RadarID: Radar-Based User Identification in Smart Environments

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Abstract

This report presents the RadarID project, which explores the use of radar technology for user identification in smart environments. As smart homes advance, the need for precise and non-intrusive identification of residents becomes crucial for personalizing interactions. The main objective of the RadarID project is to develop a radar-based system capable of identifying individuals through their movements in a less intrusive manner, leading to fewer concerns and less opposition to the technology, facilitating its acceptance and integration into everyday life.

To achieve this goal, we adopted a user-centered design approach, focusing on understanding the target users and their needs to define system requirements. We began by defining personas and scenarios to extract functional requirements, which guided us in developing our system's architecture. This led to the development of a pipeline that integrates several models, including data acquisition, filtering, feature extraction, and subject identification.

The main results include the implementation of a prototype capable of identifying two users with an average accuracy of around 88%. As a proof of concept, we developed a simple interface that changes the text on a monitor depending on the identified user, highlighting the potential of radar as a promising tool for identification in smart home environments. Although challenges remain, such as refining models and adjusting radar configurations to support more users, the RadarID project provides a foundation for future research and development.

Keywords: radar technology, user identification, smart homes, transfer learning

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Acronyms

mmWave Millimeter-Wave

UWB Ultra-Wideband

MWDR MicroWave Doppler Radar

FFT Fast Fourier Transform

CNN Convolutional Neural Network

RF Random Forest

FMCW Frequency Modulated Continuous Wave

Bi-LSTM Bidirectional LSTM

NBC Naive Bayes Combiner

KNN K-Nearest Neighbor

SVM Support-Vector Machines

AM4I Adaptive Multiplatform Multidevice Multilingual Multimodal Interaction

FR Functional Requirements

NFR Non-functional Requirements

IEETA Institute of Electronics and Informatics Engineering of Aveiro

DETI Department of Electronics, Telecommunications and Informatics

MQTT Message Queuing Telemetry Transport

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Chapter 1

Introduction

1.1 Context

In the contemporary era, our living spaces are transitioning into intelligent environments capable of collecting detailed data about their inhabitants. Some devices incorporate a variety of sensors that retrieve information about the space itself and the individuals within it. Many sensors, such as microphones, motion detectors, and biometric scanners, contribute to a comprehensive data set.

Microphones can pick up audio data, potentially capturing conversations and ambient sounds. Motion detectors register movement within the space, providing insights into the occupants' activities. Biometric scanners, including facial recognition technology, can identify individuals and track their movements. These sensors collectively contribute to a wealth of information that reflects the people's behaviors, preferences, and routines in these intelligent environments.

The implications of such data collection raise concerns about privacy, surveillance, and consent. Striking a balance between the benefits of enhanced functionality and the protection of personal privacy is a critical aspect of designing and implementing these intelligent systems. As we navigate this technological landscape, we must consider ethical standards and legal frameworks to ensure the responsible and transparent use of the gathered data.[1]

1.2 Motivation

In the broader context of intelligent environments, our motivation is centered on achieving effective individual identification, a fundamental aspect for realizing the full potential of smart spaces. This potential involves recognizing people, adapting interactions to individual preferences, and improving security by detecting guests or unfamiliar individuals. As smart homes offer a wealth of information, the actual value lies in linking these data to specific individuals, particularly in shared spaces. The work aspires to contribute to the responsible and transparent integration of technology into homes, fostering adaptability, security, and personalized interactions.

1.3 Challenges

Human identification has long been a domain that presents substantial data acquisition and security challenges. Privacy concerns are one of the public's main drawbacks, especially when the data acquisition involves recording visual data. Therefore, an improvement to this drawback might rely on radars since they do not capture images of the humans subject to identification. However, this alternative approach introduces its own set of challenges.

Radars are primarily employed to detect and track objects based on their different attributes, such as position and velocity. An attempt to repurpose radars to perform human identification is a complex task that requires specialized technologies such as biometrics.

Designing an effective radar system for human identification poses a multifaceted challenge. Determining the optimal number of radars required, single or multi-radar setup, is essential. With each radar comes the concern of strategically placing them within a given space, range, and sensitivity.

Furthermore, the absence of protection for sensitive information gathered by the radar would only escalate the public's concern about privacy. The system must be designed to safeguard the data collected to avert this.

The performance of radar-based identification can be affected by various environmental factors such as furniture layout, multiple people in the same space, and non-human movements (like pets). Overcoming these interferences is essential for the system's good performance.

Another challenge is ensuring compatibility and seamless integration with various existing smart home technologies and systems. Therefore, it is essential that the system is adaptable and flexible to work in diverse settings.

1.4 Objective

The primary objective of this project is to develop a system that utilizes radar technology to accurately identify individuals. This involves detecting a person's presence and obtaining unique characteristics that distinguish one individual from another. We aim to achieve accurate results in identification, where we can reliably monitor people and adapt each user's interaction with the house.

1.5 Expected Results

The expected outcomes of our project include the successful development of a prototype radar-based solution for human identification utilizing methods to extract relevant data. Then, that data will be used to obtain and train a model that identifies users within a smart environment using machine learning.

We anticipate the prototype's ability to distinguish residents, guests, and potential intruders, facilitated by algorithms for prompt and accurate radar data processing.

Privacy compliance is a fundamental aspect of our design. Therefore, the prototype should be crafted to adhere to privacy standards and safeguard user information.

Moreover, new modules should be able to add or improve the system's architecture without significantly changing the main architecture, allowing for broader adoption and practical implementation in diverse settings.

The prototype is intended to lay the foundation for future enhancements and explore more sophisticated applications of radar technology within smart environments.

1.6 Document Structure

This report initiates with Chapter 2, an overview of the current state-of-the-art. This chapter synthesizes critical studies, summarizing their findings on human tracking, vital sign detection, and identification systems. This chapter presents the results of a literature review, including a synthesis of key studies and their findings in these areas. Subsequently, our exploration extends to the literature that provided critical insights that supported the selection of tools and technologies for developing our solution.

Chapter 3 includes detailed personas and scenarios that act as the guiding compass for system development, which enabled us to extract both functional and non-functional requirements.

Chapter 4 initiates a detailed exploration of the system architecture utilized. Starting with a holistic system overview, we break down the user identification modality and delve a little into the intricacies of model evaluation and training.

Chapter 5 details the design and execution of all protocols and experiments for developing the model for subject identification.

Chapter 6 concludes the report, reflecting on the project's outcomes and discussing potential future directions and opportunities created by our work.

Chapter 2

State-of-the-Art

This chapter begins with an overview of the current state-of-the-art. Within this chapter, we synthesize critical studies, summarize their findings on human tracking, vital sign detection, and identification systems, and conduct a literature review. We also delve into the literature that provided critical insights supporting the selection of tools and technologies for developing our solution. This chapter serves as a reference point for existing knowledge related to our topic, reiterating the relevance of our work.

2.1 Related Work

Before we started working on our project, we looked into many articles. This search helped us learn more about how radar is used for identification, showing us different ways it is applied. Below, we share six important examples from our research that helped shape our project, showing radar technology's variety and technical details.

Our method involved researching specific keywords related to radar technology and human identification. We used Google Scholar as the primary tool to find relevant research papers and articles.

We applied filters to narrow our search, focusing on articles from the last decade to ensure their relevance and up-to-date information. Additionally, we selected articles that explicitly utilized radar technology, a criterion emphasized to ensure alignment with our project's goals. This strategic approach contributed to the selection of articles that significantly influenced our project's development.

2.1.1 Studies Summary

Table 2.1 summarizes the articles read, analyzed, and considered relevant to our project. Through observation of the different kinds of articles, we are capable of concluding the diversity of elements of every paper, such as the usage of different types of radars like the Millimeter-Wave (mmWave), the Ultra-Wideband (UWB), the MicroWave Doppler Radar (MWDR) and the Frequency Modulated Continuous Wave (FMCW) and its distance from the subject being analyzed. In that case, distances between 1 meter and 5 meters were used.

Even though the studies cannot be directly compared, since they are diverse from data acquisition to methods validation, the accuracy is predominantly high, ranging between 90% and 99%.

Reference (Year)	**Radar Type**	**Algorithm**	**Distance from Radar**	**Accuracy**
Wankhade at al. [2] (2022)	UWB	Fast Fourier Transform (FFT), Convolutional Neural Network (CNN), Random Forest (RF)	1.5 m, 3 m and 5 m	94.38% (two targets) and 73.33% (three targets)
Zhao at al. [3] (2021)	mmWave	FFT, Hungarian Algorithm, DBSCAN	-	99%
Li at al. [4] (2021)	FMCW	Trilateration Algorithm, Bidirectional LSTM (Bi-LSTM), Naive Bayes Combiner (NBC), RF	-	93%
Kang at al. [5] (2021)	Microwave Doppler radar	Levenberg–Marquadrt back propagation, CNN	1.5 m	90%
Hämäläinen at al. [6] (2021)	UWB	Trilateration Algorithm, Bi-LSTM, NBC	3.1 m to 4.3 m	99%
Islam at al. [7] (2020)	mmWave	Levenberg - Marquardt Back Propagation Algorithm, K-Nearest Neighbor (KNN), Support-Vector Machines (SVM)	-	95%

Table 2.1: Summary of the selected related works on Human identification, including information regarding Radar Type, Algorithm, Distance from Radar and Accuracy.

