Radar-Based Activity Recognition in Smart Environments

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Glossary

FMCW	Frequency-Modulated Continuous Wave
mmWave	Millimeter Wave
CNN	Convolutional Neural Network
FFT	Fast Fourier Transform
UWB	Ultra-Wideband
HAR	human activity recognition
DVCNN	dual-view convolutional neural network
DSP	digital signal processor
CW	Continnous Wave
MLA	Machine Learning Algorithms
ML	Machine Learning
NLP	Natural Language Processing
LSTM	Long Short-Term Memory
AI	Artificial Intelligence
RS	ResNet
HID	Human Interaction Devices

Abstract

With the rise of an aging population and older individuals living in isolation, there has been an increased search for at home monitoring systems. However, the solutions for this problem raise quite a few privacy concerns regarding data captured from users. In this project, we investigate ways to solve this issue in the least intrusive way possible. To achieve this, we aim to create a system that monitors the activity of a person with the use of radars (to be the least intrusive possible) and categorize these activities with the use of machine learning. The information gathered with this process will then be used to extract relevant information to the user. In this report we have thought of personas based on the expected users of our system, thought of scenarios where those personas would benefit from using our it and from there extracted our systems requirements. Finally, from the analysis of these requirements, we have created the first draft of our systems architecture.

CHAPTER 1

Introduction

1.1 Context

In recent years, there has been a notable increase in the number of older individuals living in isolation or vulnerable conditions. Some articles have been published that highlight this issue. On November 3rd, 2022, Lusa had an article published in Publico[1] about how 44,500 older people are living in isolation or vulnerable conditions. There was additionally another Lusa story, now appearing in Expresso[2] on September 17th, 2024, which reported an increase in the number of older population living alone in 2021.

This raised awareness about the growth of this issue. Older adults' mental health and well-being are being neglected because of physical isolation but also by feelings of exclusion and lack of community integration. Insufficient support can lead to a lower quality of life for this age group.

Moreover, the needs of the aging population are being reevaluated due to the demographic evolution and the emerging concept of active aging. Active aging itself promotes the improvement in life quality throughout aging and promotes that this stage can involve ongoing development through social, mental, and physical activity. So, encouraging healthy lifestyles and promoting socialization becomes crucial for enhancing older adults' life quality.

Technological advancements, such as smart homes, are a significant factor that can play a significant role in allowing aging people to live independently in their own homes for longer, potentially delaying or reducing the need for institutional care. The demand for this kind of product has been increasing, not only among the older population, but whole regular families are a good part of this new and increasing demand. [3] All the above is expected to raise demand for and adoption of smart homes, making them a more relevant solution. In this way improving the well-being of people of all ages.

1.2 Motivation

Many of the older population support services currently in place have serious drawbacks. For example, services like nursing homes and day centers are usually too expensive and out of reach for a large percentage of the population. So, we can conclude that current solutions have not been enough, despite the increasing need to address this issue.

These factors highlight the clear need for a new approach to care strategies for the older population. It is critical to create solutions that meet the physical and emotional needs of the aging population while also encouraging independence, social inclusion, and healthy lifestyles. A new approach must therefore take healthy and active aging as a starting point, supplementing practices that promote overall well-being with tailored strategies that provide physical, mental, and social support.

1.3 Challenges

A significant challenge in home monitoring systems is creating less intrusive solutions, and respecting individuals' privacy and comfort while still supporting and promoting their well-being. Some other approaches often compromise on these aspects: for example, camera-based systems can feel invasive, violating the sense of privacy, while wearable devices like watches or wristbands may create a constant feeling of being monitored and even physical discomfort.

Furthermore, designing intuitive and accessible interfaces, particularly for older users, requires special attention. Many current solutions fail to adequately address this demographic's specific needs, limiting adoption and usability.

Finally, accurately distinguishing between various daily activities is essential for identifying routines and detecting any unusual or concerning patterns.

1.4 Objectives

With this project, we aim to create a system that will monitor the daily activities of an older person in their own home throughout the day.

To achieve this main goal we will need to keep in mind the following objectives:

- The system will be able to capture the movements being performed by the subject and then categorize them.
- The system will be able to store the data collected and, from it, extrapolate information relevant to the user
- After capturing, analyzing, and identifying the actions, the system will then be able to present the processed data to the user simply and intuitively.
- The system will perform all of its functions while being the least intrusive possible, by relying on minimally intrusive devices, avoiding the capture of unnecessary data, such as image or audio.

The use of this system will aid caretakers and family members in monitoring the physical activities of people with less mobility, helping them improve this aspect of their daily lives. This improvement in physical activity will, hopefully, lead to an overall improvement in quality of life and autonomy.

