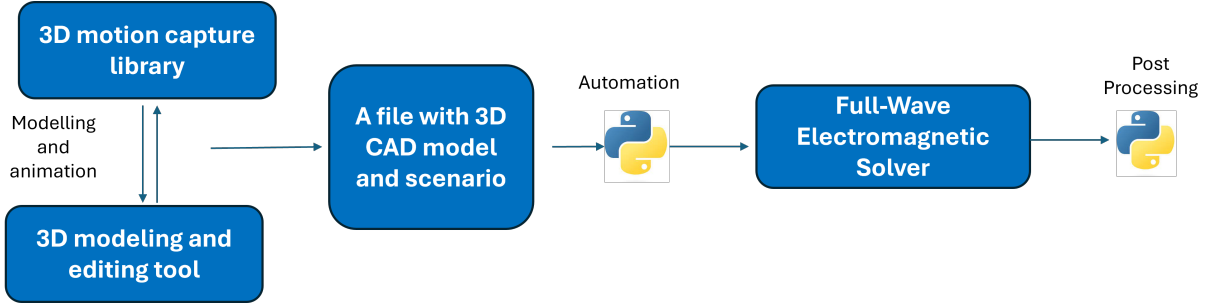


Figure 2.10: A block diagram of the proposed framework of the DT for healthcare applications

approach proves to be computationally expensive and requires high processing power, as well as introducing non-idealities stemming from the radar hardware into the simulations. This is a crucial point for creating the DT proposed in this work, which is based solely on simulations.

Following up on the discussed frameworks from the literature, the proposed framework developed for healthcare applications, which includes a human model to be emulated, is as follows. The main components of this framework include a 3D CAD model that is human-like, software tools for editing or creating 3D CAD parts for greater suitability for the application, and transformation matrices that control the motion of each part of the 3D CAD model. The framework also includes software or a program to automate scene creation, editing, and updating over time. The final and core component of the framework is software capable of performing full-wave electromagnetic simulations with both speed and accuracy. Fig. 2.10 shows a block diagram of the proposed framework with connections between each part.

Following this framework, Fig. 2.11 shows an example of a DT in a real environment where the humans in the room are modeled with STL CAD files. This example shows two human models, one sitting on a chair and the other walking. The specialized implementation of this framework for radar and 5G systems will be illustrated throughout the rest of the thesis, explaining which software was used for each step.

Full-Wave Electromagnetic Solver

Full-Wave Electromagnetic Solvers are crucial for accurately representing the physical world within DT models, which integrate physics-based simulations to emulate real-world

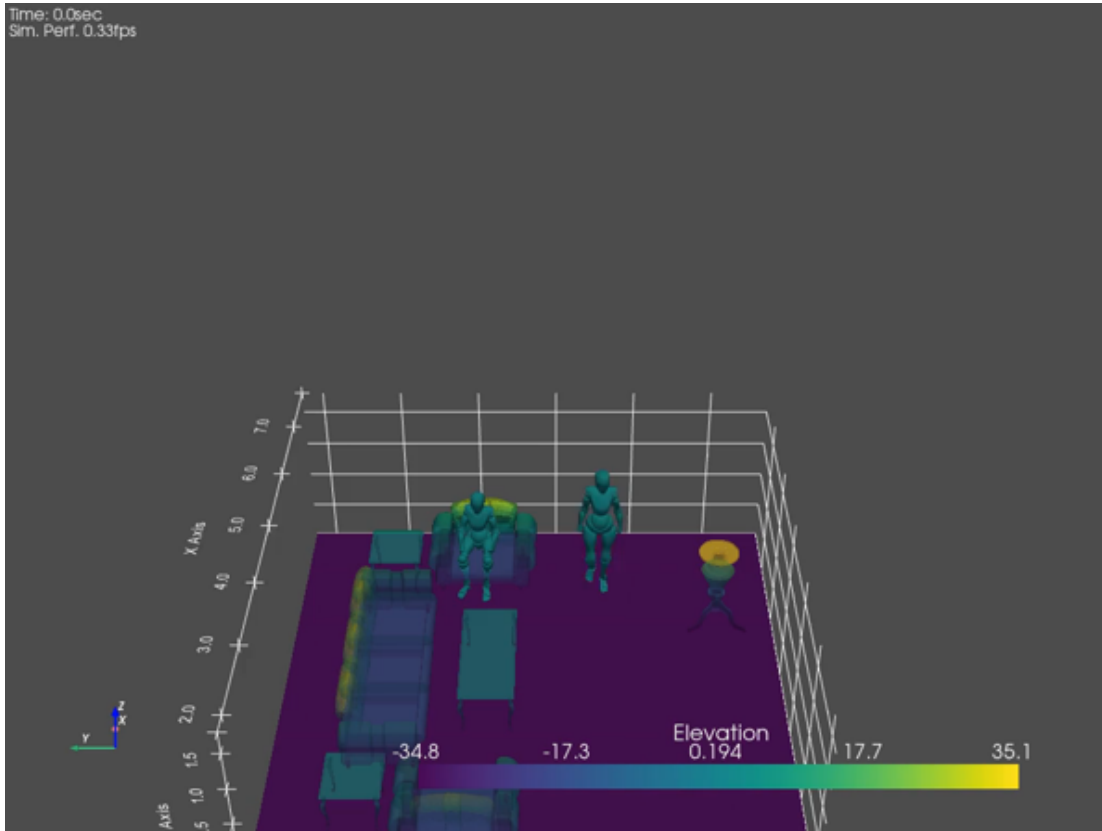


Figure 2.11: Example of an environment generated using the suggested DT framework. This example shows two Human models, one sitting and the other is walking in 3D model of living room. This frame work was developed utilizing ANSYS RTR tool.

scenarios with precision. These solvers employ various numerical methods to solve Maxwell's equations, such as the Finite Difference Time Domain (FDTD) method, the Finite Element Method (FEM), and Shooting and Bouncing Rays (SBR). In this work, the SBR method is used to solve the electromagnetic fields within dynamic environments. This technique accurately represents electromagnetic physics by computing scattered fields generated from transmit antennas, which are then radiated to receive antennas. The SBR approach is implemented using the Ansys Perceive EM simulation tool, capable of simulating electrically large, time-dependent scenes, including multipath propagation, diffraction, real materials, and real antenna patterns. The solver is highly efficient, thanks to GPU hardware acceleration and algorithmic enhancements to the SBR technique, enabling near real-time simulations. This efficiency and accuracy make the SBR method suitable for

modeling complex environments, including penetrable materials like furniture and walls, and for generating data at a scale that is useful in training AI/ML perception models.

2.5 Key Challenges

Throughout the literature review presented on radar and JCS systems for fall detection, several key challenges have been identified. As discussed in the previous sections, the general framework of these systems typically involves three main components: the sensing device, the processing unit, and the classification unit. Machine learning algorithms have been widely adopted for classification tasks instead of manual feature extraction methods. However, these algorithms require a very large dataset to generalize the classification model effectively. This is a common challenge in the field of fall detection as well as other complex sensing applications. Throughout the literature, to the best of our knowledge, researchers have needed to conduct measurement campaigns to collect the data required for classification tasks. This process introduces significant challenges that are detailed as follows:

- **Safety of The Participants:** The process of collecting data for fall severity is risky and may lead to severe injuries, such as bone fractures or traumatic brain injury [9]. To ensure the safety of the participants, researchers need to take the necessary precautions to prevent any injuries, which may limit the types of falls that can be performed and introduce additional costs to the data collection process.
- **Dataset Size:** Since the size of the dataset is a key factor in the performance of the machine learning model, researchers need to have a sufficient number of participants to perform the falls multiple times to generate a large dataset. Table 2.1 shows how the size of the dataset is limited in the literature.
- **Time Consumption:** Due to the need to set up a safe and controlled environment and perform the falls multiple times for a large number of participants, the time consumed for data collection is a significant challenge. Additionally, the problem of corrupted measurements, which need to be repeated, adds more time to the data collection process.

Table 2.1: Dataset Characteristics in Radar-Based Fall Detection Studies

Reference	Number of Participants	Dataset Size	Radar Type	Activity Classes
[1]	9	400	UWB	Different types of falls
[27]	11	330	UWB	Falls vs. non-falls
[17]	6	180	CW Doppler	Falls vs. non-falls
[24]	8	460	FMCW	Different types of falls
[26]	-	500	FMCW	Falls vs. non-falls
[28]	-	97	FMCW	Falls vs. non-falls
[29]	3	216	FMCW	Different types of falls
[5]	6	1440	CW Doppler	Falls vs. non-falls
[25]	20	4058	2 FMCW	Different types of falls

To address these challenges, the implementation of DT solutions [79] emerges as a transformative approach, efficiently accelerating data generation. DT not only resolve this issue but also bring the added benefit of eliminating the necessity to expose participants to hazardous situations. This dual advantage not only expedites research endeavors but also ensures a safer and more ethical data collection process. Another benefit emerging from DT is the capability of generating a more diverse set of training data, including various scenarios and environments that are generated programmatically.

Chapter 3

Revolutionizing Geriatric Care: Radar and Digital Twin Technology for Fall Severity Detection

3.1 Relevance

This chapter presents the proposed system architecture for severity-of-fall classification using radar systems enhanced by digital twin technology. The proposed system addresses the challenges of dataset generation for dangerous fall scenarios. Through the rest of this chapter, the system architecture is presented in detail, including integration of the severity classification task within a healthcare facility. The chapter also discusses the steps of creating the digital twin for the radar system, and the simulation and measurement setups. Towards the end of the chapter, results of this part of the work are discussed, followed by future enhancements for the proposed system.

3.2 System Architecture

Considering the implementation within healthcare facilities, our proposed system primarily targets seniors in [LTC](#) settings, where residents often spend significant time alone in their rooms. Our technology’s significance lies in its effectiveness during these solitary instances, ensuring timely assistance and appropriate intervention. While in the presence of others, falls can be observed and responded to directly, reducing reliance on automated alerts for

severity classification. Therefore, our system is specifically designed for instances where the resident is alone, emphasizing its critical role in such scenarios.

Fig. 3.1 shows the proposed system flow diagram for fall classification. The system deploys a radar sensor that continuously records data. The radar sensor is configured to consistently capture data, producing a continuous stream of raw information that requires further processing. The first detection model employed is the people counting algorithm, which determines how many people are in the room. The recording rate for this algorithm can be more relaxed than that of the fall detection algorithm, as people typically leave the room walking, allowing for power savings by periodically putting the radar into sleep mode. Once only one person is detected in the room, the second unit of the system is activated to detect falls and other human activities, a task well-established and extensively studied in the literature. Upon detecting a fall, the third unit of the system determines the severity of the incident, which is a complex task as falls share many similar features. The implementation of fall detection and people counting is beyond the scope of this work and we refer interested readers to [80,81] for more details.

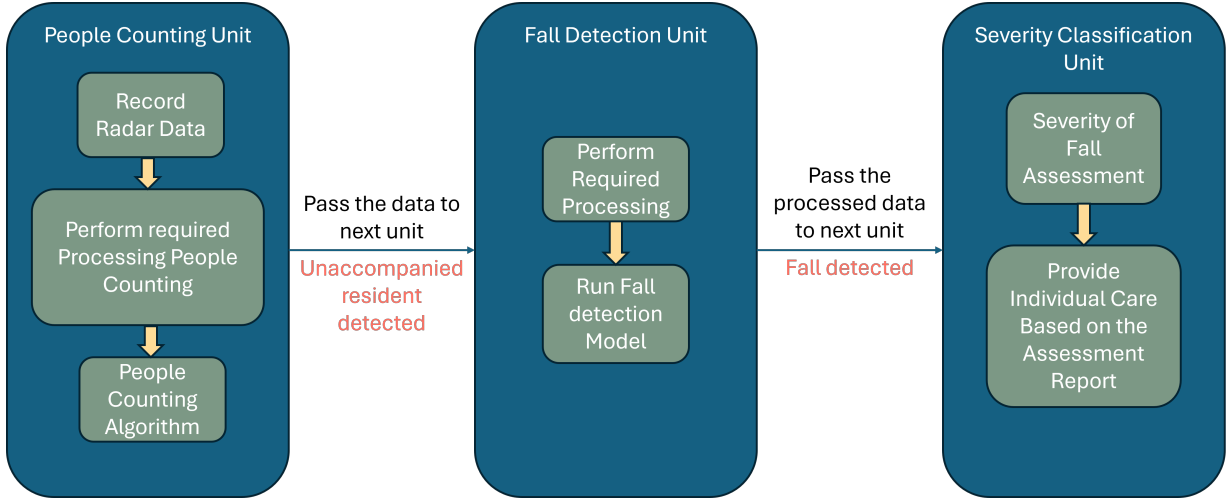


Figure 3.1: Flow Diagram of the Proposed System Architecture for Deployment in Healthcare Facilities.

Since the primary goal of this work is to classify the severity of falls, the focus is on the third unit of the system. The key challenges, as mentioned in the background section, include the lack of a comprehensive dataset, the inherent risks associated with the data collection process, and the time-consuming and costly nature of data collection. To address these challenges, Digital Twin (DT) technology is integrated into the system. The following

sections detail the steps involved in creating the digital twin for the radar system, as well as the simulations and measurements conducted to validate the system.

Digital-Twin

The first aspect, scene or world generation, includes capturing the kinematics of a human, along with any environmental geometry, and storing this as a digital representation. Capturing these time-sequenced motions could be done with various approaches, including animated models created within computer animation software such as Blender [82] or from dedicated real-world motion capture systems. There are multiple motion capture datasets such as the Carnegie Mellon University (CMU) Motion Capture Dataset [83] and the animation dataset provided by Mixamo [84]. In the CMU dataset, 12 infrared cameras were used to capture motions performed by professionals in a specific environment. Data generated by the cameras are then processed to generate files that contain information about the skeleton and its joints, including details about body dimensions and mathematical transformations related to movements. In Mixamo’s motion capture library, the dataset is also generated by professionals and imposed onto various animation characters and 3D CAD models. These libraries ensure that the generated kinematic models accurately represent real human activities and motions. While those datasets form a base for accurately modeled activities, Blender tool can be used to further manipulate the activities, 3D CAD models, and surrounding environments. The resulting motion vector is subsequently linked to a 3D model representing a human with the required body size and shape. Subsequently, the scenario is imported into physics-based simulation to model the radar sensor performance within the digital representation of the real world using the animated CAD model previously defined.

The second phase, automating scene generation, involves interfacing with the API and simulation software. Fig. 3.2 illustrates the sequence of steps undertaken in this process.

