D9.6 Installation of the prototype system

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Table of Contents

1. Introduction

1.1. Background

With the rapid development of telemedicine, home health monitoring, and an aging society, there is a growing demand for technologies that can continuously monitor human physiological states without requiring wearable devices or active user cooperation. Radio-frequency (RF)-based non-intrusive sensing technology has gained attention for its ability to reliably capture human activity under challenging conditions such as no light, occlusion, and even through walls.

1.2. Motivation

The core motivation behind this project is to provide terminally ill or elderly patients with technology enabling continuous health monitoring in a home environment, allowing them to receive effective care without prolonged hospitalization. Compared to enduring loneliness, stress, and discomfort in a hospital setting, patients can remain at home surrounded by family, achieving significant improvements in emotional well-being and quality of life.

To realize this vision, we must address the following key challenges:

1. **Identifying the patient among family members:** In household settings where multiple individuals are present, the system must accurately distinguish the patient from family members to ensure the validity of monitoring data.
2. **Integrating multi-target tracking, identity recognition, and potential motion/fall detection:** The system must continuously track all active subjects in multi-person environments and precisely locate individual patients through identity recognition. This enables the extraction and analysis of patient data only, without storing or processing data from other household members. Additionally, future capabilities should include motion recognition or fall detection functionality.
3. **Extracting Health-Related Features from Millimeter-Wave Radar:** Radar technology was not originally designed for health monitoring, necessitating the development of new algorithms to extract medically relevant information from sparse point clouds. This includes data such as activity duration, abnormal movements, trajectory distribution, or changes in daily routines.
4. **Design an intuitive and user-friendly interface:** Provide patients and caregivers with a simple, clear, and understandable interface that enables non-professionals to access real-time status updates.

2. Related Work

In the fields of remote health monitoring, millimeter-wave radar sensing, and multi-target tracking and identification, extensive research has laid the technical foundation for this project, yet critical gaps remain. This section reviews key areas, including non-contact vital signs monitoring, millimeter-wave human behavior recognition, multi-target tracking and identification in home environments, and fall detection and digital twins in medical applications, citing representative literature.

2.1. Non-contact Vital Signs and Home Monitoring

Early work primarily focused on utilizing radio frequency signals for vital sign detection, such as respiration and heartbeat rhythms. For instance, the WiTrack system proposed by Adib et al. [1] demonstrated the feasibility of human localization and respiration detection via RF signals. Subsequent studies employing WiFi or FMCW radar enhanced the ability to identify indoor respiration, sleep quality, and basic health behaviors [2, 3].

However, most such studies were limited to single-person scenarios with restricted functionality, making direct application to patient monitoring in complex home environments challenging.

2.2. Human Behavior and Gesture Recognition Using Millimeter-Wave Radar

In recent years, millimeter-wave radar has achieved breakthroughs in motion recognition. For instance, Google's Soli project demonstrated micro-motion gesture recognition capabilities [4], while point cloud-based behavior recognition methods—such as PointRNN proposed by Zhao et al. [5] and Salami et al.'s research on angle generalization [6]—have further advanced applications in the mmWave domain.

However, existing work remains primarily focused on "gesture recognition" or "small-scale motions," lacking health behavior analysis tailored for medical scenarios, such as bradykinesia assessment or habit change monitoring.

2.3. Multi-Target Tracking and Identification

In home environments, simultaneous activities by multiple people are commonplace, necessitating concurrent handling of MOT (Multi-Object Tracking) and Re-ID (Re-Identification). Classical visual methods such as DeepSORT [7] and FairMOT [8] provide robust synchronous tracking-recognition frameworks. However, millimeter-wave radar point clouds are sparse and structurally unstable, rendering these visual methods inapplicable directly.

Millimeter-wave-specific MOT systems, such as the radar-based tracking-by-detection framework proposed by Kim et al. [9], can track multiple people but cannot yet perform robust re-identification, let alone handle complex household dynamic scenes.

2.4. Fall Detection and Digital Twins in Healthcare Settings

Fall detection is a critical component of home monitoring. Existing millimeter-wave radar research has demonstrated potential in fall recognition, such as the method proposed by Wang et al. for fall classification using FMCW point clouds [10]. Meanwhile, the medical community is increasingly recognizing the role of digital twins in patient monitoring and intervention prediction. For instance, Bruynseels et al.'s review [11] highlights their potential in personalized medicine. However, integrating millimeter-wave radar data with digital twin frameworks for long-term health trend analysis remains an under-explored domain.