2.1.2 Detailed analysis of the articles

In this subsection, we provide detailed summaries of each article listed in Table 2.1, dedicating a unique subsubsection to each article.

2.1.2.1 Human tracking and identification through a millimeter wave radar

In this paper [3], a novel human tracking and identification system named mID is introduced, utilizing mmWave radar technology. This system addresses privacy concerns associated with visual tracking methods by using a non-intrusive radar approach. The mmWave radar, a single chip device operating in the 77-81 GHz band, is capable of penetrating thin materials, allowing it to be concealed in furniture or walls, thus enhancing user acceptance. mID generates sparse point clouds to create trajectories and employs a deep recurrent neural network for person identification, achieving an identification accuracy of 89% and intruder detection accuracy of 73% for 12 individuals. By extending observation time from 2 seconds to 7 seconds, identification accuracy increases to 99%. This research demonstrates the effectiveness of mmWave radar in accurately tracking and identifying individuals, providing a promising solution for non-intrusive identification in smart spaces.

2.1.2.2 Multiple Target Vital Sign Detection Using Ultra-Wideband Radar

This paper [2] introduces an advanced radar-based method for detecting multiple living beings through walls or under debris, overcoming the limitations of traditional single-target detection. Utilizing UWB radars, the method employs FFT for identifying the number of targets and their breathing frequencies. A novel aspect is the usage of a CNN for faster pre-processing and classification of the number of targets. The research demonstrates that combining CNN as a feature extractor with a RF classifier yields high accuracy rates: 94.38% for two targets and 73.33% for three targets, without needing pre-processing of radar data. This approach significantly reduces detection time compared to conventional algorithms and offers a reliable and efficient solution for vital sign detection in rescue operations, with the potential for future expansion to more targets and diverse wall structures.

2.1.2.3 Sequential Human Gait Classification With Distributed Radar Sensor Fusion

The paper [4] presents a study about the classification of human gait patterns and fall detection through the usage of a network of radar sensors, such as FMCW radar and three UWB pulse radars.

The research used different patterns of gait, individual and sequential, involving multiple walking styles. Different information fusion approaches are used in the study, operating at signal and decision levels. In signal-level fusion, a trilateration algorithm is implemented using range data from three UWB sensors, yielding good classification results with a Bi-LSTM neural network classifier without relying on micro-Doppler information. In decision-level fusion, the classification results of individual radars using the Bi-LSTM network are combined using a robust NBC, showing improvements compared to using a single radar. The dataset has 14 participants and 12 different walking styles, achieving overall classification accuracy of 93% and 90% for the two fusion approaches.

2.1.2.4 Identification of Human Motion Using Radar Sensor in an Indoor Environment

This paper [5] introduces an approach to continuous motion analysis by utilizing mmWave radar sensor data. The proposed technique addresses privacy concerns associated with camera-based sensors by capturing distinct patterns in human motion without requiring direct physical contact or line-of-sight.

Several experiments were conducted using a small radar sensor operating in the mmWave band with high-range resolution. The integration of the developed technique with camera sensors is intended for indoor movement detection and monitoring. This integration provides an excellent solution for identifying and tracking human motion in different environments. This work signifies an advancement in radar-based motion analysis, showing the potential for improved indoor monitoring.

2.1.2.5 Ultra-Wideband Radar-Based Indoor Activity Monitoring for Elderly Care

This paper [6] introduces a remote monitoring architecture designed for the seamless monitoring of elderly citizens in their homes, employing UWB radar as the primary sensing device. Using an experimental approach, the study shows the extraction of different kinds of movements (walking, falling), steady positions (standing, sitting,) and other things like breathing and coughing from the collected UWB radar data. The paper uses a k-nearest neighbor machine learning algorithm to automatically discriminate and classify static postures, achieving a classification accuracy exceeding 99%. The study was conducted with only one device per room, striking a balance between implementation cost and achieved detection accuracy.

2.1.2.6 Radar-Based Non-Contact Continuous Identity Authentication

The paper [7] explores the usage of microwave Doppler radar in continuous identity authentication, offering a non-contact, privacy-preserving alternative to traditional biometric methods. This technology captures unique physiological signatures without direct physical contact or line-of-sight, addressing privacy concerns from video-based sensors. It reviewed various studies employing Doppler radar for detecting individual-specific patterns in respiration and heart dynamics to demonstrate the importance of employing radar for continuous monitoring and authentication. The Doppler radar systems operate at frequencies that detect skin-surface motion (primarily), being able to discern subtle physiological movements caused by heartbeat, respiration, or arterial pulsation. The singularity of cardiopulmonary motion, influenced by individual physical characteristics and neural or chemical control, makes it a reliable marker for identity verification.

This technology's challenges and future potential are examined, particularly its application in diverse and practical settings, and the need for a more extensive dataset validation with different physiological states and activities. Integrating machine learning and big data analytics amplifies the effectiveness of radar-based authentication, potentially evolving how continuous identity verification is conducted in various domains.

2.2 Tools and Technologies

This section provides an overview of the technologies and frameworks selected for our project. We start with a brief introduction to radar technology and the types of radars available. Then, we discuss existing frameworks for multimodal interaction, which are essential for integrating our user identification modality with other modalities in smart environments.

2.2.1 Radars

From the articles [3], [5] and [7], we managed to gather the information below about radars.

Radars are systems that use radio waves to detect, locate, and track objects. The term "radar" stands for "radio detection and ranging". These systems play a crucial role in various applications, including military, aviation, weather monitoring, and traffic control. There are various types of radars, including pulse radar, continuous wave radar, and Frequency-Modulated Continuous Wave (FMCW) radar. The last one is the most notable example of our project.

The FMCW radar operates by emitting a continuous wave signal whose frequency varies in a known pattern over time. Upon encountering an object

- such as a person - this signal is partially reflected back towards the radar. The radar then measures the difference in frequency between the transmitted signal and the received signal. This difference, known as the frequency shift, is used to calculate the distance to the object based on the time it takes for the signal to return. Moreover, by analyzing the frequency shift over time, the radar can also determine the speed and direction of the object's movement.

The AWR1642 radar's advanced sensing capabilities will be instrumental in accurately identifying and tracking people within a given space. This radar technology offers precision and reliability, key factors in environments where real-time monitoring is crucial.

2.2.2 Multimodal Interaction Architectures and Frameworks

Multimodal Interaction Architectures and Frameworks are essential for navigating the intricacies of contemporary smart environments. These frameworks provide a distributed and modular solution, fostering seamless interaction among systems, devices, and sensors. Their core strength lies in adeptly supporting and integrating diverse communication methods, adapting to evolving contexts and user preferences.

These architectures facilitate the development of multimodal interactions, enabling users to engage with their environment through various channels like speech, gestures, or touch. They streamline the integration of different devices, dynamically managing them as they evolve. Designed to evolve with emerging technologies, these frameworks serve as versatile solutions for smart homes, buildings, and cities.

The AM4I framework ensures flexibility and seamless integration, essential for modern smart spaces. It allows various elements, such as sensors and interaction devices, to operate independently or in unison, creating a cohesive smart ecosystem. Notably, the AM4I architecture is designed to evolve with emerging technologies and interaction designs, making it future-proof.

Built on this architecture (Figure 2.1), the AM4I framework provides a practical approach for implementing multimodal interactive capabilities in smart environments. It manages various input and output modalities through an Interaction Manager equipped with Fusion and Fission services, offering an integrated user experience. Notably, the framework's multi-device capability supports a wide range of devices, from smartphones to environmental sensors, across different operating systems like iOS, Windows, Android, or Linux.