CHAPTER 2

State of the Art

In this section, we will go over the research we have done on the state of the art when it comes to the context of our project. We have read and reviewed some articles on previous work done in radar-based activity recognition, which we then wrote a comprehensive summary of. We also present the research we have done on the various technologies relevant to our project, namely the different types of radars, machine learning algorithms, and system development tools.

2.1 Related Work

We reviewed prior studies and advances related to radar-based activity recognition systems to contextualize the current research within the broader field by highlighting relevant methodologies, technologies, and findings from past research. By analyzing existing approaches, such as the use of Ultra-Wideband (UWB) and Millimeter Wave (mmWave) radars alongside machine learning models, this section identifies the strengths and limitations of previous efforts, providing a foundation for understanding how the current project can build on diverge from established methods.
To aid our research, we opted to use Google Scholar as a way to find a diverse number of articles and studies related to our project. Then, to select which articles were more relevant to our work we filtered them using keywords we thought considered relevant as well as selecting only articles published in the previous five years.

Table 2.1 and Table 2.2 Shows a summary of these studies, highlighting .

Table 2.1: Technical details of radar-based human activity recognition studies.

Name	Year	Keywords	Sensor	Algorithms
Recognizing Activities of Daily Living from UWB Radars and Deep Learning[4]	2020	Activities, UWB radar Recognition	Ultra-wideband (UWB) radars	Stacked Long Short-Term Memory, Convolutional Neural Network combined with a Stacked LSTM network and a Residual Net86 work
Patient Activity Recognition Using Radar Sensors and Machine Learning [5]	2020	Radar, Activity recognition, Machine Learning	Millimeter wave radars (mmWave)	Convolutional neural network, Range-Doppler maps, Micro-Doppler maps
Vid2Doppler: Synthesizing Doppler Radar Data for Privacy-Preserving Activity Recognition [6]	2021	Radar, Privacy, Activity recognition	Millimeter wave radar (mmWave), AWR1642	VGG-16-based convolutional neural network
Noninvasive Human Activity Recognition Using Millimeter-Wave Radar [7]	2022	Radar, Activity recognition	Millimeter wave radar (mmWave), IWR6843ISK-ODS	Dual-view convolutional neural network (DVCNN)
Exploration of Self-Learning Radar-based Applications for Activity Recognition and Mental Health Monitoring [8]	2023	FMCW, Radar Based Activity Recognition, Exercise Detection, Active Aging	mmWave radar BGT60TR13C	MAML (Model-Agnostic Meta-Learning)

Table 2.2: Performance and participant-specific details of radar-based human activity recognition studies.

Name	**Accuracy**	**Number of Participants**	**Target Audience (Elderly)**	**Activities Detected**	**Singular Person (Y)**
Recognizing Activities of Daily Living from UWB Radars and Deep Learning	90%	10	X	Daily tasks (drinking, sleeping, cooking, brushing teeth, etc.)	Y
Patient Activity Recognition Using Radar Sensors and Machine Learning	73%*	9	X	Stand up, sit down, lie down, fall, get up	Y
Vid2Doppler: Synthesizing Doppler Radar Data for Privacy-Preserving Activity Recognition	95.90%	10	X	Walking, cleaning, jumping, lunges, cycling	Y
Noninvasive Human Activity Recognition Using Millimeter-Wave Radar	98%/97.61%*	4	X	Walking, sitting, standing, lying down, falling	Y
Exploration of Self-Learning Radar-based Applications for Activity Recognition and Mental Health Monitoring	Above 90%	24	X	N/A	N/A

As shown in Table 2.1 and Table 2.2, we focused our research on mmWave radars, as it is the type of radar our project will be using.

From the articles we reviewed, we came to several conclusions regarding activity recognition systems. The activities captured were usually in line with what we had initially planned for our system, mostly walking, sitting down, and falling, with only a couple of extra activities in some of the studies. In these studies, the system managed to correctly identify the activity most of the time, four of the five studies displayed an accuracy of over 90%. We also found that the most common machine learning algorithm among all the studies was the Convolutional Neural Network (a deep learning algorithm), appearing in three of the five studies we selected. Finally, in all studies we reviewed, only one person was captured at the time and, unfortunately, we could not find any relevant studies involving older people.

In the following subsections, we will go over each article chosen in more detail, highlighting the most important parts of each one.

2.1.1 Noninvasive Human Activity Recognition Using Millimeter-Wave Radar

In this paper, the team presents a noninvasive human activity recognition (HAR) system using mmWave. Their system converts the radar's signals into point clouds (sets of coordinates in a 3d environment) and processes them using a machine learning module, more specifically a dual-view convolutional neural network (DVCNN). The system was tested with the aid of 4 volunteers across different environments, with each person being tested for 10 minutes. The system managed to detect falls with up to 98% accuracy and other activities with up to 97.61%.