3. System Implementation

3.1. Non-contact Vital Signs and Home Monitoring

The RF-sensing subsystem is built upon a multi-radar fusion architecture using several TI IWR1443 mmWave radars deployed at different positions in the home environment. All radars are connected to a single ASUS mini PC, which acts as a local edge-computing node, responsible for real-time data collection, synchronization, and visualization.

3.1.1. Multi-Radar Deployment and Fusion

Each IWR1443 radar independently collects range–Doppler and point-cloud data at approximately 77 GHz. To overcome the limitation of single-device occlusion and small field of view, we fuse multiple radars with partially overlapping coverage. This allows the system to:

- maintain persistent coverage of the entire living space,
- increase the robustness of body-part reflections,
- reduce blind spots and multipath artefacts,
- obtain richer spatial information for tracking and identification.

All radars stream raw point-cloud frames to the ASUS mini PC via USB, where timestamps are unified to ensure frame-level temporal alignment. A lightweight fusion module merges multiple point clouds into a common coordinate system using predetermined transformation matrices.

3.1.2. Real-Time Display and Local Processing

The mini PC hosts a real-time GUI that visualizes:

- fused 3D point clouds,
- detected clusters representing individuals,
- estimated trajectories and activity statistics.

This enables caregivers or researchers to monitor the system at home without requiring specialized hardware.

3.2. Data Processing Pipeline

The data processing pipeline extracts health-relevant information from raw radar point clouds, as shown in the Figure 1. It consists of six stages:

3.2.1. Point-Cloud Preprocessing

Raw radar points suffer from noise, static clutter, and multipath. We apply: distance-based and density-based filtering using Isolation Forest. Each point is represented as (x, y, z, v, t), where t is the global timestamp synchronized across radars.

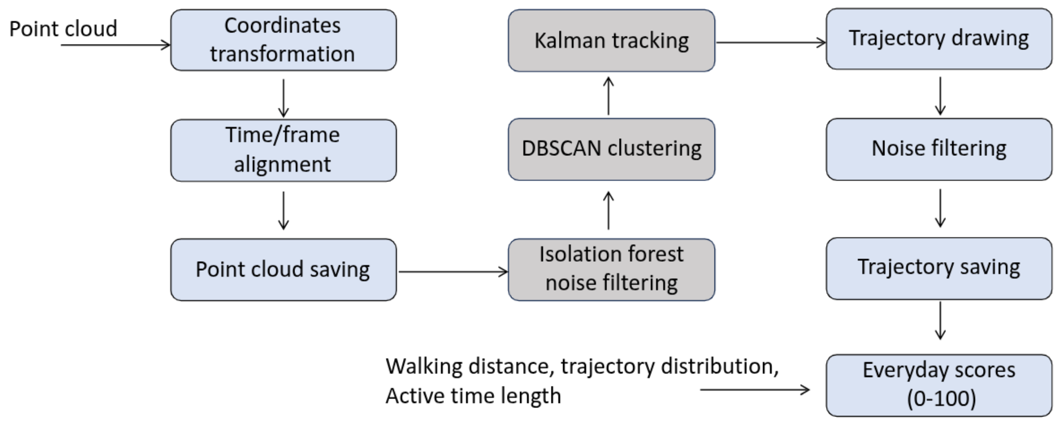


Figure 1: Data processing pipeline

3.2.2. Temporal & Spatial Alignment

All point clouds are: aligned to a global coordinate system, interpolated to ensure consistent frame rates across sensors, and assigned unified timestamps. The system also records point-cloud videos for later review, enabling retrospective inspection of unusual events.

3.2.3. Clustering & Multi-Target Tracking

The customized DBSCAN separates individuals. Tracking combines: Kalman filtering, multi-sensor association and identity maintenance. Since only the patient's data is needed for downstream analysis, clusters associated with family members or visitors are ignored. This selective processing reduces computational load and enhances privacy.

3.2.4. Trajectory Recording

Tracked patient positions including raw (x, y) paths, denoised trajectories segment-wise movement summaries and are logged continuously. These trajectories form the basis of long-term behavioural analysis.

3.2.5. Feature Extraction

From daily radar streams, the system computes health-related mobility metrics such as walking distance, activity duration, trajectory density maps, area coverage and movement diversity, and periods of inactivity or abnormal behavior. These metrics are combined into a daily activity score, estimating the patient's physical status and enabling early detection of behavioral changes.

3.3. Cloud Service & Interaction Interfaces

The system includes a lightweight cloud service and two user-facing interfaces for patients and caregivers.