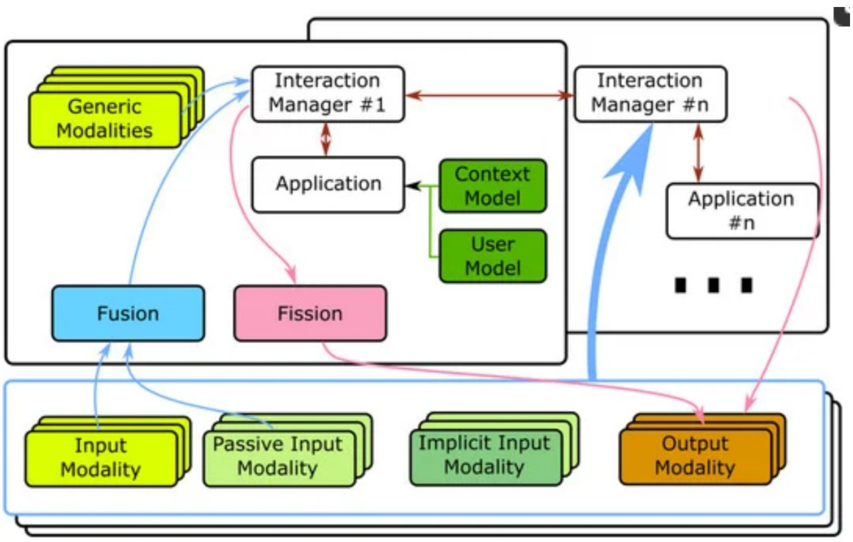

Figure 2.1: Main modules of a multimodal interactive architecture as provided by the AM4I framework. [8]

Chapter 3

Requirements Gathering

This chapter explores the methodologies used for gathering requirements. We adopted a user-centered design approach, analyzing a group of individuals primarily consisting of family and friends. Following this, we crafted personas based on the insights gathered from those reunions.

These personas were instrumental in developing scenarios to address each persona's specific challenges, using innovative ideas we conceived. Subsequently, we analyzed these scenarios to identify and extract the requirements that needed to be integrated into our system.

3.1 Personas and Scenarios

To help understand potential clients' needs, interests, and behaviors, we depicted various personas with diverse physical and psychological attributes, representing members of a typical family. The personas include a grandmother, a father, a mother, and a son.

Our primary objective is to gain a practical understanding of how the members of this family, with their unique personas, would use and interact with the system in real-life scenarios. By incorporating a variety of profiles and scenarios, we can extract this system's diverse requirements, making it more comprehensive and adaptable.

3.1.1 Personas

We aim to develop a system capable of catering to a broad range of individuals, encompassing diverse demographics and unique needs. By creating four personas representing a family, we can effectively address the varied requirements of potential users.

To define these four personas, we were inspired by discussions with individuals who possessed enough qualities to be considered target users. Our engagement ranged from colleagues to members of the families of those directly involved in the project. This approach ensured that, while adhering to our predefined criteria for potential customers, there remained a margin for differentiation based on various attributes, including age and other physical traits. The diverse user representation and personalized user experiences were vital in obtaining precise and well-articulated requirements.

Presented below are the personas that encapsulate our target users. Each persona includes a name, a detailed description highlighting the most relevant aspects of their lives, and their specific motivations for utilizing the proposed system.

Luísa

- Mrs. Luísa, an elderly woman, was born in a village in Guimarães, where she has lived her entire life without the advancements of technology. She stands out as an independent and persistent person who prefers to manage without assistance. However, due to her health issues, her son encouraged and convinced her to leave her home and move in with the family, where her physical condition could be better attended. The doctor recommends that she engage in physical exercise throughout the day. However, the doctor and the family doubt her compliance with the prescribed activities. Consequently, she was provided with a smartwatch to monitor and record her physical activities throughout the day. Due to her limited computer knowledge, Mrs. Luísa struggles to understand how to use the device and chooses not to use it.

- **Motivation:** As she is unable to record her daily progress through the recommended device, she seeks another method to track her activities. This way, she can demonstrate to her family and the doctor that she has fulfilled the prescribed requirements.

Ricardo

- Mr. Ricardo, the son of Mrs. Luísa, is an adult man who spends most of his day working as a teacher. He is known for being dedicated and cautious, preferring prevention instead of exposing himself to risks. Recently, Mr. Ricardo decided to entrust his son with the responsibility of carrying the house keys, a privilege that his son earned. However, despite this show of trust, Mr. Ricardo has some concerns. He worries about the potential for his son to misplace the keys, which could pose a risk to the entire family. This insecurity is causing him to reconsider the decision he made.

- **Motivation:** As he does not want to sadden his son, Mr. Ricardo is looking for a security system that allows him to distinguish his family from intruders. He seeks a solution that empowers him to react promptly to dangerous events, thereby reducing his concern about his family's safety.

Maria

- Mrs. Maria, the wife of Mr. Ricardo, is an adult woman who works as a preschool educator. She is known for being dedicated and patient, placing extreme importance on the happiness of children. Despite her passion for her profession, she considers it tiring sometimes, as children's energy is occasionally expressed through excessive noise and restlessness. She views her home as a refuge of comfort and tranquility. However, she is constantly bothered when entering her home after a day of work by the loud music played by her son.

- **Motivation:** As her son does not lower the volume of the music when Mrs. Maria arrives home, she wishes the volume could automatically decrease without causing discomfort upon entering her sanctuary.

Pedro

- Pedro, the young son of Mr. Ricardo and Mrs. Maria, is a high school student. He is characterized as forgetful and irresponsible despite his attempts to correct these traits. Recently, due to his parents' absence, who are busy with their professions, he was tasked with cooking dinner whenever he arrived home before them. However, due to habit and inconsistency in his parents' schedules, he often forgets to fulfill his duties.
- **Motivation:** As he does not want to disappoint his parents and maintain his bad habits, Pedro wishes to receive a notification whenever he does not stay in the kitchen for a short period, even when his parents are not home.

3.1.2 Scenarios

To illustrate the potential applications of our interaction system, we created specific scenarios for each family member. These situations showcase the various ways these family members can interact with our system, taking into account their unique characteristics and motivations, as detailed in subsection 3.1.1.

We used the scenarios to extract the system requirements, which are indicated within parentheses in the scenarios themselves. The complete list can be found in section 3.2.

3.1.2.1 Healthy Commitment

Mrs. Luísa, with a steadfast commitment to adhering to medical advice, has decided to investigate alternative methods for monitoring her physical activities at home. Upon discovering a sophisticated motion radar system designed for indoor environments, she recognizes the potential to track her movements without the need for a smartwatch. This radar efficiently identifies her activity patterns and systematically documents her daily efforts without the need for personal identification. As a result, it provides her with a reliable means to demonstrate to her family and physician that she is faithfully adhering to the prescribed exercise regimen, all without leaving her home. As an integral part of this experience, she can, for example, use a tablet after a week of using the system, automatically accessing the control panel to show her family how her physical activity has increased throughout the week (*FR1*, *FR4*).

3.1.2.2 Ensuring Security

Motivated by a deep concern for his family's safety, Mr. Ricardo chooses to install an intelligent home security system tailored for indoor use. Using a presence radar, he establishes a protected zone for his family. If the radar detects the presence of family members, it keeps the system in a deactivated state. However, if it identifies suspicious or unfamiliar movements, it autonomously triggers security protocols, notifying Mr. Ricardo and allowing him to promptly respond to any potential threat (*FR6*, *FR7*). This approach allows him to safeguard his family without infringing upon his son's privilege of carrying the house keys, thereby fostering contentment among all family members in light of this positive change (*FR1*, *FR3*, *FR4*).

3.1.2.3 Peaceful Home

Mrs. Maria consistently prioritizes a tranquil home environment and implements an intelligent volume control system inside her house. By installing a presence radar at the entrance, she configures the system to automatically lower the music volume upon her arrival (*FR4*, *FR5*). This refined solution allows her to enjoy personal comfort without the disturbance of excessive noise from her son. As a result, Mrs. Maria can maintain a peaceful atmosphere within her home, regardless of occasions when her son neglects to regulate the audio levels. This scenario emphasizes how personas, like Mrs. Maria, use and interact with the system to enhance their living environment (*FR1*, *FR2*, *FR3*).

3.1.2.4 Culinary Commitment

With an unwavering commitment to meet his parents' expectations, Pedro integrates an alert system into the kitchen. By installing a presence radar, he adeptly sets up notifications triggered if he fails to remain in the kitchen for a specified duration. If this timeframe expires without detecting his presence, the system promptly sends an alert to his mobile device, reminding him of his culinary duties (*FR2*, *FR3*, *FR5*). This thoughtful arrangement ensures that, even on days marked by erratic schedules, Pedro receives timely reminders to ensure a prepared dinner upon his parents' return home. This scenario illustrates how personas like Pedro use and interact with the system to enhance their daily routines within the household.

3.2 Requirements

Through the scenarios described in the section above, it was possible to establish an initial set of requirements that can guide us in the good development of the system by analyzing key user needs and performance criteria. Functional requirements refer to the actions that the system must be able to perform. Non-functional requirements refer to the characteristics and/or qualities that the system must present. Below, two tables present the Functional Requirements (FR) (Table 3.1) and Non-functional Requirements (NFR) (Table 3.2).

Functional Requirements	**Description**
FR1	Identify user movements.
FR2	Identify individuals at a designated location.
FR3	Detect the number of individuals in the environment.
FR4	Distinguish users based on their unique movement patterns.
FR5	Automatically adjust environment settings based on the user.
FR6	Activate security protocols when suspicious activity is detected.
FR7	Notify users of potential security threats.