2.1.2 Recognizing Activities of Daily Living from UWB Radars and Deep Learning

This study presents a novel approach to recognizing daily activities using UWB radars and deep learning models. By employing three radars within a realistic apartment setting, they simplify the task of activity recognition by focusing on a single sensor type, and it reduces the complexity and enhances privacy compared to multi-sensor solutions. The system can distinguish 15 activities with a classification accuracy exceeding 90%, utilizing a combination of three deep learning models (Stacked Long Short-Term Memory (LSTM), Convolutional Neural Network (CNN)-LSTM, and ResNet (RS)) and a voting system to optimize performance

These approaches apply machine learning models, especially deep learning, to boost the accuracy of activity recognition by processing complex sensor data and capturing temporal patterns.

2.1.3 Vid2Doppler: Synthesizing Doppler Radar Data from Videos for Training Privacy-Preserving Activity Recognition

This study focuses on generating data (through Doppler radar datasets) of human activities to train HAR models. The motivation behind this study is the fact that radar is one of the least intrusive technologies for human activity recognition, however, unlike the more intrusive audio and video, the data needed to train these systems is not abundantly available. The team used an AWR1642 radar to capture their data and a VGG-16-based CNN to test its quality. The study found that the system could identify real-world activities with up to 90.2% accuracy but synthetic ones with only up to 81.4%. This work is an important stepping stone to make these kinds of systems more commercially available.

2.1.4 Patient activity recognition using radar sensors and machine learning

In this paper, the team explored solutions to capture human activities using minimally intrusive systems. To achieve this, they set up Frequency-Modulated Continuous Wave (FMCW) radar sensors to capture the activities of the subjects. A total of 9 adult subjects were present in this study, however, the test was conducted with only one subject being monitored at a time.

The test took place in two different environments: a synthetic hospital room (a controlled environment, with controlled furniture and lighting) and a real hospital room (a room where those factors vary). Furthermore, the actions were captured with the subjects using a variety of mobility aids, such as walkers and canes. The study also focuses on the models used to map the data obtained by the radar sensor, two different models were used: a Micro-Doppler model and a Range-Doppler model.

The Micro-Doppler model emphasizes motion-related information, like speed, so it proved more efficient for recognizing activities based on motion patterns. The Range-Doppler model on the other hand emphasizes the spatial positioning of the subject, making it more suitable to detect smaller, more localized motions.

Overall, the Micro-Doppler model outperformed the Range-Doppler model in the real hospital room, obtaining 73% accuracy at best, while the latter obtained only 66%.

2.1.5 Exploration of Self-Learning Radar-based Applications for Activity recognition and Mental Health Monitoring

This paper looks into the use of Machine Learning (ML) in radar applications to monitor health and recognize activity. The radar sensor used is a mmWave device. This sensor detects and monitors human activities and vital signs without the need for contact, making itself look less intrusive.

This study focuses on using few-shot learning algorithms, such as Model-Agnostic Meta-Learning to help overcome challenges with few accessible data. This approach allows the models to quickly adapt to new contexts and scenarios, resulting in reliable and precise performance even with limited training data. Potentials investigated, include hand gesture recognition, people counting, and respiratory signal monitoring. For example, finger actions of swiping, pulling, and pushing were correctly identified, as well as monitoring human respiration for reliable assessment of breathing rates.

The thesis brings very relevant results. Accuracy levels above 90% for the key tasks demonstrate, how useful a radar-based solution is in various real-world scenarios.

2.2 Tools and Technologies

This section focuses on outlining the technologies and tools that already exist and also that are important in the scope of our project development. In order to build the system as efficiently as possible, we will dive into what radars already exist and also into the data processing, storage, and display technologies that are relevant for the front-end and back-end. Additionally, we will also go over basic machine learning concepts specifically some algorithms related to the classification of tasks and other subfields of machine learning.

2.2.1 Radars

Radar, which stands for radio detection and ranging, is a technology essential for non-invasive activity recognition within smart environments. It detects and locates objects by sending out radio waves and analyzing the echoes that bounce back. By measuring these echoes, we can tell the distance, speed, and direction of the objects, making it incredibly useful for our study case.

In the spectrum of radar types, we will give more attention to the Continnous Wave (CW) radar and the FMCW radar.

The main aspect of CW radar is that it sends out a constant-frequency signal, which is great for measuring the velocity of moving objects by analyzing the Doppler shift (how the frequency changes as an object moves). The major limitation of these types of radars is that they can't measure the distance to an object because they don't capture timing information.