3.3.1. Cloud Synchronisation

Processed data, daily summaries, and point-cloud videos are uploaded to Google Drive. This provides:

- secure cloud storage,
- historical archive of patient activity,
- cross-device access for clinicians.

Uploads occur in the background without interrupting real-time operations.

3.3.2. Remote Access

The miniPC runs a passive desktop-sharing module using TeamViewer, configured for password-less access for authorized caregivers. This enables:

- remote system maintenance,
- live monitoring of patient activity,
- emergency inspection in case of suspicious events (e.g., abnormal inactivity).

3.3.3. User Interfaces

Two interfaces are provided:

1. Patient Interface
    - Simple daily summary
    - Friendly feedback (e.g., “Today’s activity: Good”)
    - Minimal text designed for elderly usability
2. Caregiver Interface
    - Trajectories
    - Activity timelines
    - Daily/weekly/monthly trends
    - Downloadable raw data

The combination of radar sensing, local processing, and cloud integration forms a robust digital-twin monitoring system for long-term, in-home patient care.

4. Experiments & Results

The experiments and deployments for this study were facilitated by the clinic operated by Mr. Adam Hermann in Prague, Czech. After obtaining explicit informed consent from patients, we completed practical deployments of the millimeter-wave radar system in six patient home environments, covering living rooms, kitchens, and portions of bedrooms, thereby enabling continuous monitoring of patients' daily living environments.

4.1.1. Experiment settings

We utilize customized millimeter-wave radar monitoring devices. The deployment process includes:

- Communicating with clinics to confirm patient consent;
- Conducting on-site assessments of household layouts to determine radar coverage areas;
- Installing radar equipment and performing initial calibration;
- Deploying data acquisition and local processing terminals;

In 6 households, typical installation locations include:

- Living room: To cover primary activity areas;
- Kitchen: For monitoring high-risk activities (e.g., fall risks during cooking);
- Bedroom: Some households opted for deployment to monitor sleep-related behaviors.

4.1.2. Results

A series of representative results is shown below to illustrate the system's performance:

- **System interface**, demonstrating point cloud data in real time (see *Figure 2*).
- **Radar hardware setup**, including multiple IWR1443 sensors connected to a centralized ASUS mini-PC (see *Figure 3*).
- **Room layout with point-cloud visualization**, showing how different rooms are covered and how sparse mmWave reflections are fused into unified trajectories (see *Figure 4*).
- **A 14-day continuous monitoring result for a single patient**, including daily activity levels, movement trajectories, walking distances, and behavioral trends (see *Figure 5*).