Table 3.1: Functional requirements of the system.

Non-Functional Requirements	**Description**
NFR1	Non-intrusive system, requiring no changes to the user's routine and not capturing sensitive information (such as visual data).
NFR2	Reliable user identification (accuracy over 80 percent).
NFR3	Capable of handling increased data quantities.
NFR4	Easy maintenance and updates.
NFR5	Apply methods for data protection.

Table 3.2: Non-functional requirements of the system.

Chapter 4

Radar-Based System for User Identification

4.1 System Overview

Based on the objectives for this project and the system requirements, we have defined the architecture illustrated in Figure 4.1. The Dashboard is an essential component for demonstrating how the User ID modality can be used to adapt interaction with the smart home to the individual user. It allows each user to indicate their preferences for interaction, which are then stored in the database and used to tailor the system's output to the current user. The architecture comprises two main blocks: the User ID Modality and the Model Evaluation and Training. The remaining components indicated by dashed lines are not the primary focus of our project. They are included to illustrate how our solution could integrate with other smart environment solutions, leveraging the user identification modality within a smart house environment.

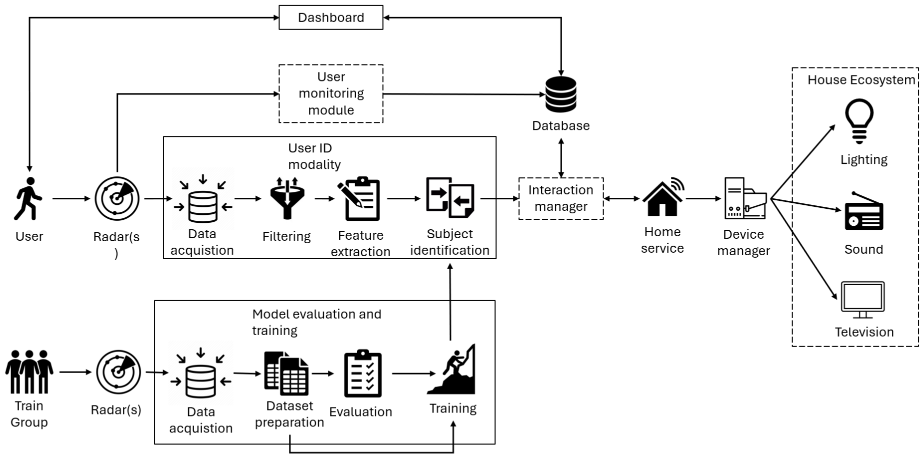

Figure 4.1: The architecture of the proposed system and its main blocks (boxes with full lines) as well as other blocks that can be implemented and integrated into the system (boxes with the dashed lines).

Our system begins with one or more radars that generate data utilized by the User ID modality for identifying users based on their movement or interactions with the system. This modality relies on a pre-trained model, which undergoes a phase involving model evaluation and the training of a final model. The output from the User ID modality is then transmitted through the Interaction Manager, instructing applications on actions to take based on user preferences.

The User ID modality is responsible for identifying the user using radar data. The Model Evaluation and Training block employs machine/transfer learning and appropriate validation approaches to train and assess models, with the best-performing model being selected for user identification. This process utilizes datasets obtained from offline radar data collected from a group of people.

The Dashboard, as a proof of concept, is a simple interface primarily consisting of text output. It is used for each user to indicate their preferences for interaction, which are stored in the database. The output is adapted to the current user according to the corresponding preferences. This includes customization options such as text color and size, which can be adjusted based on the user's needs. As depicted in Figure 4.1, the information from the User ID modality is employed by the Device Manager to instruct the Home Service in controlling the devices within the Smart House. The house's ecosystem, including smart devices, can be automated based on the information provided by our modality. For example, when a user enters a room, specific devices can be turned on or off according to the preferences predefined by that user.

4.2 Implementation

4.2.1 User Identification Modality

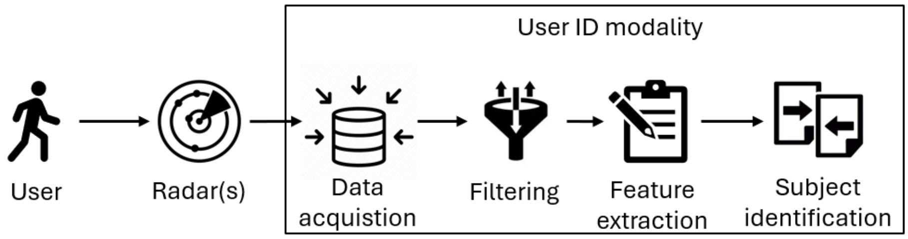

Figure 4.2: The User ID modality.

The User modality is the module set that makes the Real-Time Subject Identification. In Figure 4.2, there are five main components, whose implementation is described in more detail below:

- **Data acquisition** - Receives raw data from the radar.
- **Filtering** - Filters the acquired data using a sliding window.
- **Feature extraction** - Extracts features for each window of filtered data.
- **Subject Identification** - Uses a trained model to identify a user based on the extracted features.

4.2.1.1 Data Acquisition

We are using a AWR1642 mmWave Radar that captures and sends data in packets containing a header and Tag Length Values (TLV). These data are parsed to extract only the relevant information, which is then stored in JSON format for sending to the Filtering system.

The radar operates in three dimensions, providing the following information for each detected moving target:

- **X coordinate**
- **Y coordinate**
- **Z coordinate**
- **Doppler**

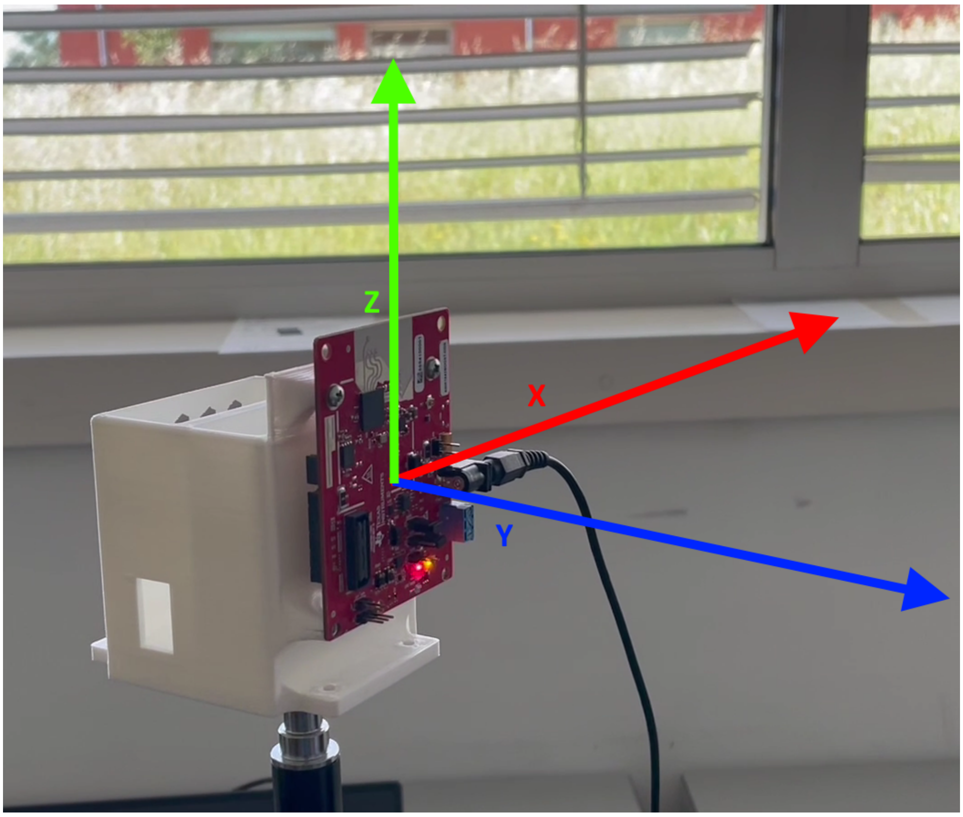

Figure 4.3: A photo of the radar with the axis of coordinates used

The 3D coordinates correspond to the target's position in each axis, considering a coordinate system centered on the radar.

Doppler indicates the movement rate towards or away from the radar, with a zero value indicating no movement.

The radar configuration is crucial as it allows fine-tuning parameters such as Frame Rate and Range Resolution. This configuration is sent to the radar at the start of online data acquisition. Our Data Acquisition module operates based on the configured Frame Rate and allows setting the data segment duration, which defines the interval at which data is sent. For instance, with a frame rate of 20 fps, data is collected and sent every 0.05 seconds, resulting in 20 samples/frames per second.