This is where FMCW radar comes in, because, unlike the CW radar, they can modulate or change the frequency of the transmitted signal over time and by comparing the frequency of the signal it sends with the frequency of the echo it receives, we can calculate both the distance and the velocity of objects. So the ability to measure both range and speed makes FMCW radar especially useful for precise activity recognition in smart environments.

AWR & IWR

Among the vast range of FMCW models that exist the AWR1642 and IWR6843 from Texas Instruments are leading solutions and each provides advanced detection capabilities and reliable performance.

The AWR1642 radar sensor stands out in automotive environments enabling reliable object tracking and even gesture recognition. It also has an integrated ARM Cortex-R4F micro-controller and has a c674x digital signal processor (DSP) which provides just enough power for complex processing tasks directly on the radar sensor.(Figure 2.1)

In contrast, the IWR6843 is an effective choice for industrial applications, such as monitoring foot traffic, occupancy, or motion in confined spaces. This radar includes a hardware accelerator optimized for Fast Fourier Transform (FFT) processing, allowing it to handle radar data efficiently in real-time.(Figure 2.2)

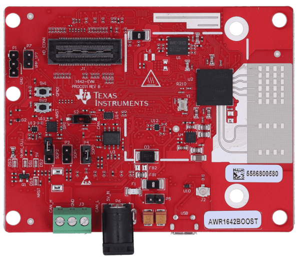

Figure 2.1: AWR1642 radar, source:[9]

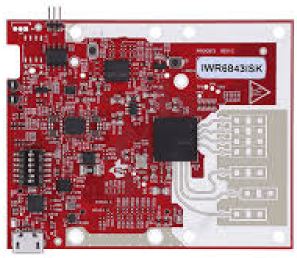

Figure 2.2: IWR6843 radar, source: [10]

2.2.2 Machine learning

ML is a branch of Artificial Intelligence (AI) that focuses on developing systems capable of learning and improving their performance from data without explicit programming. As illustrated in Figure 2.3, ML is a subset of AI, while deep learning, which will be discussed later on in this section, represents a further specialization within ML.

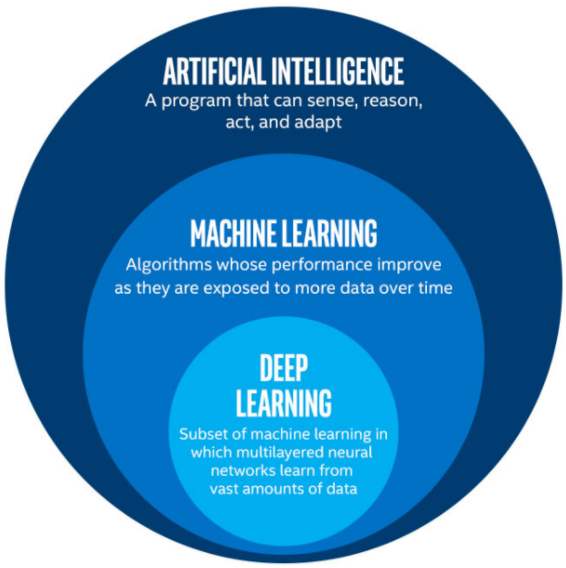

Figure 2.3: Hierarchy of Artificial Intelligence, Machine Learning, and Deep Learning. Source: [11].

We can divide ML algorithms into five broad categories such as:

- **Supervised Learning:** Trains models on labeled datasets to predict outcomes. Commonly used for classification (e.g., spam detection) and regression (e.g., predicting prices).
- **Unsupervised Learning:** Focuses on discovering patterns in unlabeled data. Common methods include clustering (e.g., customer segmentation) and dimensionality reduction.
- **Semi-Supervised Learning:** Combines a small amount of labeled data with a larger unlabeled dataset. It is useful in scenarios where labeling data is expensive or impractical.
- **Self-Supervised Learning:** Allows models to create labels from raw data, turning unsupervised problems into supervised tasks. Widely used in Natural Language Processing (NLP) and computer vision with large unlabeled datasets.

- **Reinforcement Learning:** Involves training agents to make decisions and receive rewards or penalties for their actions. Over time, it optimizes its strategy to achieve a goal. It is often applied in robotics and game development.

Following the different categories of ML algorithms we will give more attention to supervised learning and specifically to the classification of tasks and for that we have various algorithms such as:

- **Decision Trees**
- **Random Forest**
- **Support Vector Machines**
- **Logistic Regression**
- **K-Nearest Neighbors**

Deep Learning and Transfer Learning

Deep learning is a subfield of ML that leverages neural networks with multiple layers to model complex patterns in data. These algorithms are particularly effective in tasks requiring high-level abstraction, such as image recognition or speech analysis.