- **Create Scene Object:** The first step in the automation process is to create a scene object. This object encapsulates all necessary functions and variables required by the scene. It serves as the primary entity for simulating the scenario and managing the update process.
- **Load Environment:** In this step, all elements that constitute the scenario’s environment are defined and loaded. For instance, in a home environment scenario, this includes walls, furniture, and other objects. Each object’s material properties, dimensions, and location are specified during this stage.

- **Load Human 3D Model:** For each human subject in the scenario, all relevant parameters and variables are specified. This includes defining body parts as detailed in the CAD file, initial positions and orientations, paths of motion, speeds, scaling factors, and transformation matrices for each body part.
- **Add Radar Object:** This step involves selecting and configuring the radar for simulation, including its position, orientation, parameters, and overall configuration. The radar’s radiation pattern can be defined either by importing an ffd file or by specifying parameters such as beam width and polarization.
- **Perform Other Automation Functions:** This step encompasses any additional functions that enhance the dataset generation process. For example, varying the positions, orientations, and speeds of the human CAD model can automate the simulation across multiple scenarios.
- **Initiate Scene Elements:** Complementing the environment loading step, this stage imports all previously defined environment elements into the scene.
- **Add STL Files:** This step involves importing all STL files relevant to the environment.
- **Run Simulation and Extract Results:** In the final step, the simulation is executed, and results are extracted. The output data is then stored in an organized format suitable for further processing.

In this study, Ansys software [85] is used to perform the physics-based simulation, first to extract the far-field performance of the Infineon radar module, and second using this result in the Shooting and Bouncing Rays (SBR) technique to simulate the environment and human. Kinematics of the imported model in the environment are modeled as multiple vectors that represent each body part’s motion transformation. These vectors are updated for each timestamp, and the process of setting those vectors is mainly performed during the model importing step. Subsequent to the raw data generated by ANSYS, post-processing algorithms are applied. These algorithms produce a range-Doppler map for each frame, followed by the generation of a spectrogram encompassing the entire scenario. The resulting spectrogram is subsequently input into a machine learning algorithm for detection and classification of the severity of falls.

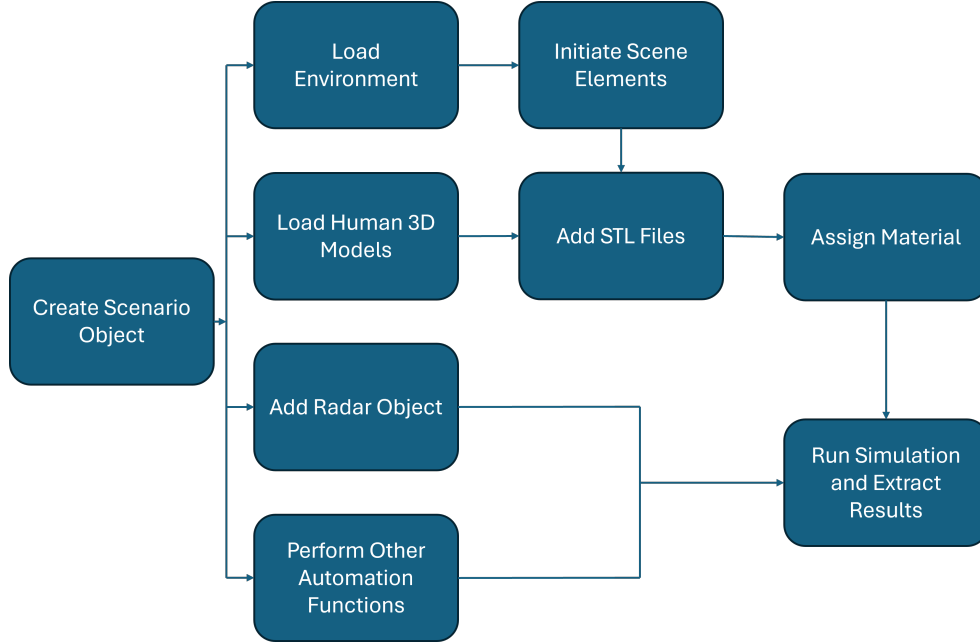


Figure 3.2: Flow diagram illustrating the process blocks for scene generation automation.

3.3 Simulations and Measurements

We used identical radar configurations for both simulation and measurement phases, enabling a robust validation process supported by precise measurements. The Infineon BGT60TR13C [86], operating at 60 GHz with one transmitter and three receivers, is utilized for this study. This radar model was imported into HFSS simulations, and the simulated data collected was used to train deep learning models. Subsequently, the commercially available radar was used in measurements to validate the simulated results and the trained deep learning model against real-world scenarios.

As illustrated in Fig. 3.3, the radar unit was positioned at a height of 2 meters and tilted 30 degrees downward. Given the hardware system of choice, the optimum radar configuration is specified in Table 3.1. This set of parameters was used both simulations and measurements.

All measurements were conducted following regulation according to University of Waterloo policy on experiments on human subjects. This study was approved by the University of Waterloo ethics board with application number 43843 under the name of Modelling Activities of Daily Living Using Smart Home Technologies. All participants provided an

informed consent for the publication of any required information.

Parameter	Value
Carrier frequency	60 GHz
Waveform	FMCW
Bandwidth	881.74 MHz
Number of samples per chirp	64
CPI duration	53.15 ms
Number of chirps per CPI	128
ADC sampling rate	1 MHz
Frame rate	10 fps

Table 3.1: Radar configuration used in simulations and measurements

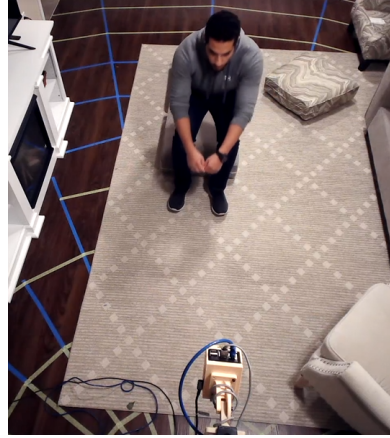
The dataset generated for this study was acquired through computations conducted on a computing system equipped with an Nvidia GeForce RTX 3050 8GB GDDR6 GPU, an Intel Core i7-13700KF CPU, and 128 GB DDR5 RAM. The computational workflow in the proposed methodology is segregated into two primary phases. Initially, the environment setup entails radar definition, importation of the 3D CAD model with movement specification, and inclusion of environmental components such as walls or furniture, predominantly orchestrated by the CPU. Subsequently, computations are executed utilizing the RTR and SBR+ solver, primarily leveraging the GPU. Each simulation scenario typically consumes approximately 30% of the computational capacity of the GPU. The duration of a single simulation case ranges from 12 to 20 seconds, contingent upon the number of frames in each scenario.

Fig. 3.3 shows an example of falling scenario in simulation and measurements. In both scenarios, the raw data were produced at a rate of 10 frames per second. Subsequently, a range-Doppler map was created for each frame, and these maps were collectively used to generate the spectrogram for each instance of a fall. During measurements, a moving target indicator filter [87] was applied to eliminate clutter. Fig. 3.4 depicts the resulting spectrogram corresponding to the simulation and measurement of the fall scenarios.

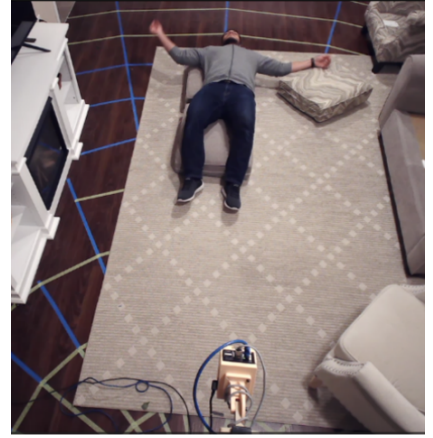
The various simulation scenarios encompassed various falling methods, distinguished by the initial impact on specific body parts during the descent. Three primary categories of falls were included among the four general activities investigated in this work: a forward-leaning fall where the knee hits the ground first due to bending, falls characterized by backward leaning resulting in the hips hitting the ground first, and falls where the



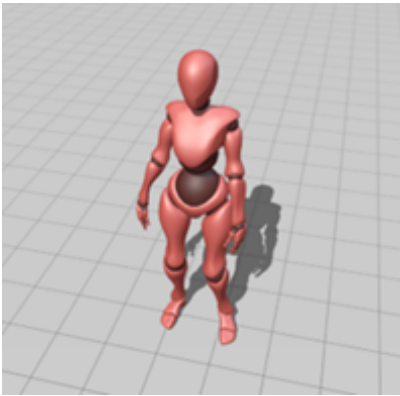
(a)



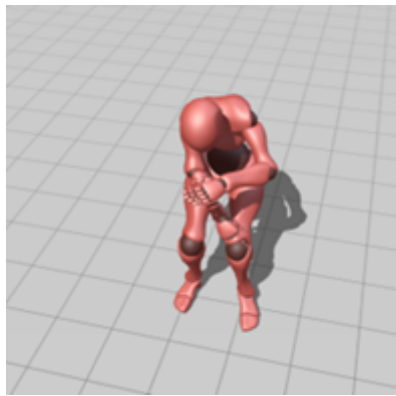
(b)



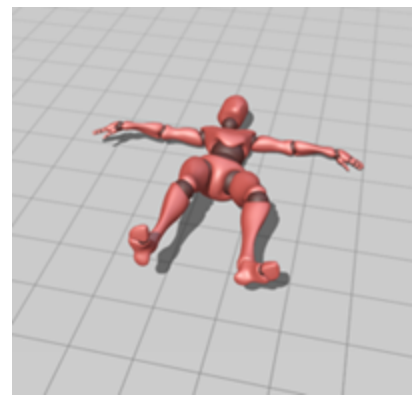
(c)



(d)



(e)



(f)

Figure 3.3: Hip first fall scenario in simulations and measurements (a) and (d) starting from a standing posture, (b) and (e) leaning back in the middle of the fall, (c) and (f) hitting the ground.

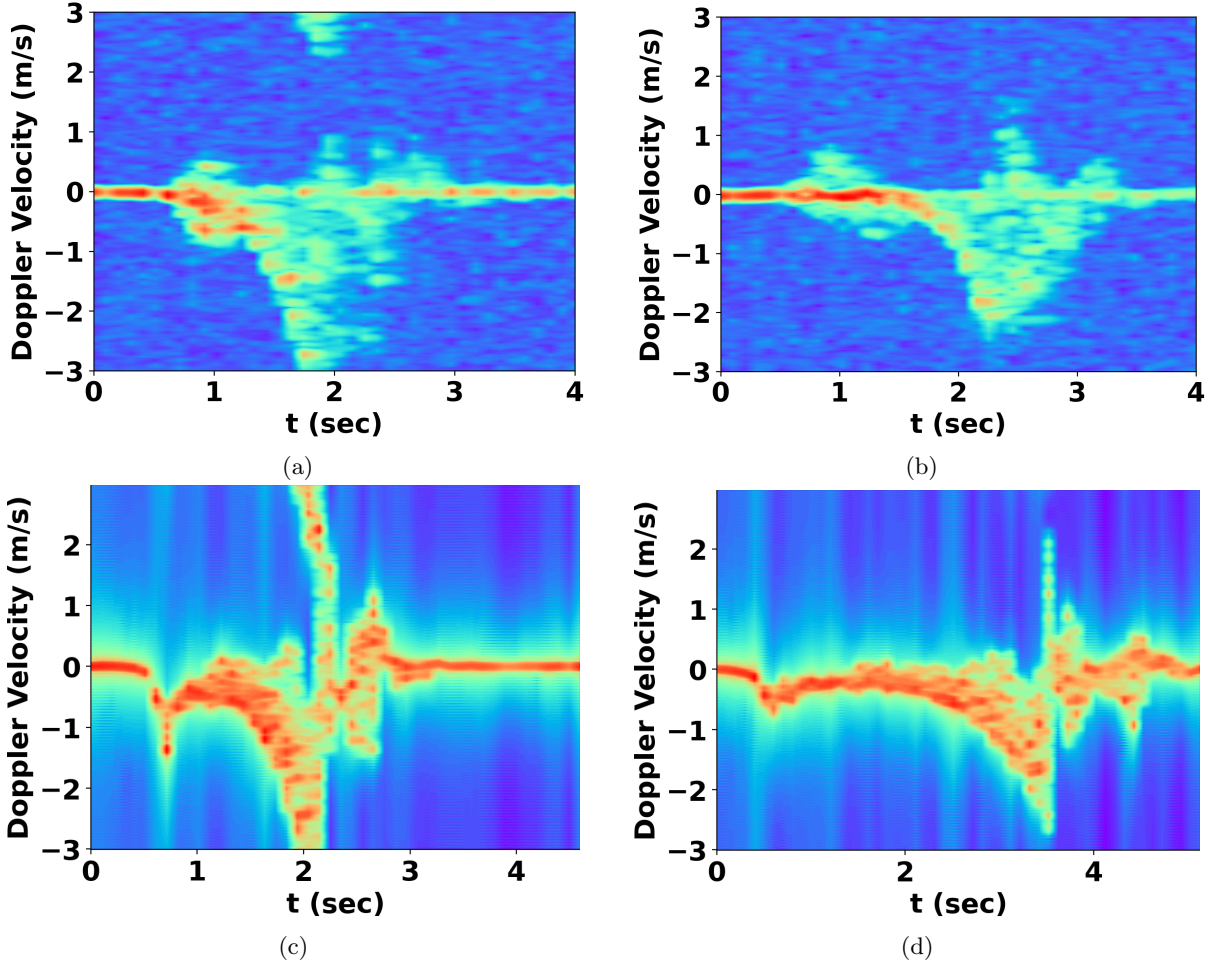


Figure 3.4: The corresponding spectrogram of the shown fall incident of a case where hips touch the ground first with different speeds (a) fast fall in measurements, (b) slow fall in measurements, (c) fast fall in simulation, (d) slow fall in simulation.