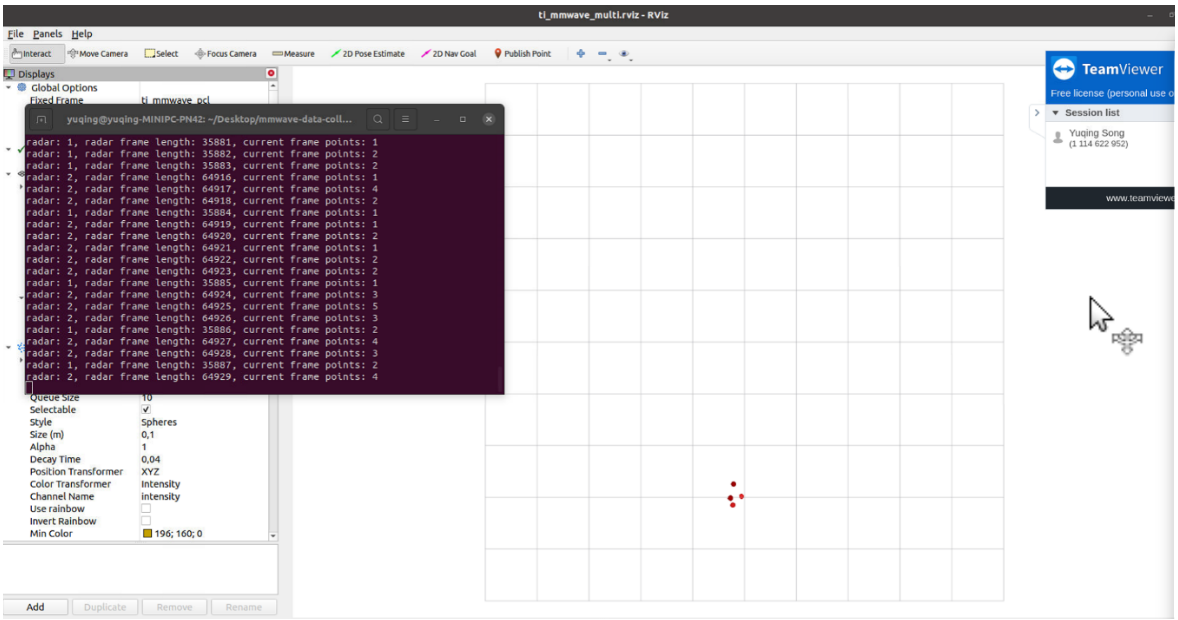
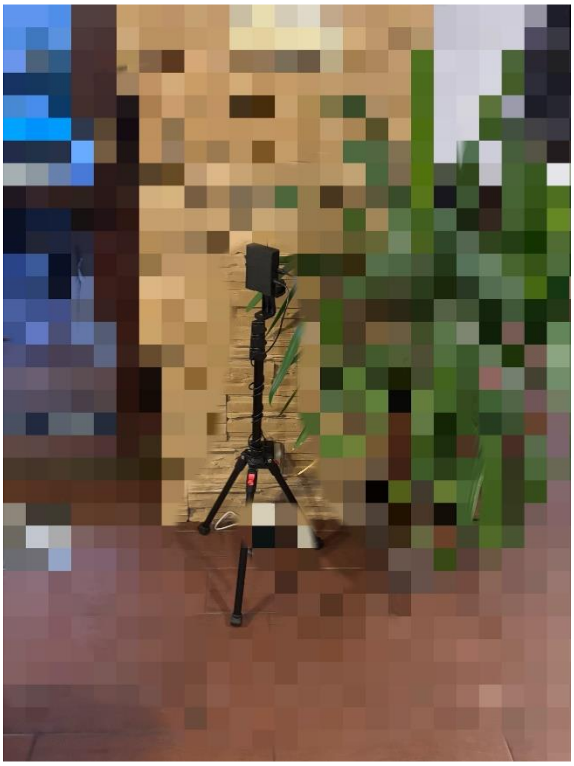
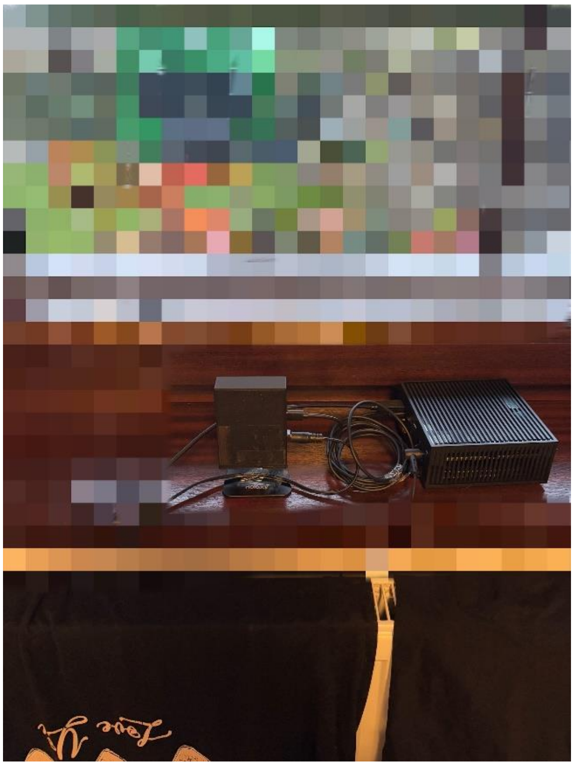