As shown in Figure 2.4, deep learning networks process data by passing it through multiple layers of neurons. Each layer learns to identify specific features in the data, starting from low-level details (such as edges and textures) to high-level abstract features (such as the shape of an object).

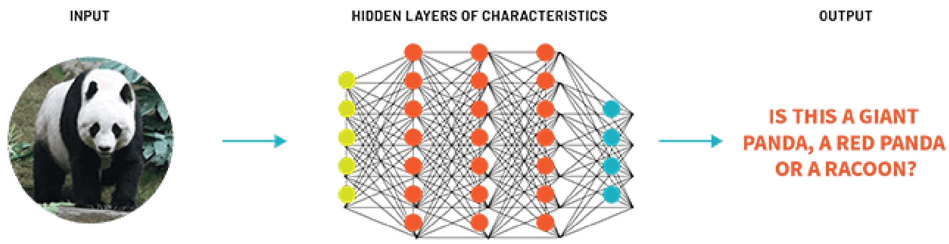

Figure 2.4: Example of a deep learning network for image classification. The network processes the image through multiple layers to classify the animal. Source: [12].

Another important technique is **Transfer Learning**, which involves reusing pre-trained models developed for one task and adapting them for a different, but related, task. This is particularly useful when large labeled datasets are unavailable for training. Transfer learning is commonly used in applications where computational resources are limited, as it significantly reduces the need for training from scratch.

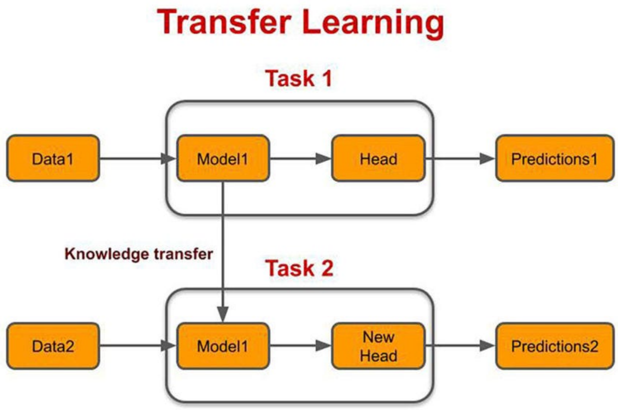

Figure 2.5: Example of transfer learning algorithm. Source: [13].

2.2.3 Technologies for System Development

In addition to using radar sensors and Machine Learning Algorithms (MLA) we will also rely on different technologies to process, store, and display the data collected by the radars. In this section, we will introduce some useful technologies for our system, related to both the back-end and front-end.

Backend Technologies

The backend will focus on managing the data collected by a module of our system and ensuring that it runs smoothly and securely. For this, there are a vast majority of technologies at our dispose

Python is a versatile programming language and enables data processing and interaction with other system components (Figure 2.6).

Flask is a lightweight web framework that facilitates communication between the backend and front end, providing a smooth interface for the system. (Figure 2.7).

In the spectrum of databases SQLite and MySQL are fundamental for storing and organizing the previously collected data, ensuring efficient data management(Figure 2.8, Figure 2.9).

Figure 2.6: Python logo

Figure 2.7: Flask logo

Figure 2.8: SQLite logo

Figure 2.9: MySQL logo

Front End Technologies

The front end focuses on presenting the processed data in a user-friendly and intuitive format. For this, there are a vast of technologies that help make it possible.

HTML5 is a well-known language that structures the web interface and ensures compatibility across modern devices and browsers. (Figure 2.10).

About defining the visual appearance of the user interface, including CSS3 is an optimal styling language(Figure 2.11).

A scripting language that is exceptionally good at adding interactivity and dynamic functionality to the web application is JavaScript. Additionally, Chart.js, a JavaScript library, is used to create clear and visually appealing charts and graphs. (Figure 2.12).

Figure 2.10: HTML5 logo

Figure 2.11: CSS3 logo

Figure 2.12: JavaScript logo

CHAPTER 3

Requirement Analysis

User-centered design (UCD) is a methodology that prioritizes the needs, expectations, and limitations of end-users throughout the development process. This approach ensures that the system is not only functional but also intuitive and accessible. UCD typically involves an iterative process of understanding user requirements, designing solutions, and refining them based on feedback. Key elements of this process include creating personas to represent different user types, developing scenarios to illustrate real-world applications, and extracting system requirements to guide the design and implementation.

This chapter explores the application of user-centered design (UCD) principles to develop a radar-based activity recognition system. By prioritizing the needs and limitations of end-users, the design ensures accessibility, usability, and functionality. The chapter is organized into three main sections: personas, scenarios, and system requirements.