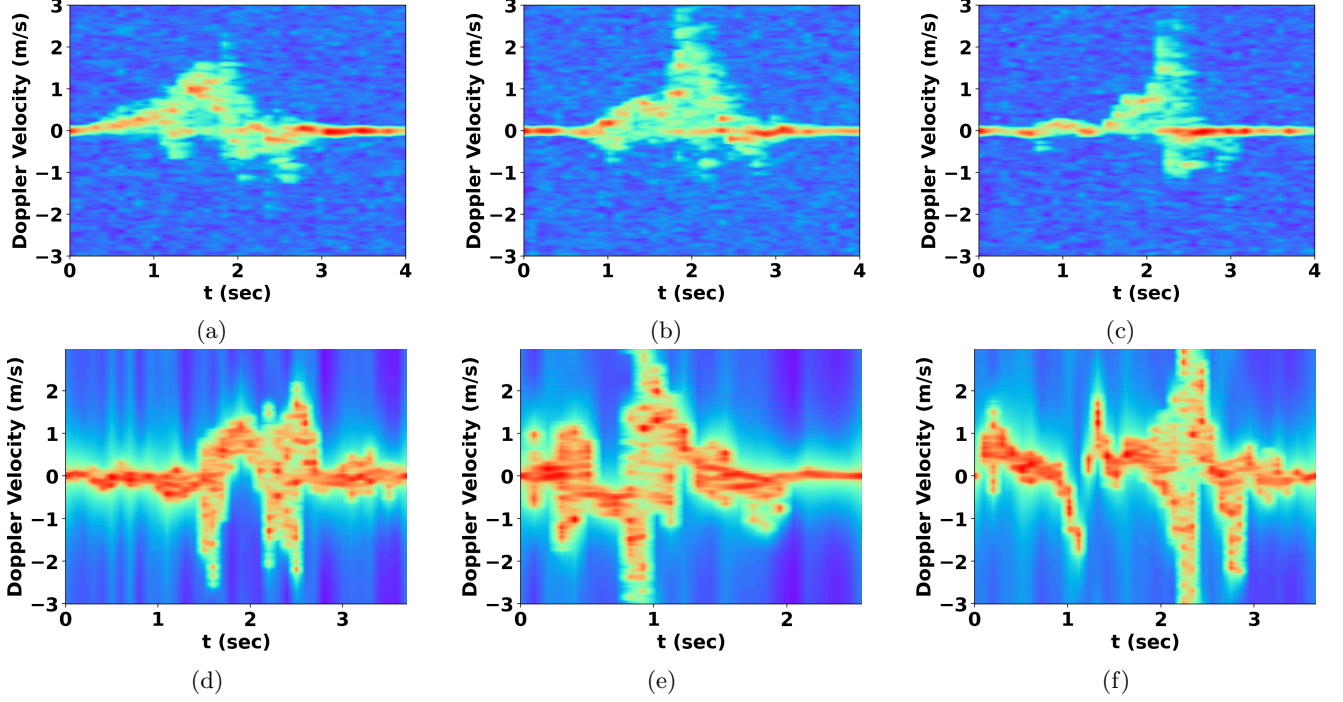


Figure 3.5: Resulting spectrograms of simulation and measurement data (a) and (d) spectrogram of the measured and simulated scenario including hit to the knee first, (b) and (e) spectrogram of the measured and simulated scenario including full body hitting the ground simultaneously, (c) and (f) spectrogram of the measured and simulated scenario including hit to the knee first.

patient leans in any direction without one body part moving more rapidly than others, causing most body parts to hit the ground simultaneously. Figures 3.4 and 3.5 illustrate distinct spectrograms associated with different falling techniques. In each measurement, participants were trying to replicate the fall as it was simulated, in order to facilitate later comparison.

3.4 Results

To validate the strong correlation between simulation results and real measurements, a 2D Convolutional Neural Network (CNN) was employed to categorize data into two of the four

groups proposed in this work will be used: falls to the knees and falls to the hips, utilizing a subset of the simulated dataset and measured dataset. Participants experiencing falls were restricted to knee-first and hip-first scenarios, as a complete body fall, including head impact, could result in severe injuries. The model underwent training using simulated data and testing using measured data. To account for the uncertainty of the exact fall time in real-life scenarios, a data augmentation layer was integrated random horizontal translation to accommodate for time shifting of the scenario. Data augmentation of random contrast was applied as well to account for different received power levels. Model’s architecture comprised multiple 2D convolutional layers for feature extraction, succeeded by 1D layers for classification considering that spectrograms inherently exhibit a 2D matrix structure, characterized by unique features. While more sophisticated machine learning architectures could enhance accuracy further, the model achieved an accuracy of 81.25% across 16 test cases. Those test cases consist of 9 measurements where participants fall to their knees first and 7 test cases where participants fall to their hips first. Accuracy of detection was based on the total number of correctly classified cases vs the total number of cases. Misclassifications include 2 cases of the knees first class and 1 case of the hips first class.

Simulated data exhibited varied patterns based on the specific movements of body parts and their relative velocities during a fall, as depicted in Fig. 3.5. Each fall demonstrated distinctive characteristics, enabling the detection of almost every unique fall scenario. In our study, falls and other instances were categorized into four classes: falls with the knee touching the ground first, falls with the hips hitting the ground first, falls with the entire body, including the head, hitting the ground, and other scenarios such as walking, jumping, or picking something up. Considering these distinctions, a 2D CNN was developed to classify the four different cases simulated in our dataset. The CNN includes 4 layers of 2D convolutional layers with relu activation function followed by three dense layers for classification. The simulated dataset comprised 28 different scenarios, each simulated at varying positions, angles relative to the radar, and with random body model sizes, resulting in a total of 6721 data points. Data is split into 80% for training and the rest for testing. The results demonstrated a detection accuracy of 99.48% on the test set of the dataset. Fig. 3.6 shows confusion matrix for detected falls.

The precision of detecting simulated data exceeds that of measured data for several reasons. Firstly, precisely replicating simulated fall scenarios proves challenging. Secondly, while simulations encompass falls with diverse positions and angles, they utilize the same fall scenario and model, implying that incorporating numerous model variations and more falls could narrow this disparity. Additionally, the relatively high noise floor in measurements contrasts with the ideal environments of simulations, adding to the differences in accuracy.

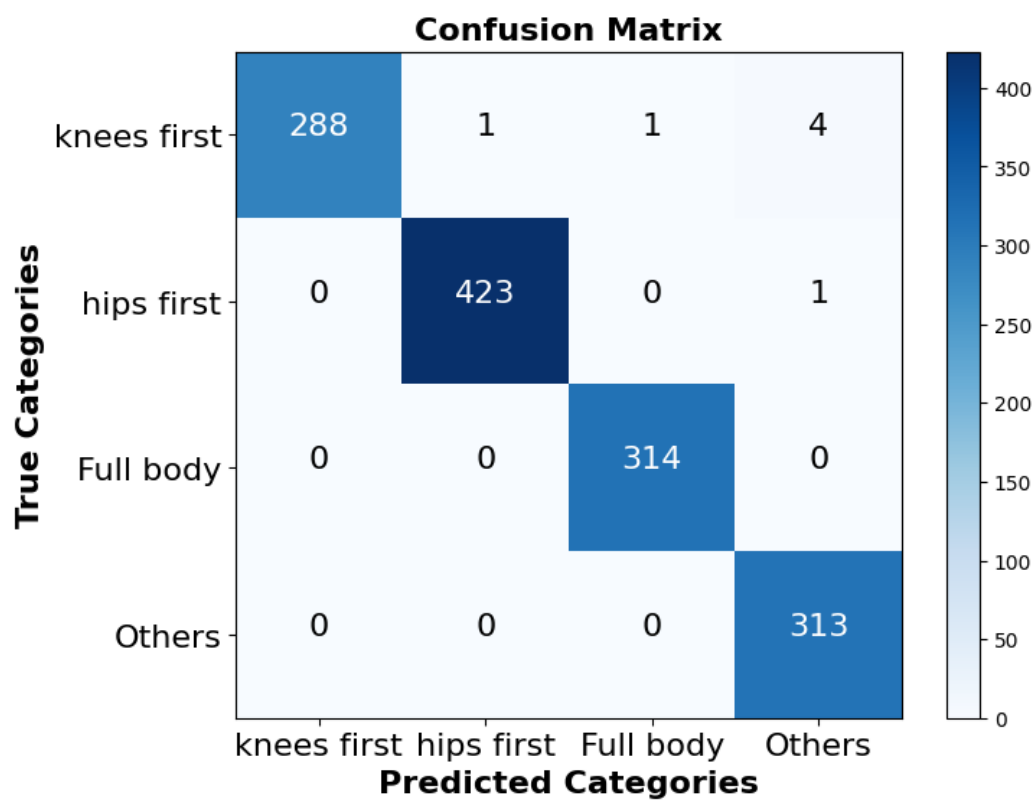


Figure 3.6: Confusion matrix of detected fall type using the simulated data.

A feature directly linked to the severity of falls is the maximum speed detected by the radar. This characteristic can serve as an initial indicator for identifying severe falls. Real-life falls were intentionally conducted at varying speeds. Fig. 3.4a and 3.4b illustrate two measured fall cases with different velocities. Simulations were also performed for the same purpose, demonstrating the ability of the proposed system to account for different velocities, as shown in Fig. 3.4c and 3.4d. In [88], speed and time of activities were used to detect falls, and this approach can be extended to assess the severity of falls. Further investigations into the influence of the detected speed can be easily conducted using a radar digital twin.

The impact of varying body sizes was studied, where some instances had a height of 153 cm, and others had a height of 207 cm. All other configuration and setup parameters remained identical. Fig. 3.7 illustrates the distinctions between the instances with different participant heights. Interestingly, it was observed that height did not significantly alter the core features within the spectrogram for the same scenario. However, variations in received power levels were noted in both cases, as different body parts were exposed to distinct power levels from the radar transmitter. This finding indicates the possibility of incorporating simulations with diverse body sizes to improve the model's detection ability.

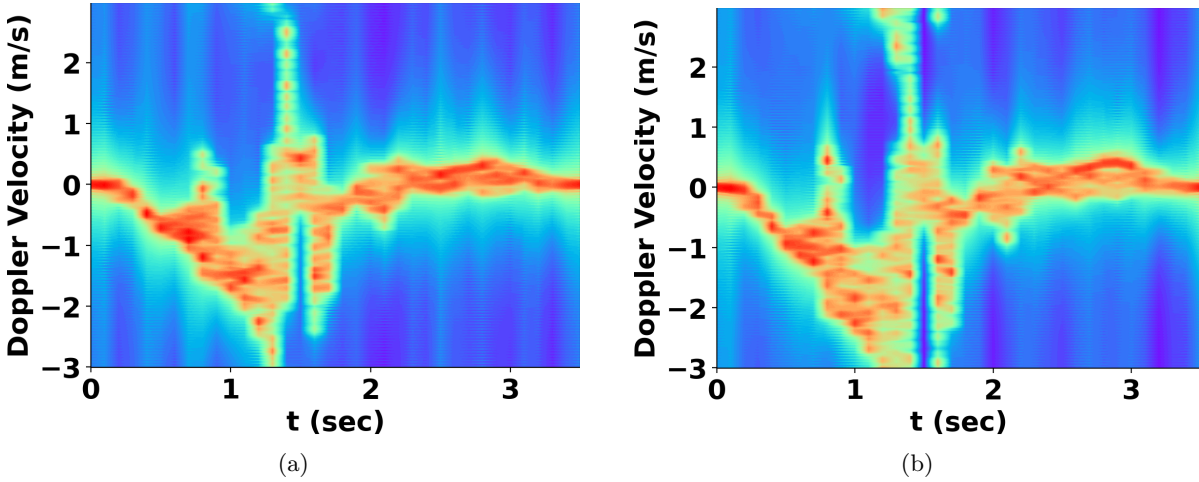


Figure 3.7: Resulting spectrograms of simulated fall scenarios with different heights of the same 3D CAD model (a) model height is 153 cm, (b) model height is 207 cm.

3.5 Conclusion

The groundbreaking study presented herein introduces a revolutionary approach in geriatric care through the amalgamation of radar sensing systems and digital twin technology for the nuanced detection and assessment of fall severity. This innovative methodology transcends traditional fall detection techniques by leveraging the unobtrusive nature of radar technology coupled with the comprehensive simulation capabilities of digital twins. Our findings underscore the critical advancements in the accuracy and sensitivity of fall severity detection, a paramount concern in the care of the elderly, where falls can precipitate significant health ramifications. The exceptional performance of our system, demonstrated by an accuracy of 99.45% while using simulated data for training and testing and 81.25% while using simulated data for training and measured data for testing, marks a significant leap forward in mitigating the challenges faced by LTC facilities worldwide. These facilities are grappling with the dual crises of staffing shortages and alarm fatigue, compounded by an aging global population. Our research not only addresses these pressing issues by reducing false alarms and enhancing care response but also pioneers a path towards the integration of advanced technologies in patient monitoring and care. Additionally, the results of this work demonstrate the ability of digital twin for resolving and investigating various features related to scenarios and environments, such as speed, power, and radar configuration.

Furthermore, our work offers a scalable and ethical framework for data collection and algorithm training, circumventing the ethical dilemmas and logistical challenges associated with human subject research. The ability to simulate diverse fall scenarios with varying severities and analyze them with sophisticated machine learning models represents a monumental stride in personalized care, enabling caregivers to prioritize interventions based on the severity of falls and, thus, significantly improving patient outcomes

Chapter 4

Digital Twin for Joint Communication-Sensing System

4.1 Relevance

Due to the abundance of Wi-Fi access points and the emergence of indoor 5G and 6G devices, the concept of JCS for severity of falls classification is gaining traction. This is because all these systems are based on the OFDM waveform, although each one adheres to different standards for defining frame structures and configurations. The 5G NR standard was chosen for this study due to the technological advances mentioned in the background section. Specifically, 5G NR can utilize up to 400 MHz of bandwidth across various frequencies and operate in low-interference environments, unlike Wi-Fi.

The rest of this chapter illustrates how the JCS approach was developed for 5G NR using digital twin (DT) technology. It includes an explanation of the development process, the simulation and measurement procedures, and the results achieved by this approach.

4.2 System Architecture

The key goal behind a JCS system is to utilize communication devices for sensing or to enable sensing devices to communicate. In this study, we aim to use the 5G NR network and devices for sensing, a method that can be easily extended to 6G technology. The purpose of using the same RF front end of communication devices for sensing is to maximize the

utilization of available bandwidth with minimal hardware, thereby eliminating the need to radiate additional power for separate sensing devices.

The main approach of this work began with selecting a frequency band on which to build the architecture. In this case, the FR1 band, which is the sub-6 GHz band, was chosen. This decision was made to facilitate the validation process using available hardware, although the same concepts can be applied to higher frequencies. Based on the choice of FR1, a suitable configuration that follows 3GPP standards was established. Table 4.1 and 4.2 shows the parameters chosen for this study.