We get this configuration by using the "mmWave Demo Visualizer," a tool supplied by Texas Instruments. This tool allows us to modify various parameters such as Range Resolution (m), Maximum Unambiguous Range (m), Maximum Radial Velocity (m/s), and Radial Velocity Resolution (m/s). After configuring these parameters, we send the configuration to the radar.

4.2.1.2 Filtering

The Filtering Component receives raw or unfiltered data from the Data Acquisition module, filters it, and sends it to the next module, the Feature Extraction.

Radar data can contain noise and seemingly random data for several reasons. Simple changes in the environment, such as windows, objects, and people walking by (even behind walls), can introduce significant variability in the data. However, the acquired data should still capture easily detectable movements, whether very fast or very slow.

To filter the acquired data, we remove all data with a speed close to 1e-5 m/s or an absolute speed higher than 10 m/s. This filtering is crucial to eliminate noise and irrelevant data points. The thresholds were chosen based on default values provided in the filtering function, ensuring that only meaningful data is retained for analysis.

This component does not filter each data frame individually but utilizes a sliding window approach during the filtering process. The data is segmented into windows with a configurable size and overlap between consecutive windows. This module receives data segments every second, and these samples are combined to account for the sliding window size. By default, the sliding window size is set to two seconds, which means that two data segments are used. However, this size can be changed to any value.

The number of samples in each segment depends on the defined sampling rate, which is parsed from the configuration values sent with the data.

4.2.1.3 Feature Extraction

The Feature Extraction module receives filtered data from the Data Filtering component. From each window with filtered data, it extracts a feature that is used to create a grayscale image.

A feature consists of a grayscale image formed by vertically concatenating the matrices corresponding to Heat Maps of the X, Y, and Z axes coordinates and Doppler values over time.

Each pixel in the image represents a sample value, with shades of grey defining the amount of movement. For example, the whiter the pixel, the more movement that has occurred, and the darker the pixel, the less movement that has occurred.

An example of this is shown in Figure 4.4, where the movement of a person walking was performed with the generated Heat Maps and features.

Figure 4.4: Feature extracted from a subject walking the first trajectory

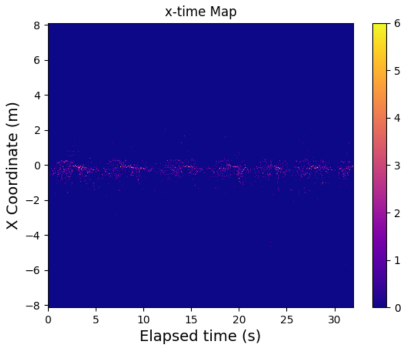

Figure 4.5: The heatmap of the X axis

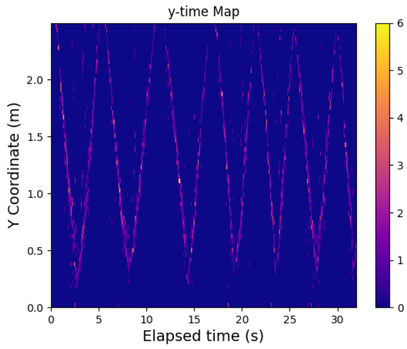

Figure 4.6: The heatmap of the Y axis

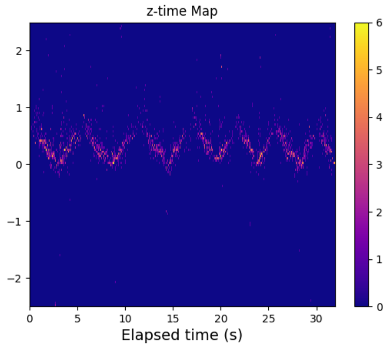

Figure 4.7: The heatmap of the Z axis

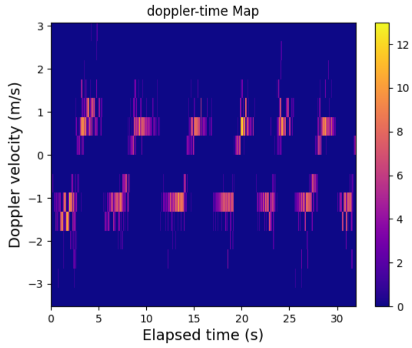

Figure 4.8: The heatmap of the Doppler data capture

4.2.1.4 Subject Identification

The Subject Identification module receives grayscale images and utilizes a pre-trained model to identify individuals. The feature extraction module processes and sends grayscale images to a designated directory. From this directory, the subject identification module retrieves the images and feeds them into the loaded model for classification. The model makes predictions about the image classes, and the balanced accuracy between the model's predictions and the actual classes is calculated. From the predictions, the module also analyzes the most recent predictions to determine the most common class.

4.2.2 Communication between modules

In the implementation of the online pipeline, the Message Queuing Telemetry Transport (MQTT) Mosquitto protocol was used to create communications between the modules, allowing the modules to be implemented on different devices (for this, it is necessary to change the "HOST" and "PORT" configuration settings of each module).

Before starting the communications between the modules, it is necessary to connect to an MQTT Broker Server, which will receive messages from publishers and deliver them to subscribers based on each subscriber's topic (in this case, the publishers and subscribers are the modules).

When starting communications, each module is defined with a unique topic, allowing message filtering among publishers and subscribers.

To demonstrate the functioning of the connections, we will provide an example of the connection between the Data Acquisition module and the Filtering module. First, we configure a connection to the MQTT Broker Server in the Filtering module with the topic "DF" and then start the connection to the server. At this point, the Filtering module is connected to the server as a subscriber and is waiting to receive messages with the topic "DF". When the Data Acquisition module finishes performing its function, it sends a message to the MQTT Broker Server containing the obtained data, with the message topic "DF". When the Filtering module receives the message, it executes a callback that filters the received data and upon completion, sends the data as a publisher to the Feature Extraction module with the respective message topic for that module.

4.3 Model Evaluation and Training

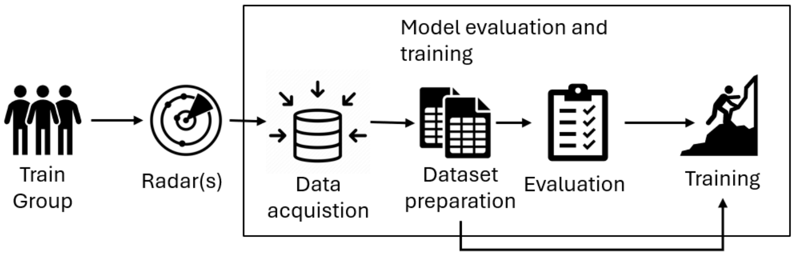

Figure 4.9: Model Evaluation modality

As explained above, to obtain the final model to be used in the ID modality, specifically in its Subject Identification component, it is necessary to perform a model evaluation to select the pre-trained model and the most suitable features to train the final model.

4.3.0.1 Offline Data Acquisition

In the most controlled environment possible, radar data was collected offline by recording the movements of multiple participants in a designated, obstacle-free area.

During the sessions, participants performed a variety of movements, such as walking straight and performing a symbol drawn on the floor, as instructed, to ensure a diverse dataset. Each session captured data points like position coordinates and velocity, which were saved in JSON format with timestamps and metadata for accurate later processing and alignment. Multiple sessions ensured comprehensive data collection.

4.3.0.2 Data Preparation

Data preparation for a radar-based ID system involves several steps to make the radar data usable for model training. First, the data is divided into overlapping segments using a sliding window technique, which helps capture continuous movement patterns. Next, the data is cleaned by filtering out noise and other unnecessary elements, improving the data's quality.

After cleaning, feature extraction is performed, where important characteristics such as location (X, Y, Z) and velocity (Doppler) are identified and extracted from the raw data. Finally, this processed data is ready to train the system's model.

4.3.0.3 Transfer Learning

We utilized Transfer Learning to leverage the pre-existing knowledge from an image classification model. This involves partially re-training a pre-trained model with our radar dataset. The chosen model, MobileNetV2, is adjusted by replacing its top layers with those specified according to our study's needs.

4.3.1 Pipeline

Several steps were followed to develop and train the subject identification model. First, there was a preparation of the dataset explained in subsection 4.2.1, which includes offline data collection, data filtering, and feature extraction. Next, the model evaluation was carried out (section 4.3) using one or more pre-trained models with features derived from the collected dataset. Finally, the trained model resulted in MobileNetV2. (section 5.3).

4.4 Dashboard

As a proof of concept, we developed a simple dashboard consisting primarily of text output. However, it allows users to specify their preferences for the text output modality. These preferences include customization options such as text color and size, which can be adjusted according to the user's needs and preferences.

The Dashboard receives the modality ID directly. In the prototype implementation, this communication is direct, but in future iterations, an interaction manager should manage it to streamline the process and enhance flexibility.

Depending on the ID received, certain characteristics of the text output modality, such as font color and size, are adjusted according to the identified user's specified preferences. This customization ensures the interface is accessible and tailored to individual user requirements.