The personas represent diverse user types, capturing their unique characteristics, challenges, and objectives to align the system's features with their expectations. Following this, scenarios are presented, illustrating real-world applications of the system and highlighting how it addresses user-specific challenges and goals. Finally, the chapter details the system requirements, categorized into functional, non-functional, and interaction aspects, which serve as the foundation for the system's development and ensure alignment with user needs and technical objectives.

3.1 Personas

Our system will present 2 types of users, a primary user(who will be monitored) and a secondary user(who will monitor the primary user). With this in mind, three personas were developed.

These personas capture the distinct characteristics and needs of the target audience, providing a clearer understanding of how the system can address their specific requirements.

Each persona includes a brief overview, describing their background and daily activities to establish context. It also highlights the primary challenges they face, outlining the difficulties the system aims to solve. Lastly, the personas define the users' main objectives, emphasizing how the system can help them achieve their goals, whether through enhanced independence, improved caregiving processes, or privacy-conscious remote monitoring.

João Ferreira, 72 years old, Retired/Former Civil Engineer

João lives alone in a spacious house on the outskirts of Aveiro. He has an active lifestyle, likes to walk around the neighborhood, and tends to his garden. With age, he began to denote some mobility difficulties, especially when standing up and squatting. João is interested in solutions that can help him monitor his physical activity and prolong his independence.

Challenges: João struggles with complex interfaces and prefers technologies that work automatically without much human intervention.

Objectives: Maintain autonomy at home, monitor physical activity in a non-intrusive way and be alerted to potential problems related to mobility.

Maria Couto, 45 years old, Caregiver of a Home Support Agency

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Maria is an experienced caregiver who focuses mainly on elderly people who live alone. She is always on the move visiting different patients throughout the day, depending on health reports to adjust her care in the best possible way. Maria needs a tool that allows her to remotely monitor the physical activity of her patients without invading their privacy. She values an interface that is quick and easy to interpret, with clear notifications about significant changes in patient behavior.

Challenges: The system must provide accurate and relevant data.

Objectives: Remotely monitor the health of her patients, optimize home visits, and improve the quality of care offered.

Carlos Ferreira, 48 years old, IT Analyst

Carlos is the only son of João and lives in Lisbon, about 253 km away from Aveiro. Although he has a busy professional life, Carlos tries to stay in regular contact with his father and is always looking for ways to help him maintain his independence at home. He has experience with technology and is always seeking solutions that can simplify João's life without invading his privacy. Carlos is concerned about his father's health but also wants him to remain autonomous.

Challenges: Carlos lives a good distance away from João and therefore needs to rely on remote monitoring tools. He worries about finding the right technology that strikes a balance between his father's independence and his safety, without being overly invasive.

Objectives: Ensure that his father stays safe and healthy without overburdening him with complicated technological solutions. Carlos wants to monitor João's health remotely and be notified about any significant changes in his behavior or health.

3.2 Scenarios

To illustrate how the proposed system can be utilized by its target users, 3 scenarios were defined, each involving at least one of the personas described earlier. These scenarios highlight practical applications of the system, showing how it can address the specific challenges and goals of different users in real-life situations.

Scenarios play a crucial role in deriving system requirements, as they help identify the functionalities and interactions necessary to meet user needs. For each scenario, the relevant functional, non-functional, and interaction requirements are outlined, ensuring a direct connection between the use cases and the technical specifications. This approach ensures the development of a solution that is both practical and aligned with user expectations.

Alert for Long Sitting Period

João is at home, enjoying a quiet afternoon while reading in his armchair. The system continuously monitors João's movements using its sensors [FR1] and detects that he has been sitting [FR2] in the same position for an extended period [FR6]. Recognizing this prolonged inactivity, the system captures and processes this movement data [FR4], triggering an alert. A sound notification is sent to João's device [IR4], reminding him to take a break and move around. Prompted by the alert, João gets up and walks around the house, maintaining his activity levels and reducing potential health risks.

Remote Monitoring by Maria

Maria, the caregiver, spends her day visiting different patients but relies on the system to keep track of João's activity levels remotely. Using the system's web application on her smartphone, Maria accesses João's profile, and with just a few touches [IR1], she reviews his recent activity data [FR9/IR3] and notices that João has spent most of the morning lying down [FR3, FR5], skipping his usual walk. Concerned, Maria decides to call João to check on him. João assures her that he is simply resting and plans to get up soon. Reassured, Maria adjusts her schedule, optimizing her time by avoiding an unnecessary visit.