Table 4.1: Some of the 5G frame parameters

Parameter	SCS	Channel BW	Grid Size	SS block pattern	Number of subframes
Value	15 KHz	20 MHz	106	case A	10

Table 4.2: CSI-RS parameters

Parameter	power	type	Density	Symbol location
Value	0 dB	non zero power (nzp)	one	6

The choice of the parameters listed in the previous tables is intended to provide an example, as the 5G frame is highly configurable, as discussed in the background section. The selection of these parameters in real-life scenarios depends on the application and the environment in which the system is deployed. For example, if the system is deployed in a high-mobility environment, the subcarrier spacing (SCS) should be increased to mitigate the Doppler effect. Additionally, other factors may arise from the application itself, such as the need for a low-latency system, which may require a wider subcarrier spacing to reduce the symbol duration.

In this part work, it is proposed that the workflow be split into three main subsystems: the Digital Twin, the Communication Module, and the Classifier System. To detect the severity of a fall, the communication system needs to continuously transmit frames according to a specified frame rate. For each captured frame, the communication system must receive the same frame in parallel and extract channel estimation frames from the CSI-RS. This continuous stream of frames is processed to detect any fall incidents, a task that is well-studied in the literature, relatively simple, and not computationally expensive. Once a fall is detected, the set of frames captured during the incident is passed to a machine learning algorithm responsible for classifying the severity of the fall.

The second subsystem, the [DT](#), is responsible for simulating a sufficient number of human activities, including various fall scenarios with different severities. These simulated data should be used to train the machine learning algorithm before deploying the system. Figure [4.1](#) shows the three main subsystems proposed in this work and how they interact.

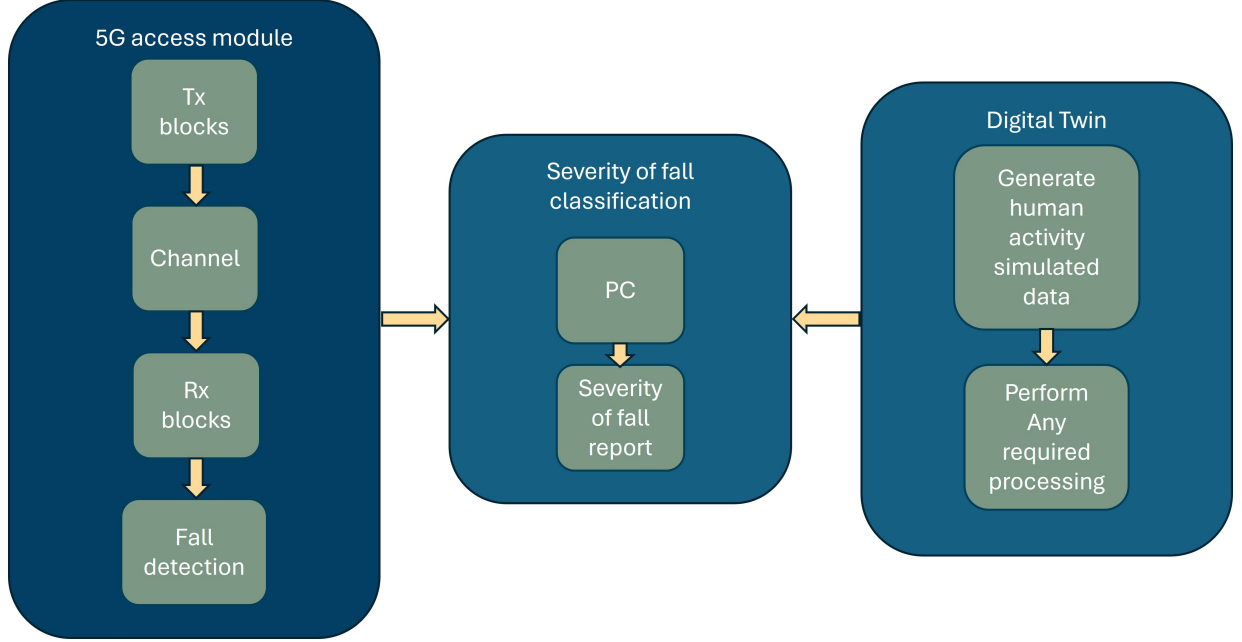


Figure 4.1: The three main subsystems proposed in this work: the [DT](#), responsible for generating the required dataset and feeding it to the machine learning algorithm for training; the 5G access module, responsible for communications and flagging any suspected falls; and the final subsystem, responsible for the classification of the falls.

- **5G access module:** This subsystem is responsible for the communication aspect of the system, where the transmitter continuously transmits frames, while the receiver captures the frames that have passed through the channel and extracts the [CSI-RS](#) frames. Once a fall is detected, the set of frames captured during the incident is passed to the severity of fall classification unit.
- **Severity of fall classification:** This subsystem is responsible for classifying the severity of the fall using a pretrained machine learning model.

- **Digital Twin (DT):** This subsystem is responsible for generating the required dataset for the machine learning model. The dataset should include various human activities, including different fall scenarios with varying severities. The role of the DT is critical prior to the deployment of the system.

The following section illustrates how this framework was implemented through simulations and then verified with measurements.

4.3 Simulations and Measurements

In order to validate the simulations with measurements using software-defined radio, it was decided to operate at a carrier frequency of 2.4 GHz. Although this band suffers from high interference due to the presence of Wi-Fi and Bluetooth systems, the system was tested in a shielded room to validate the hypothesized concepts.

Simulations were carried out using the Perceive EM software provided by Ansys Inc., which is based on Shooting and Bouncing Rays (SBR) simulations. The simulation tool can provide coupling measurements between multiple antennas, effectively serving as a channel estimation for the propagated wave. The transmitted OFDM waveform channel is simulated as a continuous wave at different frequencies, separated by specific subcarrier spacing, similar to the configuration used in 5G. The coupling between Tx and Rx antennas is configured prior to running the simulation. For the proof of concept, parametric beam antennas were defined with 120 degrees of both horizontal and vertical beamwidth.

The sequence of setting up the environment prior to the simulations is: configuring the physical environment if any environments are going to be used. This environment can consist of multiple parts, like walls, tables, and windows, for example, if the simulation is done in a room. Following this step, the 3D CAD model that behaves in a human-like manner is imported into the environment. To do this, the DAE files containing the CAD model are read, and each body part, like the torso, arms, and legs, is exported as an STL file. These STL files are then imported into the environment, with each STL file associated with transformation matrices that represent the movement of this part over time and its relation to the reference coordinate system. Fig. 4.2 shows an example of 3D model walking and its transformation vectors that control its motion.

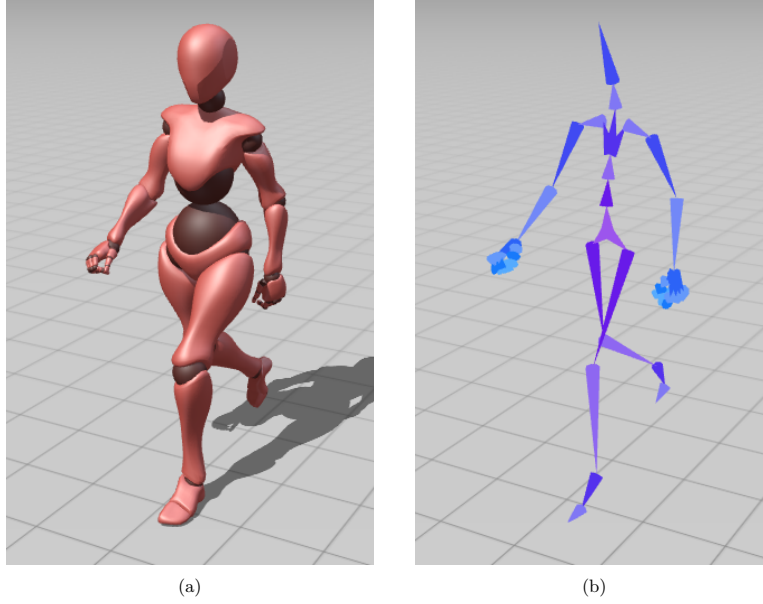


Figure 4.2: A walking 3D model: (a) meshes of each body part. (b) skeleton that shows the vectors that represent motion vectors of each body part.

Simulations were done for various cases under four general classes: falling with a hit to the knee first, falling with a hit to the hips first, falling with almost all body parts touching the ground at the same time, and a class with different activities like walking, standing up, clapping while sitting, and torso swinging. In each of the defined classes, multiple scenarios were simulated, and for each scenario, a dataset of roughly 400 simulations with random relative positions to the antenna, body scale, relative angle, and speed was created. The body scale was randomized within the range of 153 cm to 205 cm to generalize to various heights within the population. In total, 6000 cases were simulated in an environment that had only the human model to test the capability of the system, with such limited bandwidth, to differentiate different fall types from other activities. Table 4.3 shows the ranges of random values for the scenario parameters where X pos is the position along the x-axis, Y pos is the position along the y-axis, angle is the relative rotation of the body to the antennas, body height is the range of random body heights, and speed scale is the speed factor that changes the scenario length.

Due to the varying falling speeds with a constant frame rate, each scenario resulted in a random time versus channel estimation matrix size. To address this, padding with random

Table 4.3: Ranges of the random values for each parameter in the scenario configuration.

Parameter	X pos	Y pos	Angle	Body Height	Speed scale
Value	2–5 m	-3–3 m	0°–359°	153–205 cm	0.9–1.15

numbers between 0 and 0.1 was added to the matrix. To generalize the training for the machine learning model, a random number of the padded time frames were inserted at the beginning of the matrix, with the remaining frames concatenated at the end. Conversely, any frames that exceeded the chosen channel estimation matrix size were clipped. After analyzing the simulated data, it was determined that the number of frames per matrix should be fixed at 115, as this was the average number required to capture most variations in activities. Figures 4.3, 4.4, 4.5, and 4.6 presents examples of three frames from each simulated class, while Figures 4.7, 4.8, 4.9, and 4.10 illustrates the results of each of these simulated scenarios.

As mentioned, various machine learning models can be used for type of applications depending on data representation. The data representation that was chosen for this study is to capture a certain number of frames of complex numbers which represent the channel estimation for each frame. Those frames are packed together as a 2D matrix of complex numbers for each simulation case. In order to be able to perform normalization to the data prior to testing, each 2D matrix of complex numbers was processed to generate other two matrices: magnitude matrix and phase matrix. The magnitude matrix is extracted by calculating the absolute value of each complex number then taking $\log_{10}$. on the other hand, the phase matrix contains the phase of each complex value of original matrix. since the magnitude and phase matrices are of the same size both them are combined into one images at two different channels. After that, scaling is performed on to make the range of the values fed to the ML model between 0 and 1. the Input to the model has the shape of $N \times \text{Number of Frames} \times \text{Frame Size} \times \text{Channels}$, where N is the size of the patch fed to the model during each epoch and channels is 2. Since the input shape to the ML model is in the form of 2D matrices, CNN architecture was used to verify the ability of the DT to generate data that can be used to classify severity of falls, Although there are model advanced models that can achieve higher accuracy. Fig. 4.11 shows the CNN architecture used. It consists of 4 convolutional layers followed by max pooling layer and batch normalization layer. Then the output of those layers are flattened and passed to a 1D layer then to the output layer. The convolutional layers have 64,128,256,512 kernels respectively.

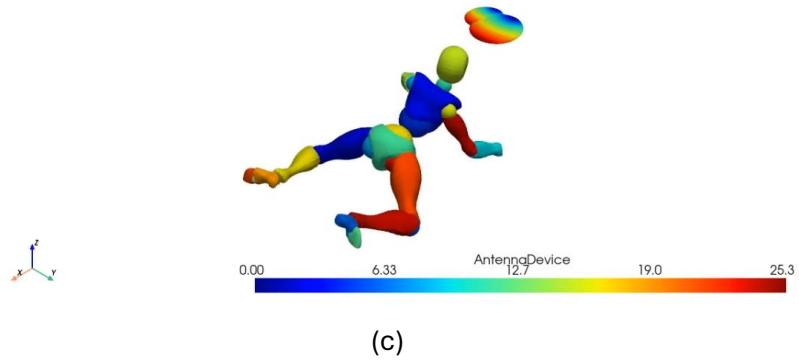
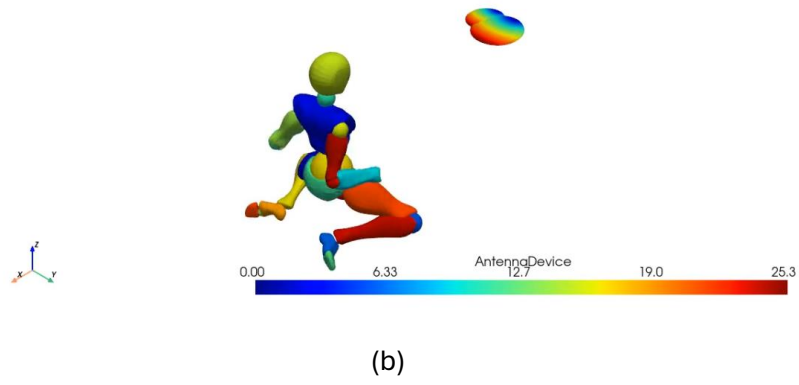
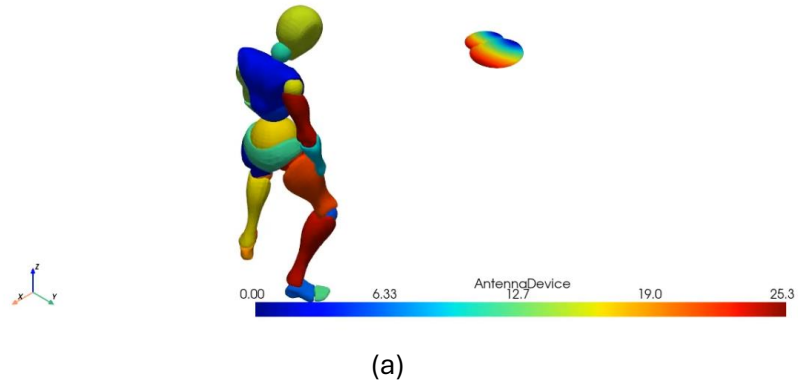