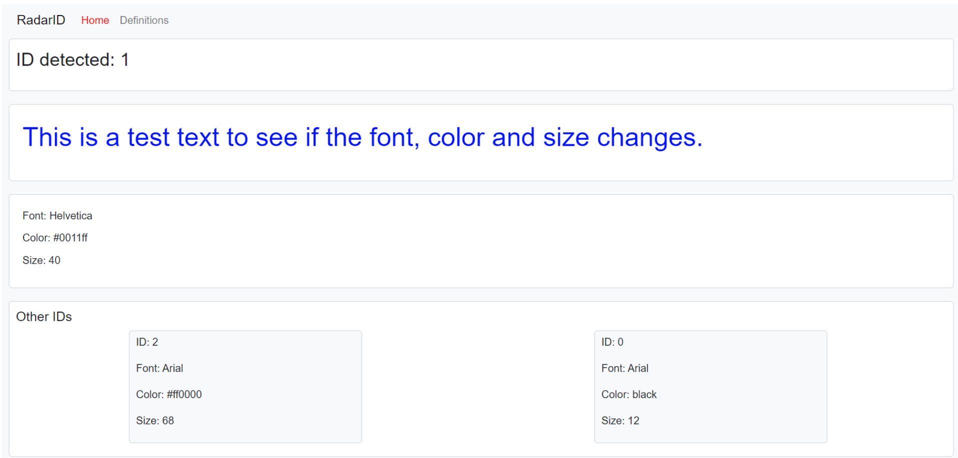

Figure 4.10: Simple interface done to show proof of our work

Chapter 5

Evaluation of the Model for Subject Identification

To integrate a model into our system, specifically for the ID modality, it is essential to first determine the best approach regarding features and the pre-trained model that yields optimal performance in person identification. To this end, we conducted two experiments described in the subsequent sections, detailing the setup and protocol used, the participants involved, the validation method employed, and the discussion of the results obtained.

To evaluate the capabilities of individual recognition, we performed two experiments. The first experiment was purely exploratory, aiming to understand and test the capabilities and possibilities of using radar to differentiate individuals in an indoor environment, as well as to familiarize ourselves with the technology used in the project. The second experiment focused on refining the model based on insights gained from the initial explorations. This phase adopted a more targeted approach, testing the radar's performance in simpler real-world scenarios, such as walking down a corridor. We aimed to determine if the radar could maintain high accuracy with a smaller, more controlled group of participants and limited movement trajectories.

In both experiments, we aimed to keep the environment as controlled as possible.

This chapter will provide an overview of how the model for subject identification was evaluated and, finally, the results of the tests conducted.

5.1 Setup

The experiment was conducted in a laboratory at Institute of Electronics and Informatics Engineering of Aveiro (IEETA), where the radar was positioned at a height of 1 meter from the ground. It was confirmed that no obstructions could interfere with the radar's field of view. The radar was centrally positioned relative to the area to be monitored, thus ensuring total coverage, as shown in Figure 5.2.

To define the radar configuration, save the configuration as a file for use in code, and verify that the ports used are correct, we used the application "mmWave Demo Visualizer" provided by Texas Instruments (Figure 5.1). This application allows us to configure parameters such as Frame Rate (fps), Range Resolution (m), Maximum Radial Velocity (m/s), Maximum Unambiguous Range (m) and Radial Velocity Resolution (m/s).

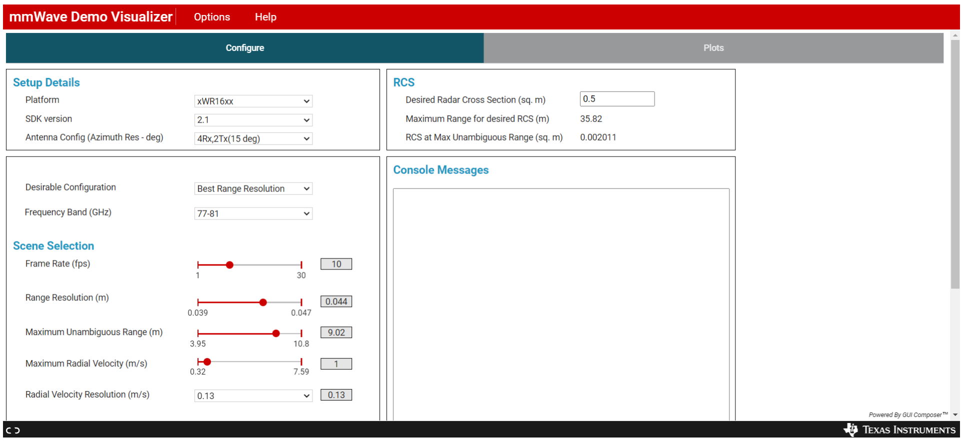

Figure 5.1: Application used to configure the parameters of the radar.

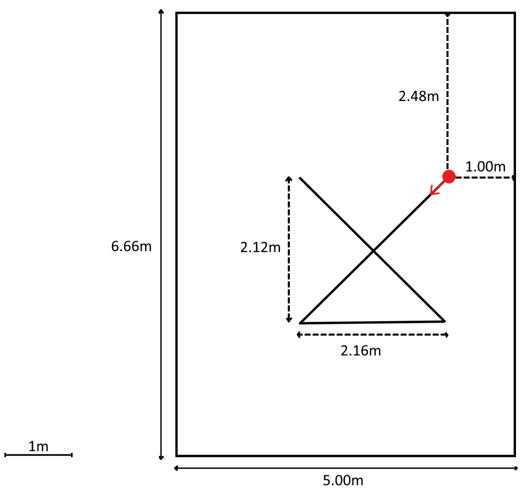

Figure 5.2: Room where the radar is located with the corresponding measurements and an arrow pointing according to the radar orientation.

5.2 Protocol and Participants

To obtain the dataset, we gathered participants and had them read and sign the informed consent form.

Afterward, we collected information about them, such as age, sex and height. We then explained the objective of our work and the tasks they would be performing. Each task was performed at a normal speed chosen by the participant, following a predetermined trajectory marked on the ground.

5.2.1 First Experiment

This initial experiment involved a group of seven individuals, all men aged between 20 and 21 years.

Before collecting the data, we considered various trajectories, all aligned with the radar's orientation. The ones we ended up using were:

- **Perpendicular trajectory**: Involved walking perpendicular to the radar's orientation (see Figure 5.3).
- **Mixed trajectory**: Involved walking perpendicular to the radar, followed by a 45º left rotation, then another 45º left rotation, ending in a Parallel trajectory to the radar (see Figure 5.4).
- **Parallel trajectory**: Required the participant to walk parallel to the radar's orientation (see Figure 5.5).

Each subject performed the three independent trajectories, which could be repeated if necessary. Two acquisition sessions were conducted for each person to ensure data accuracy and reliability. This approach provided a robust dataset for evaluating the radar's performance under different movement patterns.

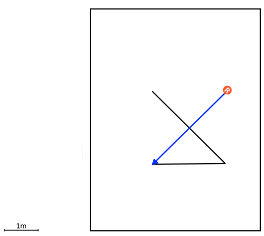

Figure 5.3: Perpendicular trajectory to radar.

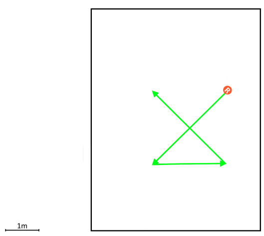

Figure 5.4: Mixed trajectory.

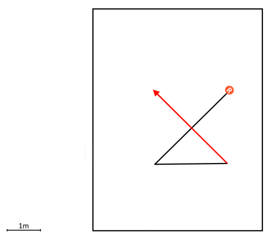

Figure 5.5: Parallel trajectory to radar.

In the figures, the radar's position is marked as the red point to indicate the reference point for the trajectories. The lines representing the trajectories are distinct to differentiate between the participants' various paths.

5.2.2 Second Experiment

This final experiment involved a group of two individuals, both men aged 20 and 21 years old. As in the first experiment, various trajectories were considered. However, based on the results obtained from the first experiment (subsection 5.5.2) using the three different trajectories, it was determined that we would only use the perpendicular trajectory. Therefore, we decided to focus exclusively on this trajectory. This decision was motivated by the recognition that the radar captures more comprehensive data when moving directly toward or away from it. Additionally, from a practical perspective, this setup is advantageous because the system can be used in a corridor, with the radar placed at the end of the corridor to identify individuals as they pass through. The trajectory considered is shown below:

- **Perpendicular trajectory**: Involves walking towards the radar's position and moving away from it, always maintaining a trajectory perpendicular to the radar, as shown in Figure 5.6.