Notifications for Activity Changes

Carlos, João's son, lives far away and uses the system to stay updated on his father's activity. Concerned after a recent fall, he enables alerts to notify him of any sudden changes [FR7]. One afternoon, Carlos receives an alert through the app, which includes an activity summary and a visual graph [IR2] showing a sudden shift from sitting to lying down. Worried, Carlos examines the data and calls João to check-in. João reassures him that he lay down to rest. Relieved by the clear and accessible information, Carlos keeps the alerts active to monitor similar situations in the future.

3.3 System Requirements

This section outlines the system requirements, which are essential specifications that define what the system must achieve to meet user needs. These requirements serve as a foundation for designing and implementing the system, ensuring that it fulfills both user expectations and technical objectives.

The requirements are divided into three main categories:

- **Functional Requirements**: These specify the core capabilities of the system, such as detecting user activity, storing data, and sending notifications. They describe what the system must do to achieve its intended purpose.
- **Non-Functional Requirements**: These define the system's overall qualities. They ensure the system works efficiently while being respectful of users' comfort.
- **Interaction Requirements**: These define how users will interact with the system, detailing input and output methods, interface design, and accessibility features.

The requirements are presented in Table 3.1, which also includes an indication of their priority. Priorities were determined based on the importance of each requirement to the overall functionality and usability of the system, as well as their impact on user satisfaction. High-priority requirements are critical to the system's core functionality and must be addressed first during implementation. Medium-priority requirements enhance the system but can be implemented in later stages. Low-priority requirements, while beneficial, are considered optional and may be included if resources allow.

This structured approach ensures that the most critical aspects of the system are implemented first, while allowing flexibility for future enhancements.

Priority	Requirement Reference	Requirement Type	Requirement Description
High	NFR1	Non-Functional	Be as least intrusive as possible.
High	IR1	Interaction	Allow touch input.
High	IR2	Interaction	Allow text and graphics output.
High	FR1	Functional	Capture movement information from a given person.
High	FR2	Functional	Recognize basic activities based on the captured movement data (e.g., sitting, standing, lying down, walking).
High	FR3	Functional	Store recognized basic activities.
High	FR4	Functional	Extract additional information based on the stored recognized activities information (e.g., is seated, is up, is lying down).
High	FR5	Functional	Store extracted additional information.
Medium	FR6	Functional	Identify if the Primary User is inactive for a certain amount of time.
Medium	FR7	Functional	Allow viewing Primary User activities information of a given period of time.
Medium	FR8/IR3	Functional/ Interaction	Allow a Secondary User to access the information about Primary User activities.
Low	IR4	Interaction	Allow speech output.
Low	FR9	Functional	Send alert notifications (e.g., inactive for a long time, ...).
Low	NFR2	Non-Functional	Easy to use.

Table 3.1: Requirements for the system, categorized as functional, non-functional, and interaction. Each requirement is associated with its priority level.

CHAPTER 4

Proposed System

In this chapter, we present the general view of the proposed system, which integrates multiple components designed to fulfill specific roles in data acquisition, processing, and interaction. We will explain how these components interact with one another.

4.1 Overview

Based on the requirements outlined in the previous chapter, we propose a system, whose general view is presented in Figure 4.1, which provides a general view of its structure. The system is divided into three main modules: *Data Acquisition*, *Home Server*, and *Interaction Devices*. Each module interacts with each other to ensure data flow from data acquisition to the storage of information on their activity and regarding the interaction between the users and the system to obtain that information. In the following subsections, we explain each module by giving a brief description of how its components contribute to the overall operation of the system.