Figure 4.3: Knee Fall simulation case

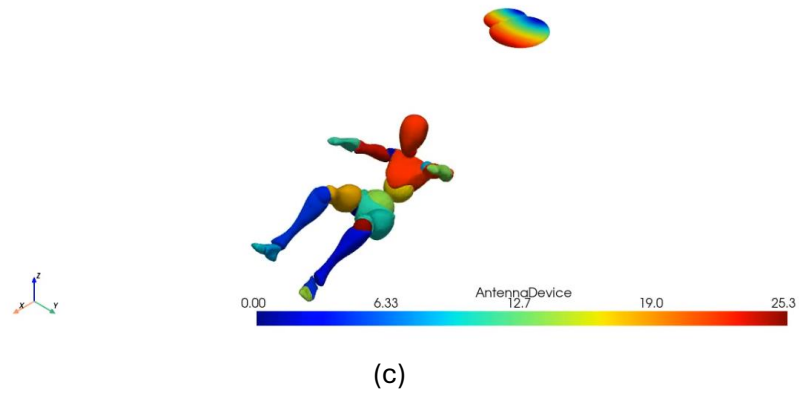
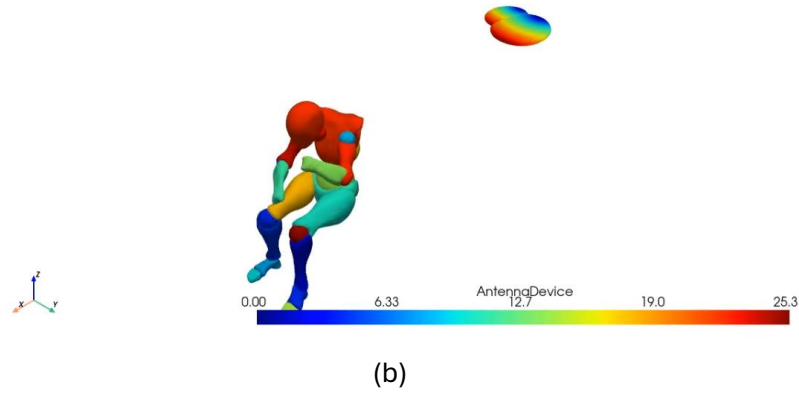
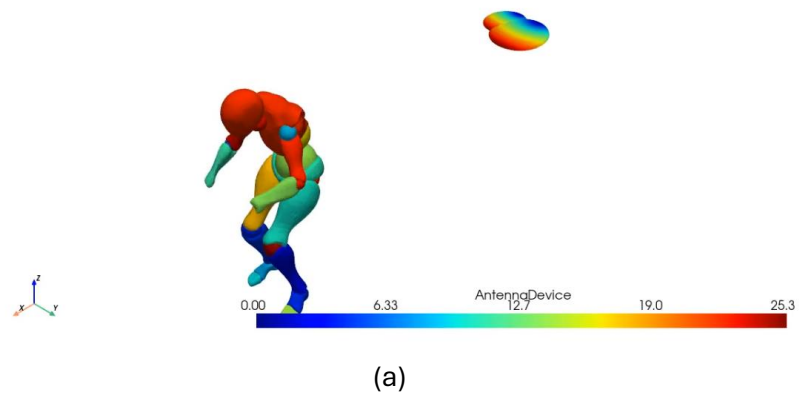


Figure 4.4: Hip Fall simulation case

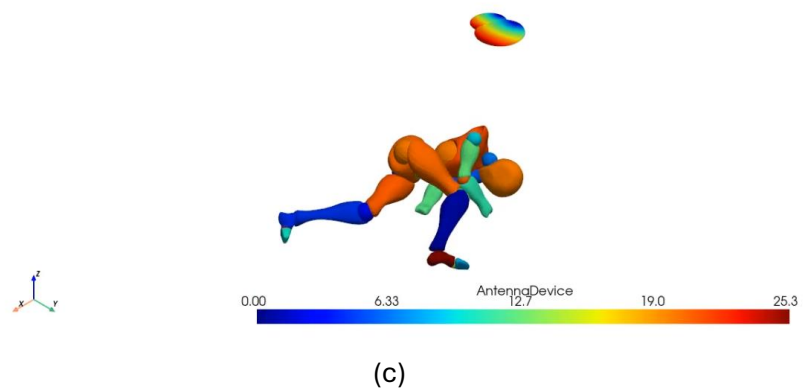
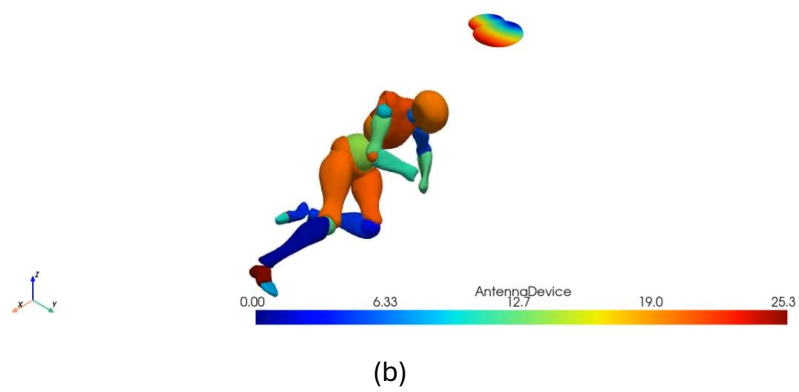
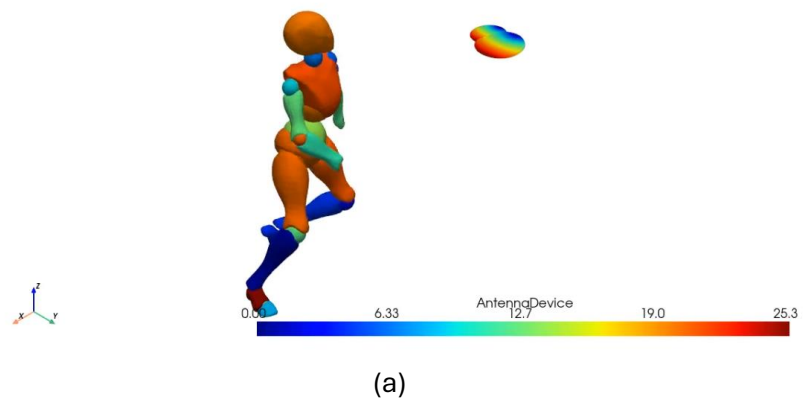
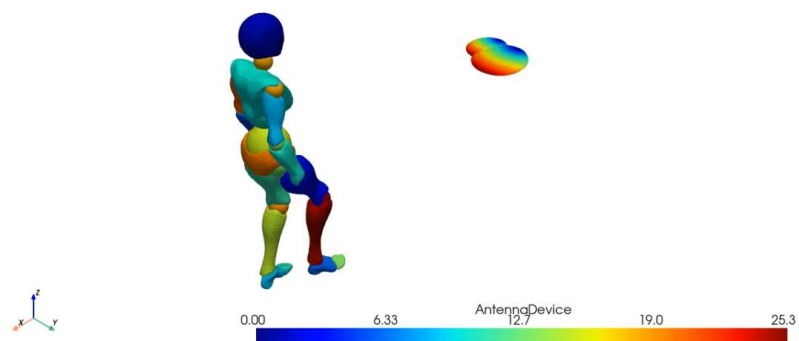
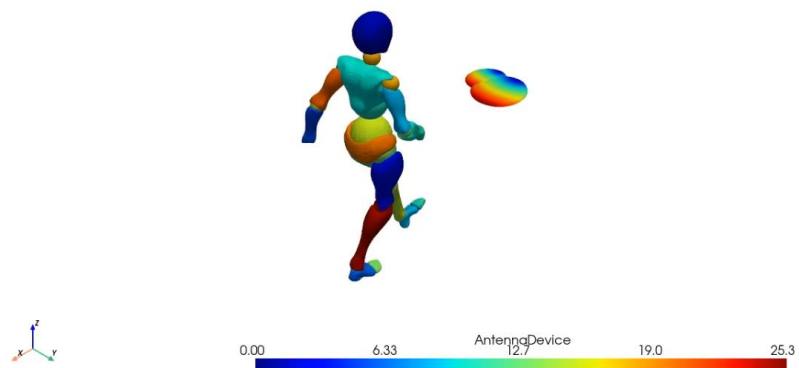


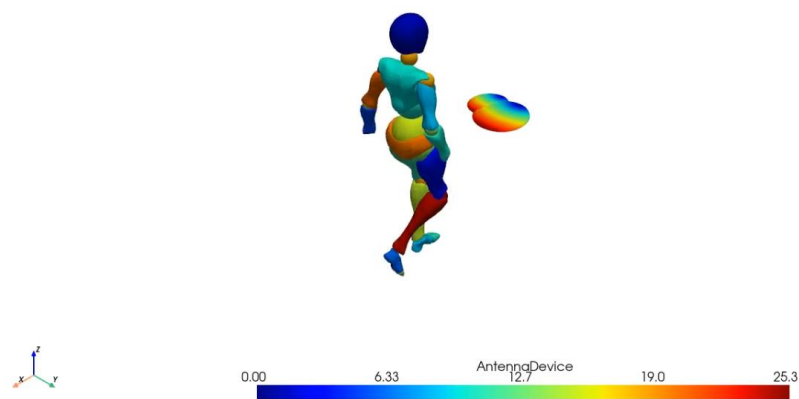
Figure 4.5: All body Fall simulation case



(a)



(b)



(c)

Figure 4.6: Walking simulation case

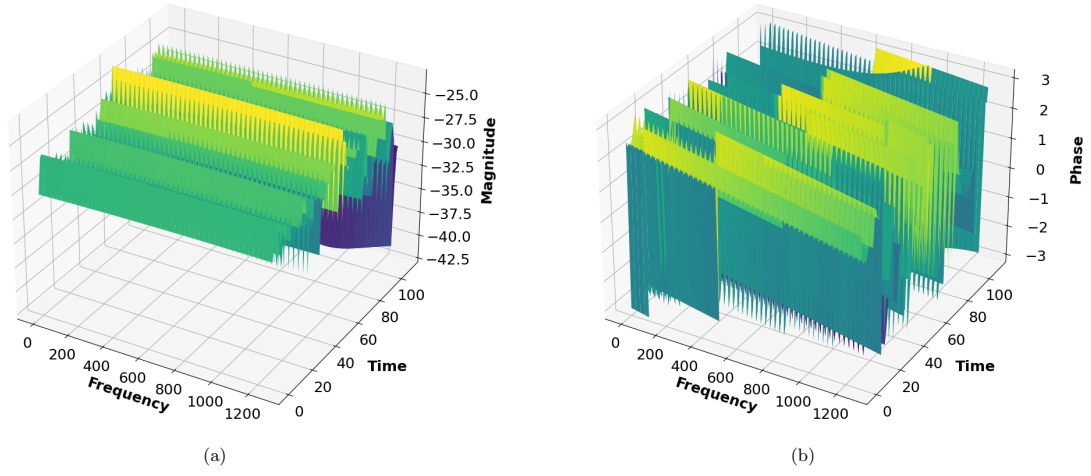


Figure 4.7: Results for the knee fall class: (a) Magnitude and (b) Phase.

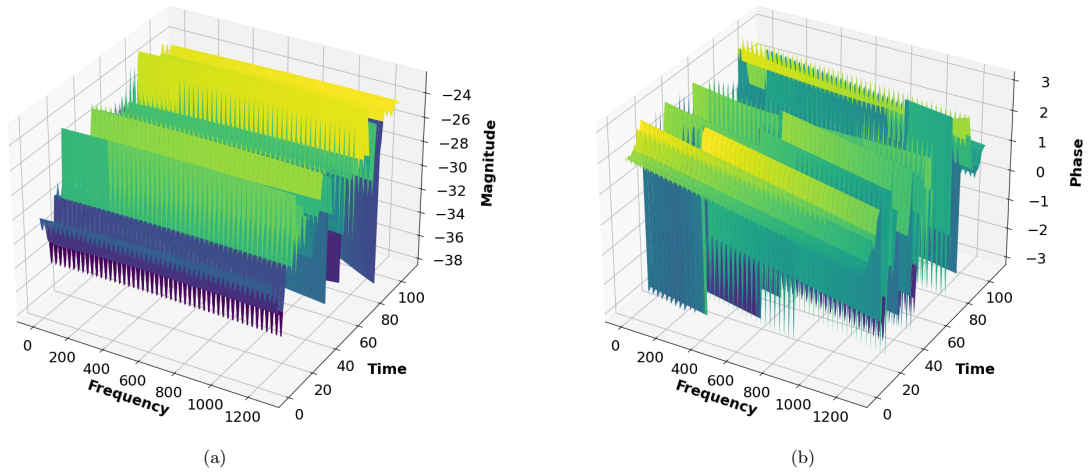


Figure 4.8: Results for the hip fall class: (a) Magnitude and (b) Phase.

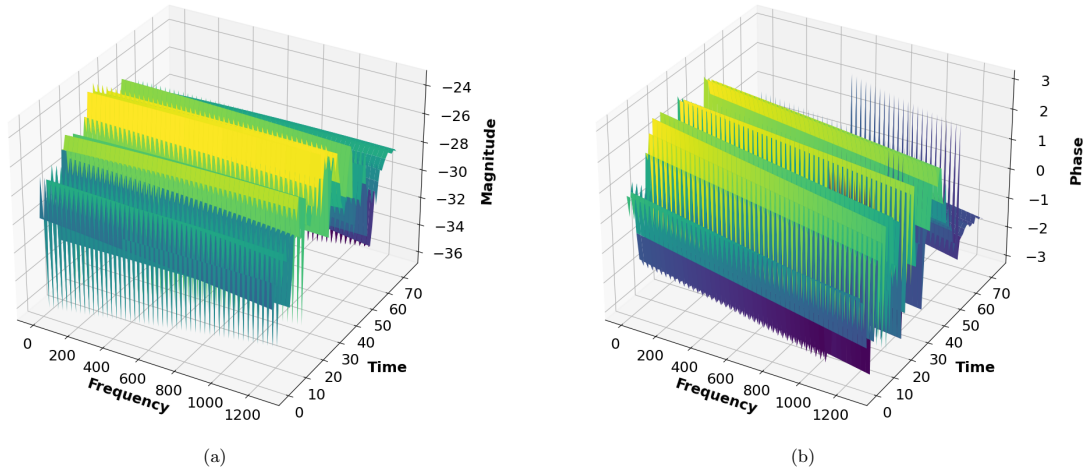


Figure 4.9: Results for the all body fall class: (a) Magnitude and (b) Phase.