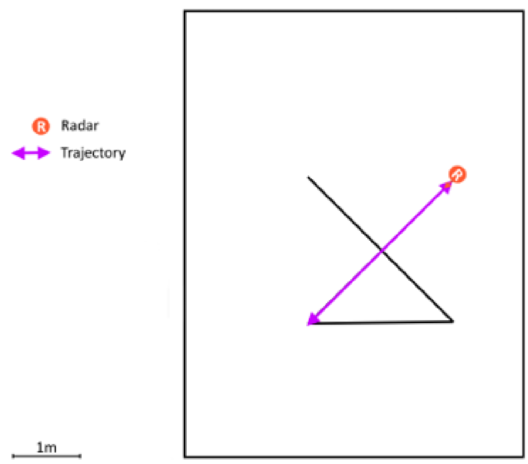

Figure 5.6: Perpendicular trajectory to radar.

During the second experiment, we tested various values concerning window size and overlap, as well as model training parameters in the User Identification Modality and model training. After extensive testing, we identified the value set that produced superior results. The values used were as follows:

- **Overlapping**: Indicates how much the data windows overlap with each other during processing. In the case of a value of 90, it means that 90% overlap is being applied, implying that 90% of the data from one window is included in the next window.

- **Window Size**: Refers to the size of the data window used for processing. In this case, a window of 2 seconds is being used to analyze the data.
- **Min-Delta**: 0.01
- **Hidden Neurons**: Indicates the number of neurons in the hidden layer of a neural network. In this case, a value of 256 is being used.
- **Patience**: 8
- **Dropout Rate**: None

These parameters were crucial in determining the behavior and effectiveness of the model in analyzing and processing the data during the final experiment.

5.3 Pre-Trained Model

Regarding model training, we used Transfer Learning. This technique involves using a pre-trained image classification model and retraining its final layers with our dataset, which was obtained by extracting features from collected radar data. Transfer Learning allows us to leverage the knowledge the pre-trained model has already acquired from large image datasets, saving time and computational resources. So, we explored the pre-trained MobileNetV2 model.

MobileNetV2, developed by Google, is a convolutional neural network architecture tailored for mobile and embedded vision applications that require efficiency and speed. It is designed to work exceptionally well on devices like smartphones and IoT devices, which often lack extensive computational power.

The architecture cleverly uses inverted residuals and depthwise separable convolutions, significantly reducing the number of parameters and computational complexity. This allows for fast processing without sacrificing accuracy. Additionally, pointwise convolutions transform features to generate the final output, maintaining a balance between performance and resource use.

A standout feature of MobileNetV2 is its incorporation of linear bottlenecks and shortcut connections. These elements are crucial for enhancing the model's ability to learn from data and generalize well to new, unseen datasets. The use of ReLU6 activation functions ensures numerical stability, further boosting the model's efficiency.

The real advantage of MobileNetV2 lies in its ability to handle real-time processing of mmWave radar data efficiently. This capability makes it a perfect fit for small projects, where it delivers high accuracy without straining the limited resources of mobile and embedded devices.

5.4 Evaluation Approach

5.4.1 First Experiment

To evaluate each model's effectiveness, we employed a method known as stratified 10-fold cross-validation. This technique is crucial for preventing overfitting and providing a reliable estimate of model performance. In stratified cross-validation, the dataset is systematically divided into ten distinct subsets.

For each iteration of cross-validation, the dataset is partitioned into training (80%), validation (10%), and test (10%) segments. Each fold uses a different subset as the test set, while the remaining data forms the training and validation sets. This ensures that every part of the dataset is used for training and testing across the ten folds. Stratification within each fold guarantees a balanced representation of each subject ID—thereby enhancing the consistency and reliability of the test results.

Concerning model training, the top layers of the pre-trained model were replaced by those indicated in Figure 5.7. Other relevant parameters are included in the same figure.

Model training parameters	
Trained layers	Single fully connected layer with 256 neurons (ReLU activation function) & output layer with 5 neurons (ReLU activation function)
Otimizer	ADAM (default parameters)
Loss function	Crossentropy
Metric for evaluation during training and validation	Accuracy
Early stopping criteria	Validation loss decrease $\leq$0.1 for 5 consecutive epochs

Figure 5.7: Model training parameters.

Finally, to evaluate the performance of our models, we used two metrics: Balanced Accuracy and Weighted Average F1 Score. Balanced Accuracy is a version of accuracy that considers class imbalance, providing a fairer view of the model's performance when classes are imbalanced. The Balanced Accuracy is calculated as follows:

$$\text{Balanced Accuracy} = \frac{1}{N}\sum_{i=1}^{N}\frac{TP_i}{TP_i + FN_i} \tag{5.1}$$

where:

- N is the number of classes.
- TP_i is the number of true positives for class i.
- FN_i is the number of false negatives for class i.

The Weighted Average F1 Score is a weighted average of the F1 Scores of each class, which considers both the precision and recall of the model, providing a more comprehensive view of its performance. The Weighted Average F1 Score is calculated as follows:

$$F1_{\text{weighted}} = \frac{\sum_{i=1}^{N} \text{support}i \times F1_i}{\sum i = 1^N \text{support}_i} \tag{5.2}$$

where:

- N is the number of classes.
- support_i is the number of true instances for class i.
- $F1_i$ is the F1 score for class i.

To ensure clarity regarding the formulas used for Balanced Accuracy and Weighted Average F1 Score, we utilized the scikit-learn package.

5.4.2 Second Experiment

In our second experiment, we initially used cross-validation to ensure that only the best-performing models were selected for further testing. This approach allowed us to efficiently screen models based on their performance metrics before advancing them to the following evaluation stage on a larger dataset.

Subsequently, we tested the selected models on a completely new dataset significantly larger than the subset used in the cross-validation phase. This new dataset comprised data collected from the same subjects performing identical trajectories but recorded at different times to introduce variability. The purpose of this approach was dual: first, to leverage the rigor of cross-validation for initial model validation and refinement; second, to evaluate how well the model could generalize and perform under conditions that closely mimic real-world operational scenarios.

This staged testing methodology allowed us to optimize our resources by focusing extensive testing efforts on models that had already demonstrated a baseline level of efficacy in the preliminary cross-validation phase.

5.5 Results

This section presents the datasets obtained during the Data Preparation step of the offline pipeline for each experiment. It also discusses the results obtained with these datasets using the evaluation approach described in section 5.4 and briefly discusses these results.

5.5.1 Datasets

Since the trajectories varied and each subject walked at their own pace, the dataset corresponding to each subject and capture session produced different amounts of features. Table 5.1 displays these values:

Table 5.1: Number of Features per Trajectory and Subject, with corresponding Mean and Standard Deviation Values.

Subject	**Traj. 1**	**Traj. 2**	**Traj. 3**	**Total**	**Mean(subj)**	**SD(subj)**
Subject 1	35	102	39	176	59	37
Subject 2	27	84	34	145	48	30
Subject 3	25	89	33	147	49	34
Subject 4	34	93	32	159	53	34
Subject 5	42	118	44	204	68	40
Subject 6	41	99	37	177	59	34
Subject 7	44	106	41	191	64	37
Total	248	691	260	1199	171	244
Mean	35	99	37	171		
SD	7	11	4			

5.5.2 Results of the First Experiment

The Figure 5.8 represents the F1 score for each trajectory and the overall F1 score for all trajectories combined, based on data from seven subjects. We can see that the median value for Trajectory 1 is 88%, for Trajectory 2 is 78%, for Trajectory 3 is 81%, and for all three trajectories combined is 81%. This combination value makes sense as it represents a balance of the three individual trajectories. Trajectory 1 shows the best values because the radar detects movements better when perpendicular to the radar (along the Y-axis). This enhanced detection capability leads to higher F1 scores for Trajectory 1.