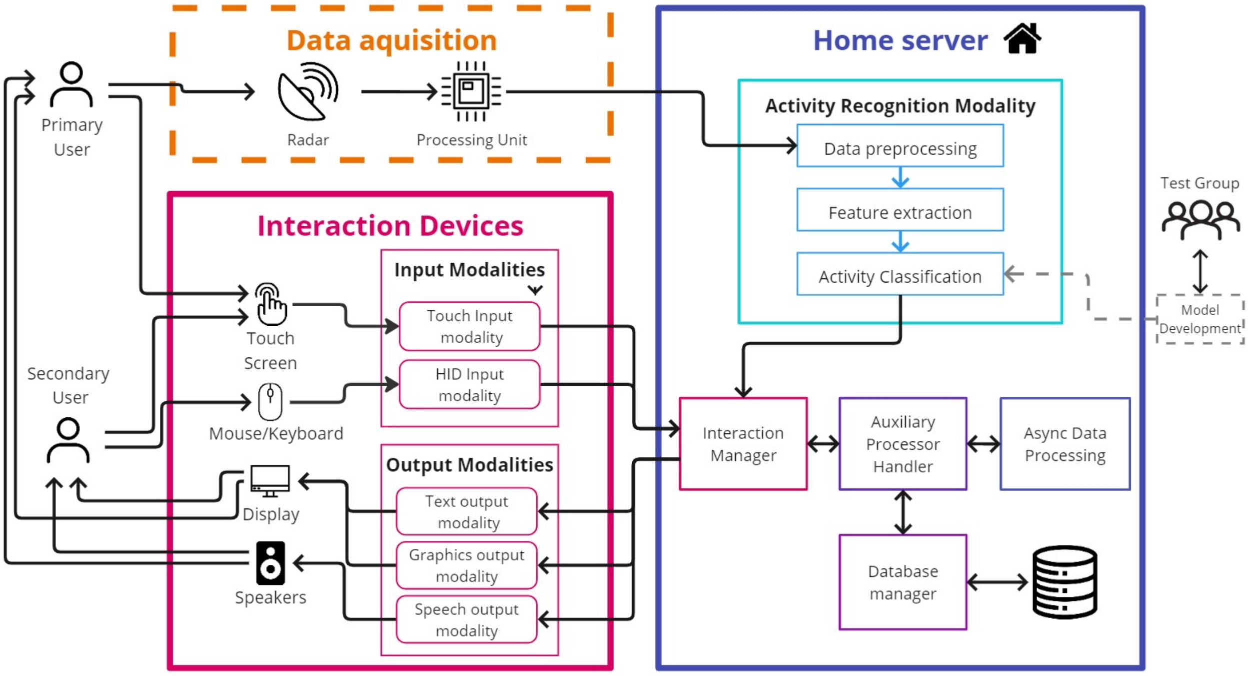

Figure 4.1: General view of the proposed system.

4.1.1 Data Acquisition Module

The Data Acquisition Module is responsible for detecting and preparing data related to movements from the primary user within a smart house environment. This module is composed of two main components: the radar and the processing unit.

- **Radar:** The radar is responsible for detecting movements in the environment surrounding the primary user. It captures it and sends it to the processing unit.
- **Processing Unit:** The processing unit receives the raw data from the radar and selects the relevant information. It converts this data into a structured format, such as JSON, and transmits it to the Home Server for further analysis.

4.1.2 Home Server Module

The home server is the core module of the system and it will be responsible for analyzing and interpreting the data received from the processing unit. It consists of 5 different submodules that are:

- **Activity Recognition Modality:**This subsystem recognizes the activities performed by a person from raw radar data obtained from that person through multiple stages:
    1. **Data Preprocessing:** Processes raw data, including filtering to remove any existing noise.
    2. **Feature Extraction:** Extracts specific features from preprocessed data that are useful in identifying or distinguishing between activities.
    3. **Activity Classification:** Uses an offline trained module to classify predefined activities based on extracted data.
- **Auxiliary Processor Handler:** Sends data to the Asynchronous Data Processing module after storing it from the activity recognition modality (via the Interaction Manager).

    Additionally, it retrieves data that users have requested, like changes in the main user's daily activities.

    Interaction Manager: Serves as a link between the interaction modalities and other modalities, such as input/output or passive/implicit modalities like activity recognition.
- **Interaction Manager:** Connects different system modalities, like activity detection, and interaction modalities.
- **Database Manager:** It has direct access to the database and is responsible for handling data storage and retrieval operations.
- **Asynchronous Data Processing:** Manages the processing of extra data regarding identified activities, like how much time a person spends moving or standing still. Users may receive notifications using this information.

4.1.3 Interaction Module

The **Interaction Module** makes sure that the user and the system can communicate and interact with each other. It allows various users to access and view information about the primary user's activity.

This module includes interaction modalities and the devices/sensors that the modalities use (such as mice/keyboards, touchscreens, or displays), and is divided into two main categories: Input Modalities and Output Modalities.

- **Input Modalities:** The system allows the user to interact through various input methods:
  - **Touch Input Modality:** Provides an intuitive and accessible option for the primary users, via touchscreens, as it allows them to interact directly with the interface.
  - **HID Input Modality:** Enables the user to interact with the system using Human Interaction Devices (HID) (mouse/keyboard) to navigate the interface.
- **Output Modalities:** The information presented to the users is provided through multiple output channels such as:
  - **Graphics Output Modality:** Allow the data to be presented through charts, graphs, or other visual indicators that simplify interpreting the results via displays.
  - **Text Output Modality:** Displays textual feedback to users via displays, such as activity recognition results or system status updates.
  - **Speech Output Modality:** Converts alerts or notifications into audio feedback via speakers, enabling accessibility for users who may have difficulty interacting with visual displays.

The interaction devices module is directly connected to the **Interaction Manager** within the home server. The interaction manager ensures that user input commands are sent to the correct sub-module to be interpreted and to the correct sub-output module so that appropriate feedback is provided through the output modalities.

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