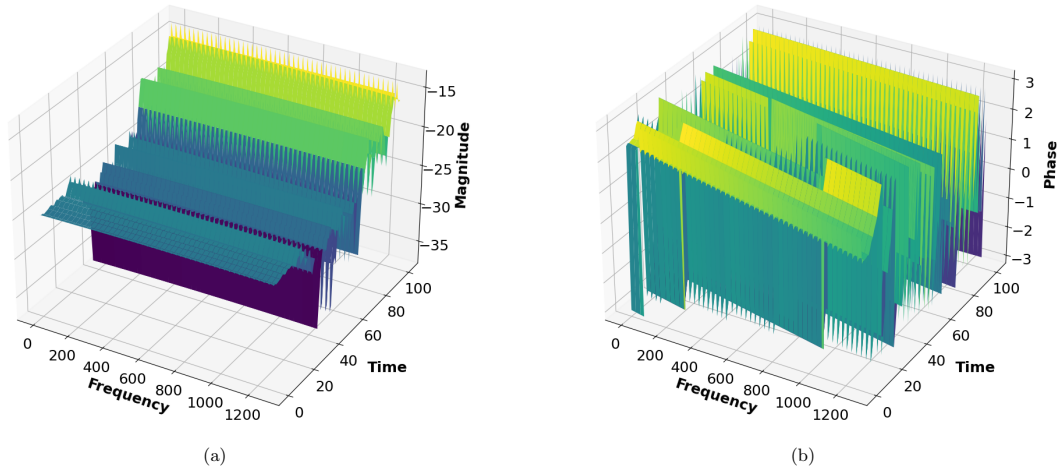


Figure 4.10: Results for the other activities class, illustrated by a walking example: (a) Magnitude and (b) Phase.

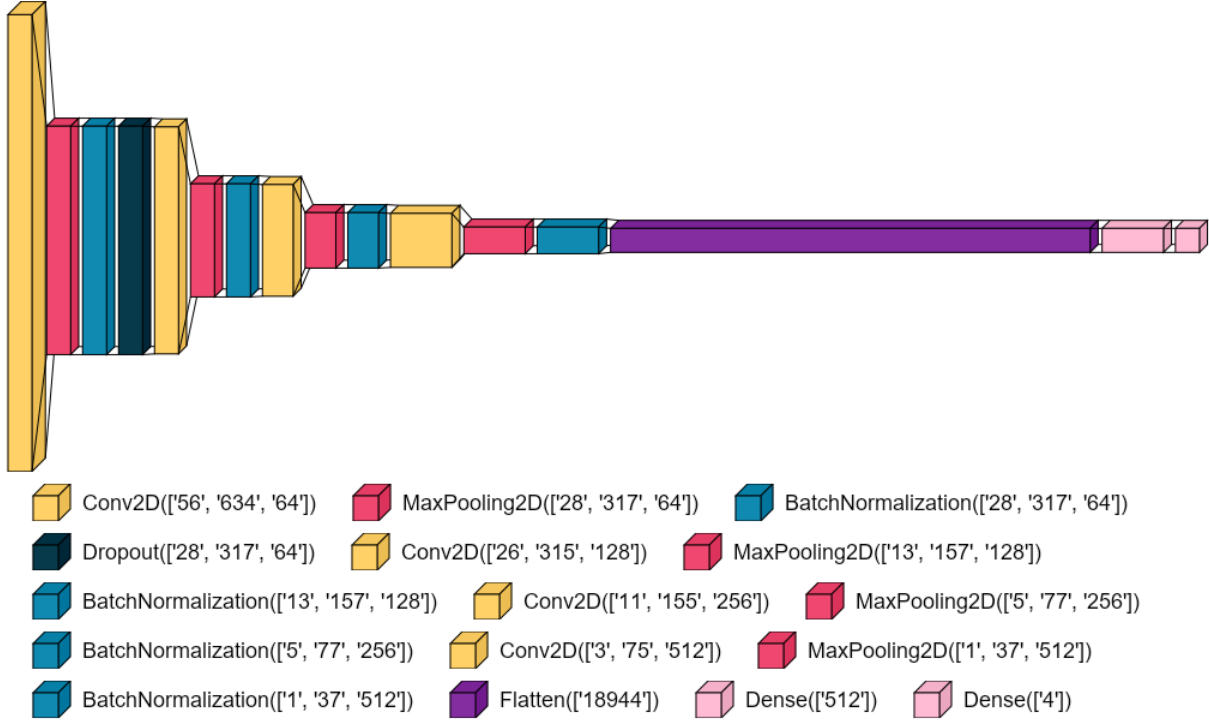


Figure 4.11: CNN architecture used for classification

Measurements

In order to validate the reliability of using simulated data for training a system that can classify real-life scenarios, multiple measurement campaigns were conducted.

To implement the [JCS](#) system, a software-defined radio (SDR) was considered. However, the initial trials showed that the SDR suffered from multiple issues that severely affected the system. Among these issues were synchronization between the transmitter and receiver clock, and the inability to initiate the transmission and reception process in parallel and with a triggered start [\[89\]](#). Consequently, a vector network analyzer (VNA) was chosen as a proof of concept, as these issues are inherently solved by the VNA.

Initially, the VNA was configured to resample the channel estimation similarly to the simulation configuration. The VNA was set to have 1272 sweep points, spanning a bandwidth of 19.1 MHz at a center frequency of 2.44 GHz. The intermediate frequency (IF) bandwidth was set to 70 kHz. With this configuration, it was found that the sweep time was around 12.5 milliseconds, which is relatively long compared to real-life scenarios. The

implications of the sweep time would lead to inaccuracies in the captured channel as the start and end of the sweep experience different channel effects due to dynamic changes. This could result in losing frames in the E5071C Agilent VNA, as the processing time to transmit captured data is longer than the time required between each frame to achieve the necessary frame rate. Fig 4.12 shows the layout of the lab where all measurements were performed.

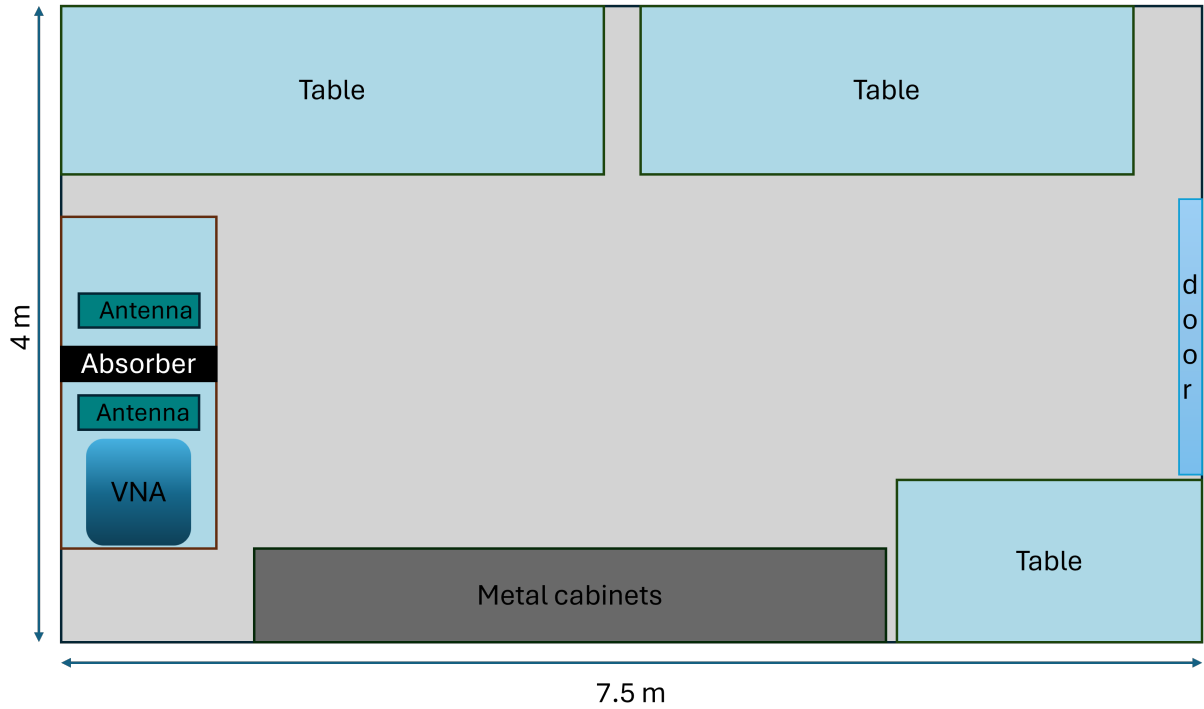


Figure 4.12: A layout of the lab where measurements were performed.

To solve this issue, downsampling was required to reach an acceptable sweep time for channel measurements and the communication link between the VNA and the PC. The effect of downsampling on classification accuracy was first studied using the simulated data. It was found that downsampling does not affect classification accuracy in ideal cases, as will be shown in the results section.

Based on this, two configurations were tested in the VNA. The first configuration was to capture 318 points per sweep at the same carrier frequency, IF bandwidth, and RF bandwidth, leading to a capture time of around 700 microseconds. The other configuration had the same parameters except for capturing 64 points per sweep, which led to a sweep

time of approximately 150 microseconds. Fig. 4.15 shows the resulting channel estimation using the 318 points configuration.

As can be seen in Fig. 4.13, the captured channel suffers from multiple effects that can overshadow the channel effects of the human activity scenario itself when studying the magnitude of the captured data. To counter these effects, multiple processing steps were undertaken, including removing the coupling and environment clutter effects from the captured frame, followed by low-pass filtering and then clipping outliers beyond a certain average. Afterward, the resulting data was normalized to be between 0 and 1, which is more suitable for machine learning input.

Once the data for a certain scenario was captured, it was noticed that the effects of coupling between transmitter and receiver antennas and antenna non-idealities were much higher than the variations in the scenario itself. To equalize this effect, 1000 frames were captured in the environment where measurements were to be conducted. Then the average of these 1000 frames was subtracted from each frame in all scenarios. Fig 4.13 shows the captured frames as reference frames.

This resulted in an equalization effect where the high-value constant clutter was removed from the captured data. After removing the clutter, it was noticed that there were very high-frequency components introduced to the data due to a high noise level compared to the data level, which was at -60 dB. It was also observed from studying the simulated data that such high frequencies should not exist because the channel does not have relatively fast-moving objects. So, a low-pass filter was applied to the data to reduce the effect of these high-frequency components. After applying the filter, it was noticed that very high variations were reduced, yet there were still deep fades in the channel which would not allow for correctly normalizing the data as required in the following step. To counter this effect, the average and variance of the data were calculated, and all sharp peaks that exceeded a certain variance were clipped to maintain the relative relationship between channel variations over time within an acceptable scale. The final step was to normalize the data to make the range of values between 0 and 1, as was done with the simulated data before training the ML algorithm. After applying all required processing, the magnitude matrix and phase matrix were packed into one variable with two channels, which is the format compatible with the ML input shape. Fig 4.15 shows a measured channel estimation before and after processing. All processing techniques were applied after studying the ideal case in the simulated data, which is an outstanding advantage of the DT: it provides data that can be considered a benchmark. Fig. 4.14 illustrates the whole process of the measurements till the data are fed to the ML algorithm.

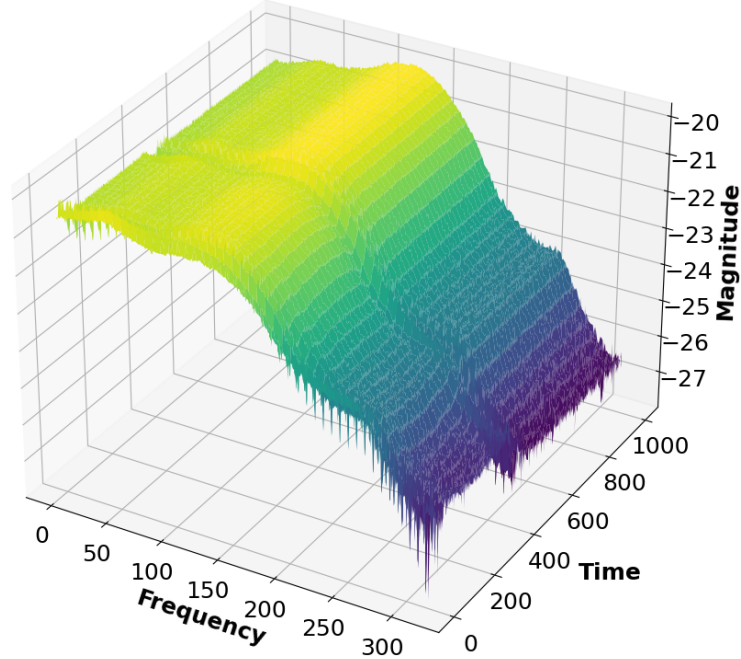


Figure 4.13: 1,000 captured frames in a static environment. These frames are used in the post-processing stage. The average of those frames over time is subtracted from all measurements taken during the same campaign.

4.4 Results

The first step was to test the capability of the simulated data to be classified into basic test cases. A basic CNN architecture was used to classify three cases: forward fall with the knee hitting the ground first, backward fall with the hips touching the ground first, and other scenarios like standing up, torso swinging, and picking up something from the ground. As mentioned before, scenarios were simulated for random relative position, angle, speed, and body size. The total number of simulated cases in this test was 2780. These were split into 20% test and 80% training cases. Hyperparameters in this chosen architecture and training process were tuned manually until an acceptable performance was achieved. The learning rate for the model was initially chosen to be constant; however, when overshooting in the learning curves was noticed, an exponential learning rate was adopted, and the parameters for the initial learning rate, decay steps, and decay rate were manually tuned. For further

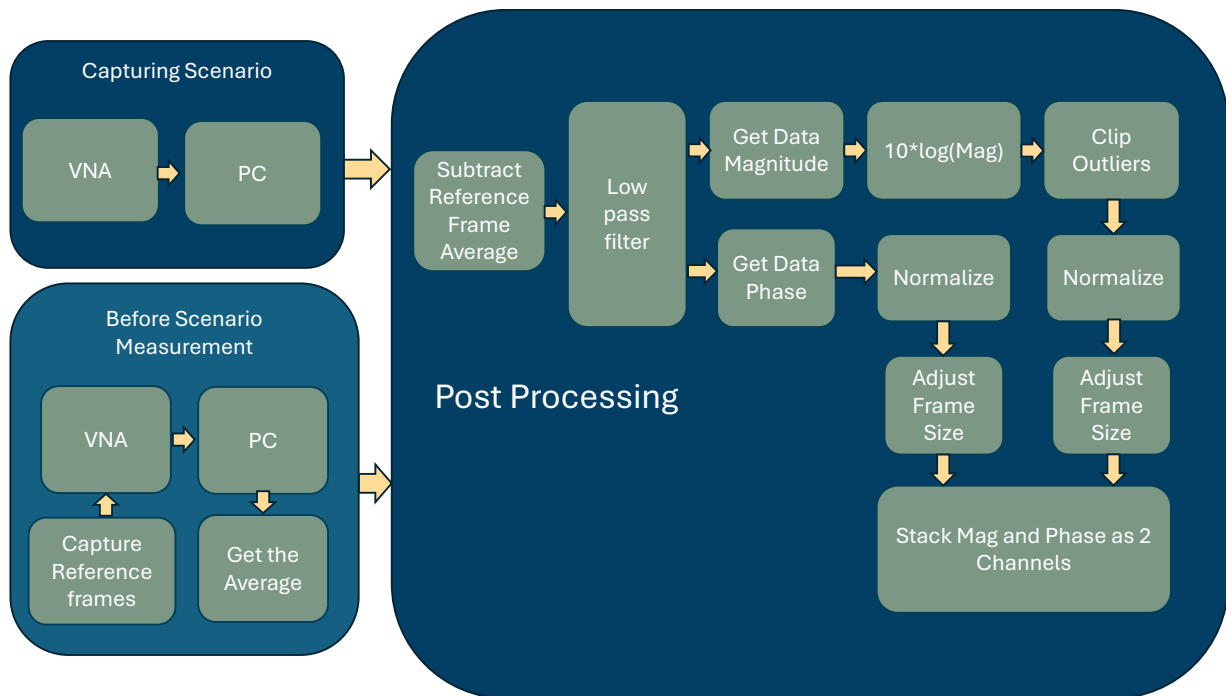


Figure 4.14: A flow diagram of the measurement process which starts by collecting reference frames prior to the measurements of the human activity scenarios. Both measurements and the reference are passed to the post processing stage where the data are prepared in the write format to be fed to the machine learning algorithm for testing.