The distribution of F1 score values for each one of the seven subjects (ID01 to ID07) is illustrated in Figure 5.9. It can be observed that the median F1 score values for all subjects are consistently above 75%, indicating good overall model performance. However, there are notable variations among subjects, with medians ranging from approximately 78% to 88%. The

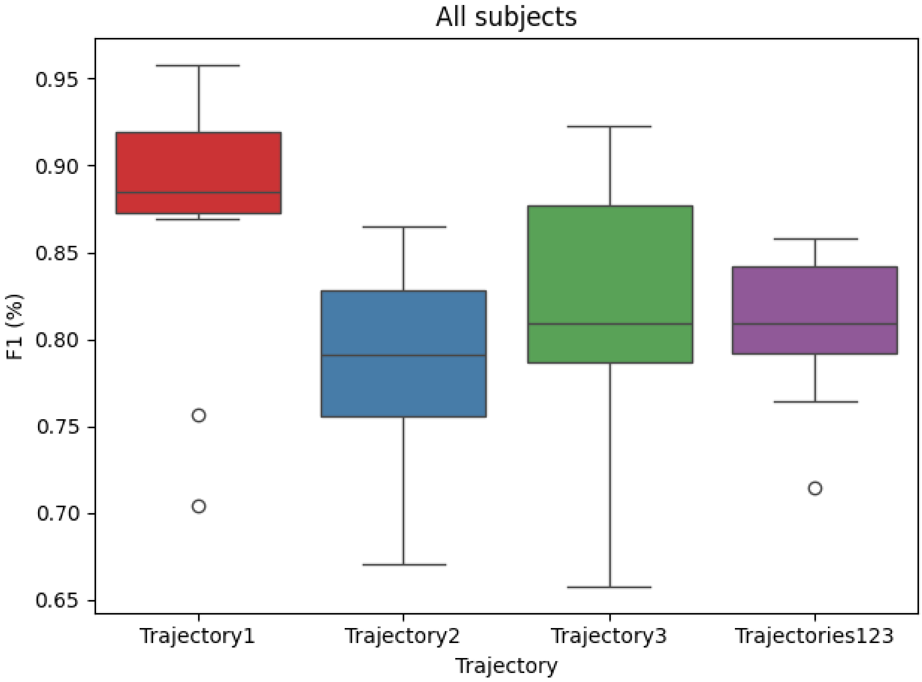

Figure 5.8: F1 score for each of the three trajectories from the initial experiment.

variability within the F1 score values also differs among subjects, with some showing a wider distribution, which can be attributed to differences in execution or radar sensitivity. This behavior indicates that, although the model has robust performance overall, it could benefit from further adjustments to better handle individual variability among subjects.

To better understand if some individuals were more accessible to identify than others, we analyzed the results separately for each ID, considering only the complete case with all three trajectories combined.

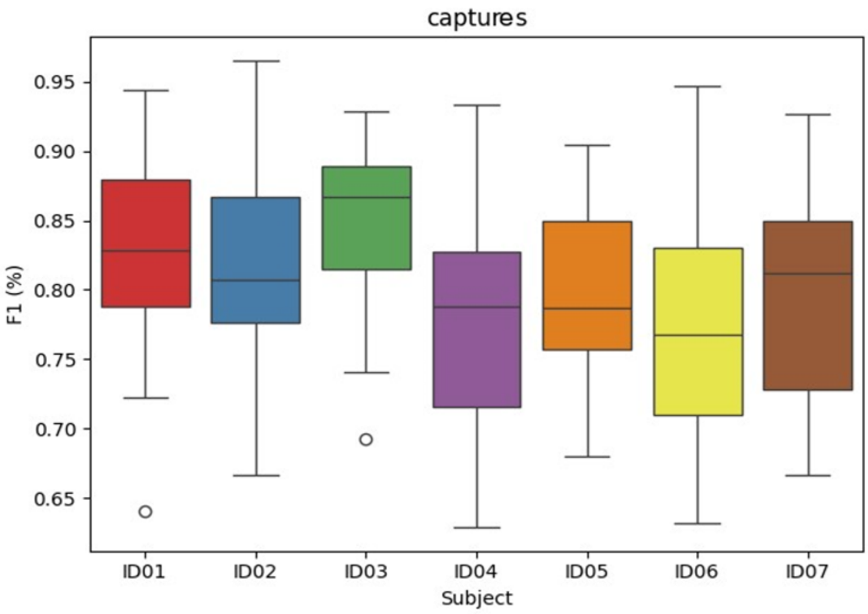

Figure 5.9: Boxplot depicting the F1 scores obtained by the model evaluated during the initial experiment for the three different trajectories considered.

After detailed analysis and discussion, we identified two main factors contributing to these values. Firstly, radar technology is susceptible to noise and reflections, complicating our recording environment. Despite the filtering done by the Filtering module (subsubsection 4.2.1.2), several data points went unnoticed. The presence of multiple people and windows in the room exacerbated this sensitivity. Secondly, our dataset was relatively limited despite our attempts to mitigate this issue through data augmentation.

To evaluate the model's effectiveness, we specifically measured the accuracy of each subject ID across the different trajectories. Accuracy refers to the model's ability to determine which gray-scale image corresponds to which class correctly. The accuracy results can be seen in Figure 5.10:

	ID01	ID02	ID03	ID04	ID05	ID06	ID07
Accuracy	25%	23%	13%	22%	31%	19%	20%

Figure 5.10: Accuracy values for each one of the 7 subjects.

The results obtained were significantly lower than anticipated, deviating from the expected performance of the model based on the metrics from the training dataset. We observed accuracy rates ranging from 13% to 31% for each subject. Despite these lower-than-expected results, it is noteworthy that, except ID03, all other subjects achieved accuracy percentages above the random baseline accuracy of 14%. This indicates that the model still performed better than random chance, suggesting some level of learning and pattern recognition capability. With these results in mind, we decided to revise and simplify our approach by reducing the number of participants. This is because the more participants we have, the more data we need from each one to differentiate them effectively.

5.5.3 Results of the Second Experiment

We calculated the F1 scores for both subjects performing the perpendicular trajectory. As shown in Figure 1, both subjects achieved scores with a median close to 90%, confirming that the perpendicular trajectory yields the best results.

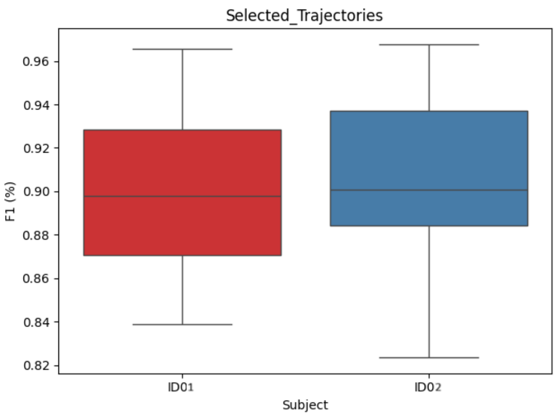

Figure 5.11: F1 Scores for two subjects using one trajectory

We then proceeded to evaluate the real-time results. Using a configured window size of 1 second with a 90% overlap, we achieved accuracy values that closely matched the F1 scores. Figure 5.12 shows the accuracy values for each subject.

	ID01	ID02
Accuracy	86%	89%

Figure 5.12: Accuracy values for each one of the 2 subjects.

Based on these results, we decided to develop the final model for the prototype using data from only two subjects. This allowed us to create a proof-of-concept demonstration, integrating it with the implemented dashboard for user interaction adaptation. We then attempted to scale the model to recognize three subjects. However, despite the model correctly identifying the subjects most of the time, we observed a significant increase in inconsistency. Given the time constraints and the lack of opportunity for further testing and refinement, we decided to maintain the two-subject setup.

Chapter 6

Conclusion

6.1 Conclusions

In this project, we proposed a novel modality for user identification in multimodal interactive environments by leveraging a radar sensor. To achieve this, we employed a User-Centered Design approach, ensuring our solution was thoughtfully created to meet the specific needs and preferences of our users. By adhering to this methodology, we successfully retrieved detailed personas and subsequently constructed realistic scenarios to illustrate how these personas would interact with our product in various contexts. This process enabled us to identify and prioritize key requirements, which were essential for devising and implementing a methodology to collect data and train a model for individual recognition.

Once trained with a substantial dataset, this model served as the foundation for the user identification modality, recognizing patterns intrinsic to a subject and thereby achieving the capability of identifying individuals. This allowed the implementation of a demonstrator, which includes a simple interface with text output that adapts to the current user according to their previously defined preferences.

The advances made through this project provide significant insights into the potential of the technology for further exploration in user identification. We posit that the system can be viable in real-world environments, particularly in smart home environments where the number of subjects is low and stable. These settings increase the potential for retraining the subject identification model, which would substantially enhance the precision of the model.

However, the initial objectives also included the investigation of free trajectory movements, which was not prioritized since the primary goal was to enhance the reliability of subject identification. This focus led to an average precision rate of between 78% and 88% for the seven-subject scenario, depending on the types of trajectories, and an average precision rate of 88%

was achieved for the two-subject scenario with one trajectory. By exploring free trajectory movements, the solution could be applied to a broader range of settings beyond specific locations such as corridors or alleys.

6.2 Future Work

In light of the technology's potential and our vision for further development, future research should focus on several key areas to enhance the system's effectiveness.

A more extensive dataset would improve the diversity of captures, enabling the model to classify previously unseen data. Incorporating retraining techniques would also allow the model to adapt to new data over time, possibly adjusting to a subject's physical changes.

Furthermore, implementing multiple radars positioned in varied locations would significantly improve the system's capacity to capture comprehensive data about the subject's movement.

Currently, the system relies primarily on Cartesian coordinates (three dimensions) and Doppler velocity. Incorporating additional features, such as micro-Doppler signatures, range profiles, and other advanced signal processing techniques, could significantly enhance the model's performance.

Investigating these enhancements within our project would improve the identification model's accuracy and thereby broaden its range of applications.

Chapter 7

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