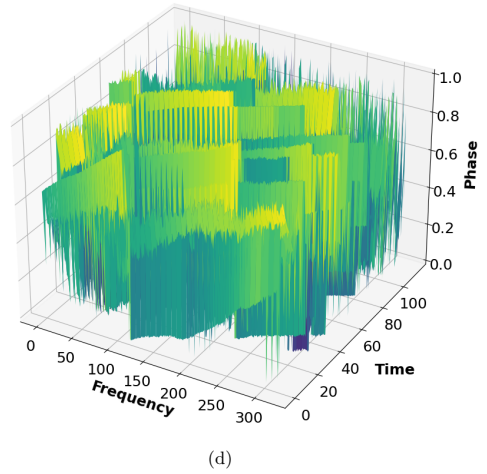
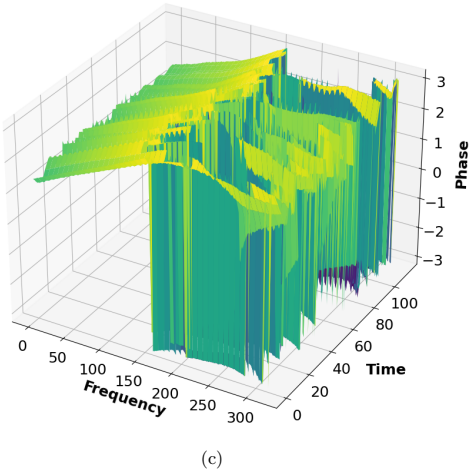
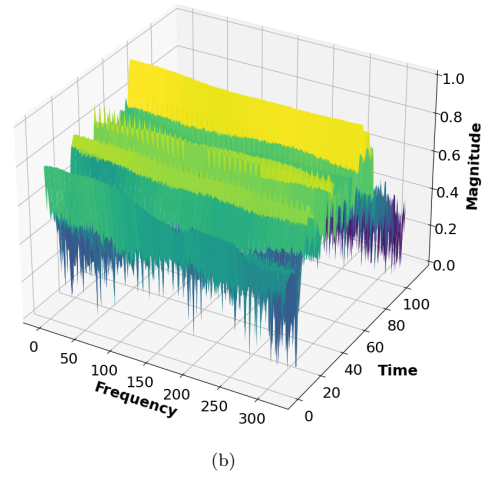
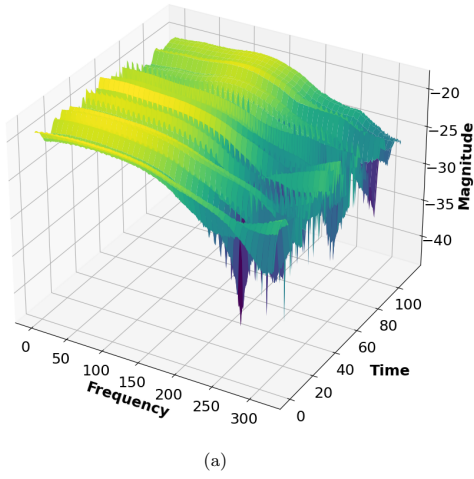


Figure 4.15: Channel estimation of the measured data before and after processing (a) Magnitude of the captured frames before processing (b) Magnitude of the captured frames after processing, (c) phase of the captured frames before processing, (d) phase of the captured frames after processing.

enhancement of the machine learning model, a validation set can be used to achieve the best possible performance of the CNN. Additionally, there are machine learning algorithms that can achieve higher performance for this type of classification problem, such as LSTM and attention models, as was shown in the background section. Results show that this CNN architecture gives 93.7% accuracy. Fig. 4.16 shows the confusion matrix on test cases, while Fig. 4.17 shows the learning curve based on this architecture. Based on these results, it can be seen that it is an easy task for this architecture with the provided bandwidth and other waveform parameters to classify falls among other scenarios, as the total number of misclassified data points in the non-fall class is only 3 points. However, results also show that the majority of misclassified points are between different classes of falls. This can be due to the limited bandwidth of the transmitted waveform, which is limiting the system's resolution. Another contributing factor to misclassification is the setup configuration where the relative angle between the falling model and receiver antenna is around 90 degrees.

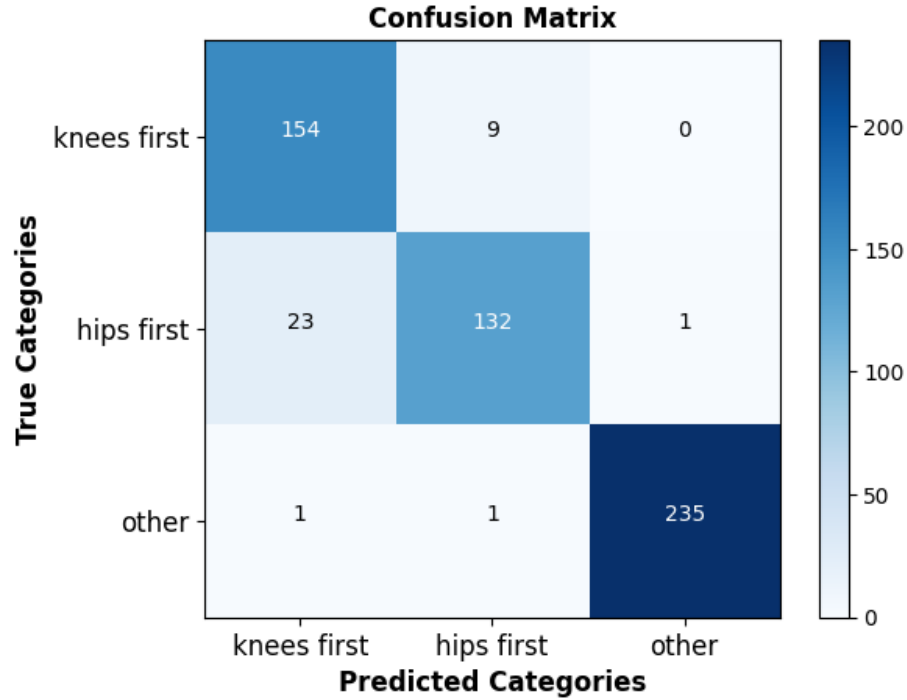


Figure 4.16: Confusion matrix illustrating the classification performance for three categories: "knees first," "hips first," and "other." The model performed best in classifying the "other" category, with 235 correct predictions, while the "hips first" and "knees first" categories had a few misclassifications. The model was trained and tested using simulated data to demonstrate the ability of the CNN model to classify these scenarios.

Based on the previous results, a more complex classification problem was studied. A fourth class of falls was introduced in the data, called "full body." In this scenario, the falling model has multiple body parts touching the ground around the same time, which cannot be fitted into the other two falling classes. After introducing this fourth class, data were also split into 80% for training and 20% for testing. The same CNN architecture used in the previous classification problem was used for this one as well, achieving 91.81% accuracy. Fig. 4.18 shows the confusion matrix of the results based on the test data, while Fig. 4.19 shows the learning curve for the training process.

From these results, it is noticed that classification accuracy for the 4 classes is lower than for 3 classes only. This is due to the increased number of dataset points used for training and testing. It can also be noticed that misclassifications are distributed among all scenarios. This can be seen from the comparison between the learning curves in Figs.

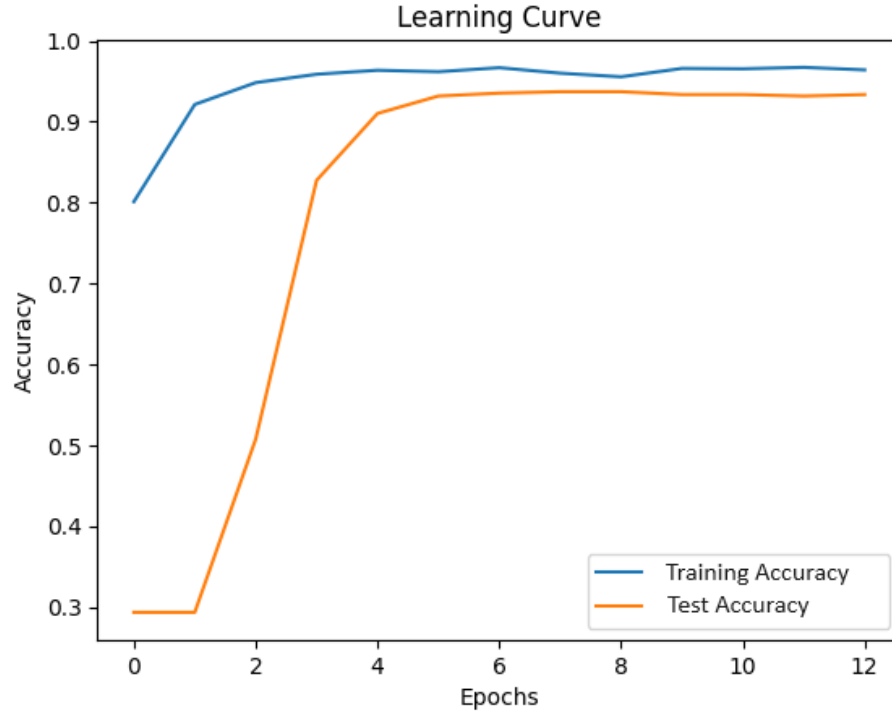


Figure 4.17: Learning curve of the training process based on 3 classes classification

4.17 and 4.19, where the learning curve for 4 classes takes more time and epochs to reach the maximum accuracy that this model can achieve.

Downsampling

As mentioned, the effect of downsampling was studied in order to determine the impact of reducing captured frame size on the accuracy of detection.

There are two degrees of freedom of downsampling frame size: number frames per seconds and number of subcarriers per frame. In both cases it is assumed that the rest of parameters are consistent. First, reducing number of frames per second by half relates to capturing data at rate of 15 frames per second instead of 30 frames per second. For this case, the same simulated data was used, making the input size to the ML algorithm 58636 instead of 115636 in the previous case. Results for 4 classes show a classification accuracy of 78.233%. This shows a reduction of almost 14%, which is significant for this kind of

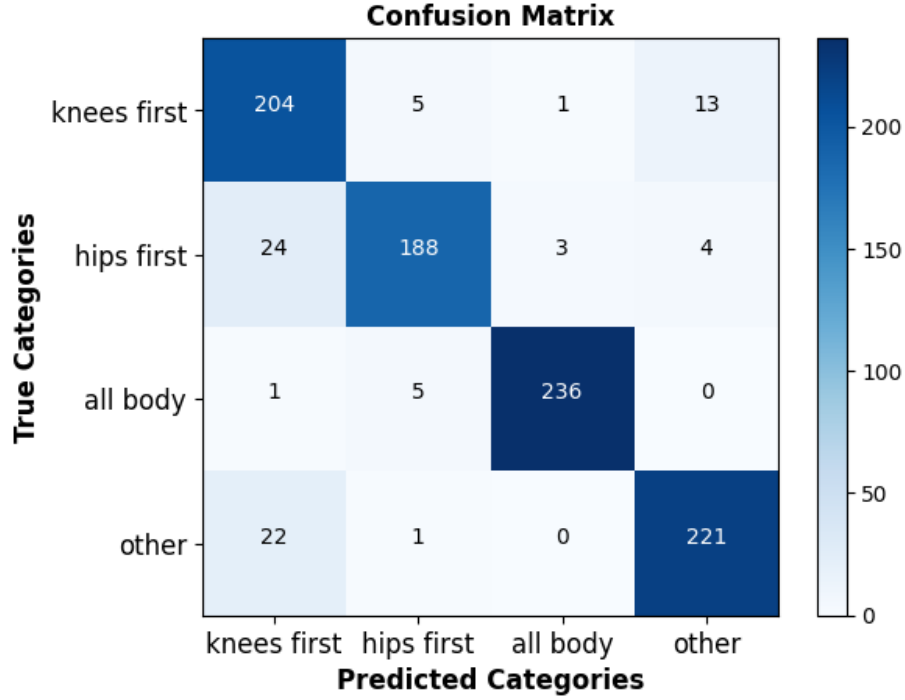


Figure 4.18: Confusion matrix illustrating the classification performance for three fall categories and the non-fall category. The model was trained and tested using simulated data to demonstrate the ability of the CNN model to classify these scenarios.

application. This result shows the high correlation between frame rate and classification accuracy, paving the way for further studies and simulations to estimate the optimum frame rate to achieve the highest accuracy possible from the provided communication resources.

Second, the effect of downsampling the frame size by half was examined. This could be related to using a subcarrier spacing of 30 KHz instead of 15 KHz used in this work. The same simulated data was used for this process, but it was processed by considering only the odd indices in each frame, which in this case made the input frame size 115*636, corresponding to the number of frames (time stamps) and frame size, respectively. Results for 4 classes show an accuracy of 92.46%. It can be noted that the results are almost the same, with a slight improvement in accuracy of 0.65%. Although this improvement is not significant, it opens the way for further study of downsampling. Compared to the original frame size of 1272 points per frame, the downsampled frames studied had lengths of 636, 318, 159, 64, and 32. All of these frame sizes had almost the same accuracy around 92%.

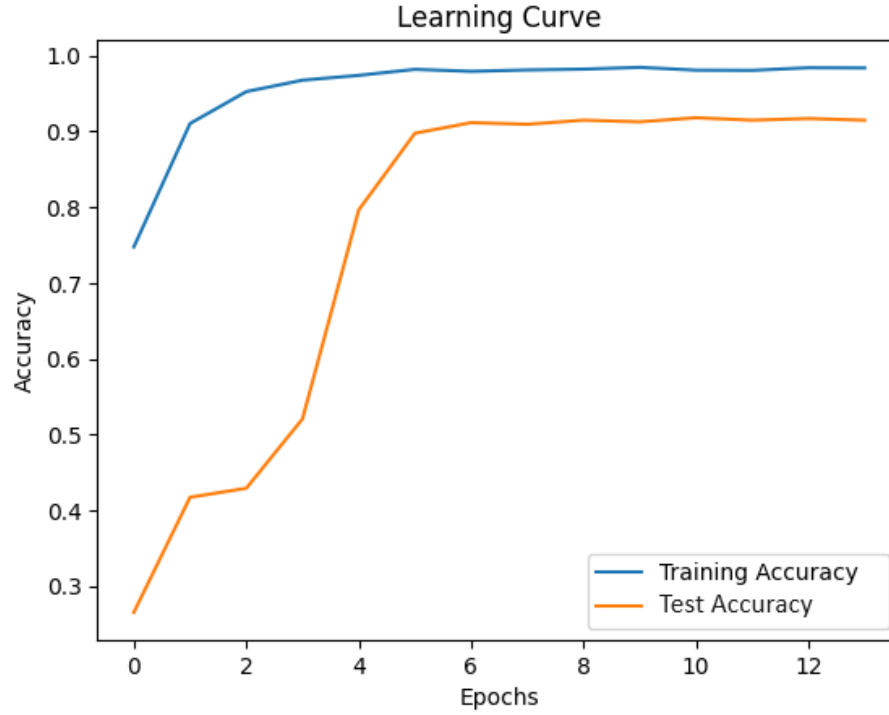


Figure 4.19: Learning curve for the training process to classify 4 classes

The CNN architecture was modified to match the input size and prevent data overfitting. This could be due to multiple reasons. Firstly, the data are generated for simulations performed under ideal conditions where the 3D CAD model was performing the scenario in an open area with no multi-path reflections and no noise. Secondly, there are no high-frequency components in ideal cases in the channel estimation, which according to the Nyquist criteria, allows the frame to be downsampled to a very low number of points without affecting the information in the signal. However, in real cases, these idealities break down, so the next results of measurements are meant to validate how low the frame size can be reduced.

Measurements

As mentioned, measurements were done in the lab using VNA. Scenarios included in the measurement campaign are Knee fall, hip fall and walking because those scenarios can be performed with a limited probability of injuries after taking safety measures in consider-

ation. Measurements were collected for two different frame sizes which are 318 and 32 subcarriers per frame. Those were considered due to the limitations in VNA external communication speed. each one of those scenarios were conducted 15 times for each one of the frame sizes. Post processing consisting of clutter removing, filtering, clipping and scaling were performed to each test case as mentioned in the previous section. The same CNN model used for classification on simulation data were used for classifying the measured data as well. yet, the main difference is that only simulated data were used for training and measured data were used for testing to validate the correlation between simulations and measurements. In the case of frame size of 32 the maximum accuracy that can be achieved after extensive tuning and training is 60% which very low for this application. For the frame size of 318 the CNN model can achieve classification accuracy of 88.9%. Fig 4.20 shows the confusion matrix of classification of measured data.

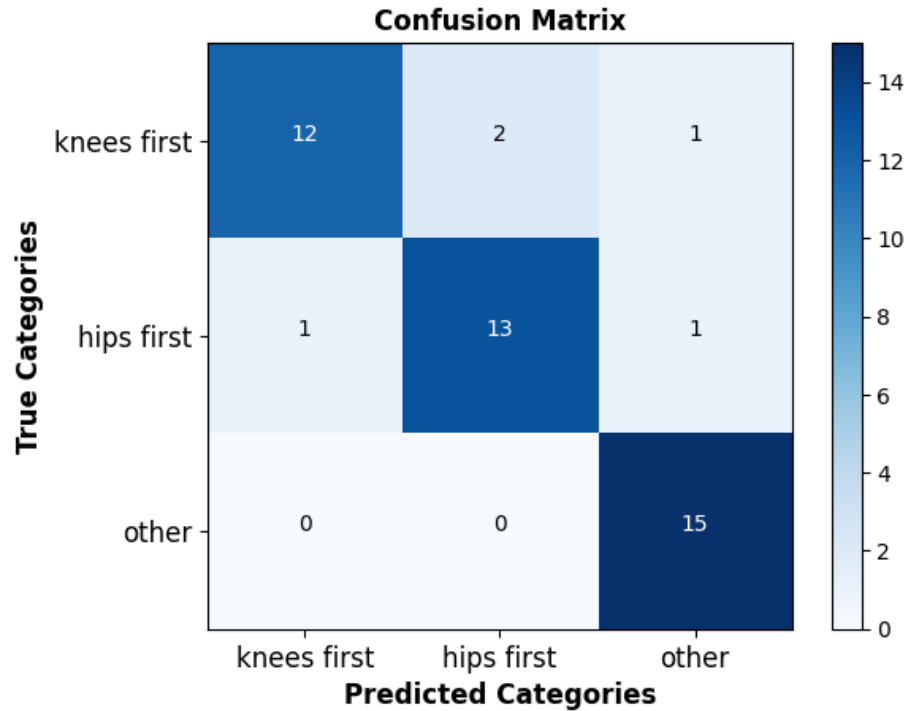


Figure 4.20: Confusion matrix illustrating the performance of the CNN in classifying measured data. The CNN was trained on simulated data only.

It can be noticed in Fig. 4.20 that all walking test cases were correctly classified as the other class, and the main confusion of the model is between knee and hip falls,

which matches the behavior of the simulated data. The comparison of different frame sizes in measurements shows that although classification accuracy was not declining, in real measurements there is a limit at which downsampling can achieve the required classification accuracy.

4.5 Conclusion

Digital Twin-based severity of fall classification systems represent a transformative approach by integrating JCS systems with advanced simulation technologies. This method eliminates the need for human participation in data collection by employing CAD models with defined motions to simulate various fall scenarios. Virtual replication of physical entities through DT enables comprehensive simulations without the risks associated with physical trials, significantly reducing development time and cost.

The DT approach offers several advantages, including the ability to simulate a wide range of fall scenarios and environmental conditions, and the potential for real-time monitoring and analysis of fall events. This enables researchers to test and refine fall detection algorithms in a controlled and repeatable environment, leading to more accurate and reliable systems.

In this work, three subsystems were proposed to detect and classify falls based on the severity of the incident. The DT subsystem was responsible for generating the required dataset and feeding it to the machine learning algorithm for training. The 5G access module handled communications and flagged any suspected falls, while the final subsystem classified the falls. The proposed system was validated through simulations and measurements, demonstrating the feasibility of using DT to train machine learning algorithms for fall detection systems.

Measurement results showed that the proposed system could achieve an accuracy of 88.9% when classifying falls based on the severity of the incident. The results also demonstrated the impact of downsampling on classification accuracy, with a frame size of 318 subcarriers per frame achieving the highest accuracy of 88.9%. The consistency between simulation and measurement results validated the effectiveness of the DT-based approach for training machine learning algorithms.

Overall, DT-based systems are particularly suited for research and development purposes, offering a robust platform for training machine learning algorithms and refining fall detection systems through extensive and varied simulations.

Chapter 5

Conclusion and Future Work

5.1 Summary

This work was developed to investigate the feasibility of implementing DT technology in sensing applications, specifically in the context of radar and 5G systems. The motivation for this research stemmed from the need to develop a fall classification system that could be used in smart homes and retirement facilities. The thesis began by illustrating the crucial need for fall classification systems and the challenges faced by existing solutions. Additionally, the potential of using radar and 5G systems for the sensing task was thoroughly investigated.

To begin, the radar system was studied, and a DT was developed to simulate the radar system. This DT was used to generate the data needed to train a machine learning model for fall classification. The results demonstrated that sufficient accuracy could be achieved by utilizing the simulated data for training. These results were then verified through measurements using a real radar system, confirming the initial findings.

Following the radar study, the 5G system was examined, and a DT was similarly developed to simulate it. The process for developing the DT for the 5G system mirrored that of the radar system, with the main differences including waveform generation and channel estimation. A measurement campaign was conducted using a VNA to verify the results obtained from the DT. The results indicated that the DT could achieve detection accuracy of 88.9

Various aspects of both radar and JCS systems were further studied and analyzed. The radar system's ability to model real-world cases such as falls with different speeds and

angles, varying heights of human-like models, and different micro-Doppler signatures of falls was thoroughly examined. Additionally, for 5G systems, the concept of downsampling the signal to reduce the system's computational complexity was explored, highlighting another potential area of improvement.

In conclusion, this study opens the door to future work in the field of DT technology. Infinite scenarios and cases can be developed to create a robust and universal human activity classification system. Moreover, more sophisticated machine learning models can be developed to achieve even better classification accuracy, paving the way for advanced applications in smart homes and retirement facilities.

5.2 Future Work

As illustrated in this work, both systems (i.e., radar and JCS systems) share many of the implementation and validation concepts, especially in the area of the DT. Therefore, in general, the future work for both systems includes:

- Simulation of more complex fall models as well as human activities for a general classification framework.
- The exploration of more sophisticated machine learning algorithms to achieve better classification accuracy.
- Explore the fusion of both systems for better accuracy.

5.2.1 Future Work for Radar Systems

In this work, only FMCW radar was investigated with a single configuration. As mentioned, this configuration controls the resolution of the radar. Therefore, future work on radar systems can include:

- Explore various types of radar systems with different configurations and operating frequencies.
- Explore different physical configurations of the radar, such as tilting and positioning, to determine the optimum configuration for a home environment.

5.2.2 Future Work for Joint Communication-Sensing Systems

The results achieved through this work demonstrate that the proposed system can be successfully deployed in 5G networks. The next step is to implement the system on a commercial device to validate the results in a real-world scenario. Software-defined radios (SDRs) have proven to be a suitable platform for intermediate implementation, as they can be easily reconfigured to perform 5G NR functions through the physical layer. For this work, the initial trials were conducted using the ADALM-PLUTO SDR, which is based on the AD9361 chip. Although this module has some limitations that impose challenges in the implementation, such as using different clocks for the transmitter and receiver and the inability to start the transmission and reception processes in parallel, it provides a good starting platform. The ADALM-PLUTO offers a bandwidth of 20 MHz, which matches the bandwidth used in this work. Additionally, this device is supported by MATLAB and Python, which facilitates the implementation of the system. Fig. 5.1 Shows a block diagram of the Pluto SDR.

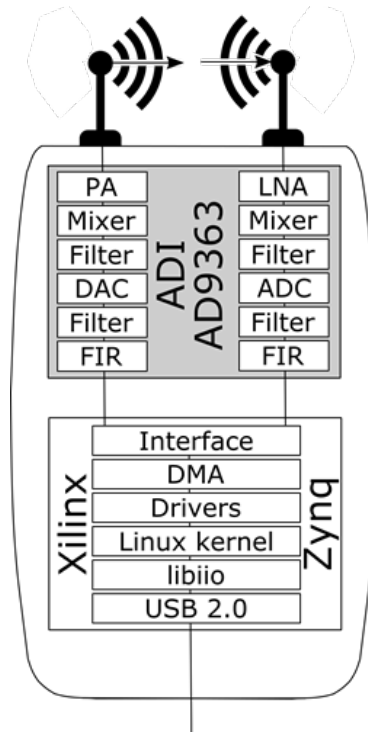


Figure 5.1: Block diagram of AD9361-based Software Defined Radio (SDR).

The early development of the system began with generating a 5G NR waveform using MATLAB's 5G waveform generator toolbox. This waveform is compliant with the 3GPP standards. However, the waveform data size is 307,200,000 samples, which is too large to be delivered to the SDR using USB 2.0 communication. This is because, with USB 2.0, the maximum data rate supported by the SDR cannot maintain a frame rate of 30 frames per second. Therefore, it was decided to transmit only one subframe containing the SS block and the CSI-RS. The SS block is used to synchronize the receiver with the transmitter, and the CSI-RS is used to estimate the channel. The processing blocks were implemented in MATLAB, which also managed the transmission and reception process. The implemented steps are as follows: load the TX waveform, set up the transmitter SDR configuration, receiver SDR configuration, transmit the waveform with a cyclic buffer to maintain continuous transmission, and receive the required number of frames. For each frame: perform synchronization using PSS, obtain the time and frequency offsets, demodulate the received signal, and estimate the channel using the CSI-RS.

The early results of the implementation revealed multiple issues. The first issue is that some of the transmitted signals are distorted in an undetermined manner. The second issue is related to post-processing of the received signal, where the channel estimation is not accurate. The third issue is that the system is unable to maintain a frame rate of 30 frames per second. The fourth issue is that the system cannot start the transmission and reception processes in parallel.

The future plan includes addressing the issues mentioned above and leveraging the processing steps that were conducted through simulations and measurements.

5.3 Publications

Chapter 3 uses the content of the following publication.

- A. Elbadrawy, H. Abedi, O. Ramahi and G. Shaker, "Severity of Fall Detection using Digital Twin for Radar Systems", IEEE MAPCON, 2023.
- A. Elbadrawy, H. Abedi, A. Sligar, O. Ramahi and G. Shaker, "Revolutionizing Geriatric Care: Radar Digital Twin Technology for Fall Severity", Nature Scientific Reports, 2024. (currently under review)

Chapter 4 uses the content of the following publication

- A. Elbadrawy, A. Sligar, O. Ramahi and G. Shaker, "Digital Twin-Based Approach for Joint Communication-Sensing and Fall Severity Assessment" (Under preparation)

The use of their content in this thesis have been approved by all co-authors.

5.4 Code Used For This Work

The files included contain the code used for data collection and data processing. The code used for simulations and scenario creation follows an NDA agreement with Ansys Inc. For any inquiries about this code, please contact Prof. George Shaker at gshaker@uwaterloo.ca.

See [GitHub Documentation on code used for this work](#)

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