Figure 2: Data collection (user side) interface

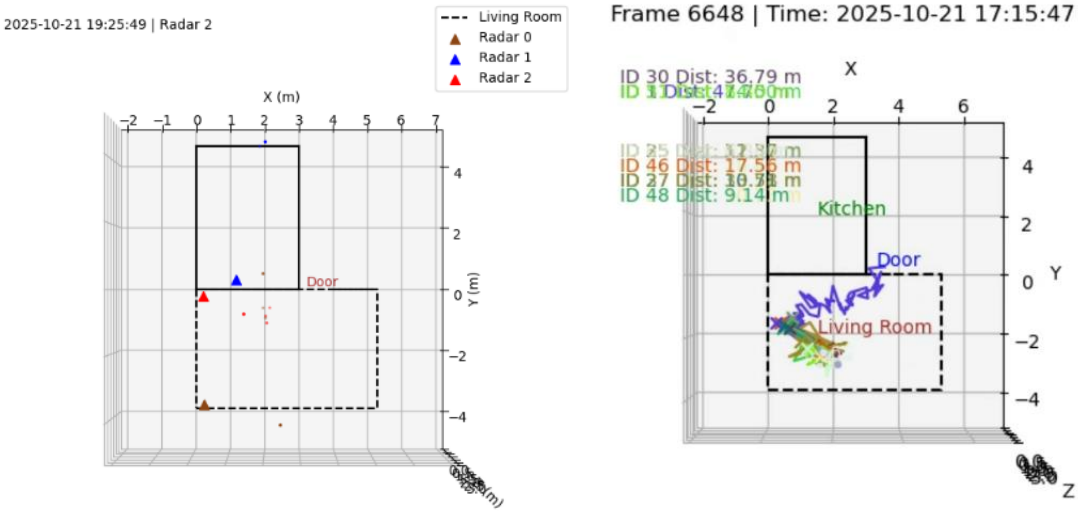


(a) Radar with a stand



(b) Radar and the miniPC

Figure 3: Radar and miniPC placement in the patient's home



(a) Point cloud and floor plan (b) Trajectories and floor plan

Figure 4: Point cloud data and trajectories shown on the floor plan

Patient3 activity monitor

Date (month.date. hour.mimute)	10.22.22.00	10.23.15.55	10.23.22.00	10.24.22.00	10.25.22.00
Activity duration	40m 24.40s	24m 2.80s	49m 17.30s	1h 38m 8.40s	36m 52.20s
Walking distance	4187.50 m	2474.67 m	4121.95 m	9343.32 m	3120.00 m
Trajectory Recorder in living room	00:40-00:55 → Kitchen/Bathroom/Outside 09:26-09:36 → Kitchen/Bathroom/Outside 09:49-09:51 → Kitchen/Bathroom/Outside 10:05-10:16 → Kitchen/Bathroom/Outside 10:22-10:29 → Kitchen/Bathroom/Outside 10:42-11:25 → Bedroom 12:19-12:19 → Bedroom 12:58-13:01 → Kitchen/Bathroom/Outside 13:10-13:19 → Kitchen/Bathroom/Outside 13:27-13:46 → Bedroom 14:20-114:51 → Kitchen/Bathroom/Outside 15:09-16:07 → Kitchen/Bathroom/Outside	17:44-17:53 → Kitchen/Bathroom/Outside 18:00-18:54 → Kitchen/Bathroom/Outside 19:02-19:06 → Bedroom 20:35-20:48 → Bedroom 21:20-21:33 → Bedroom 22:03-22:08 → Kitchen/Bathroom/Outside 22:14-22:14 → Bedroom 22:37-22:46 → Bedroom	00:22-00:29 → Kitchen/Bathroom/Outside 00:55-00:56 → Kitchen/Bathroom/Outside 09:17-09:31 → Kitchen/Bathroom/Outside 09:37-09:50 → Kitchen/Bathroom/Outside 10:01-10:01 → Kitchen/Bathroom/Outside 10:10-11:15 → Bedroom 12:26-12:27 → Bedroom 12:52-12:55 → Kitchen/Bathroom/Outside 13:04-13:05 → Bedroom 13:46-13:51 → Kitchen/Bathroom/Outside 14:08-14:51 → Kitchen/Bathroom/Outside 14:57-15:50 → Kitchen/Bathroom/Outside 16:01-18:23 → Bedroom 20:12-20:17 → Bedroom 20:52-20:53 → Kitchen/Bathroom/Outside 20:59-20:59 → Bedroom 21:38-21:42 → Bedroom 22:40-22:51 → Bedroom	01:03-01:13 → Kitchen/Bathroom/Outside 01:31-01:46 → Bedroom 08:22-08:27 → Kitchen/Bathroom/Outside 09:03-09:57 → Kitchen/Bathroom/Outside 10:17-10:41 → Bedroom 10:55-11:02 → Kitchen/Bathroom/Outside 11:47-11:57 → Bedroom 12:48-13:09 → Kitchen/Bathroom/Outside 13:18-14:51 → Bedroom 15:35-15:49 → Bedroom 16:00-16:47 → Kitchen/Bathroom/Outside 16:54-17:35 → Kitchen/Bathroom/Outside 17:43-18:04 → Kitchen/Bathroom/Outside 18:10-18:17 → Bedroom 18:40-18:40 → Bedroom 19:18-19:57 → Kitchen/Bathroom/Outside 20:03-20:30 → Kitchen/Bathroom/Outside 20:43-21:08 → Bedroom	23:02-23:04 → Bedroom 23:41-23:49 → Kitchen/Bathroom/Outside 00:07-00:10 → Bedroom 10:58-10:58 → Kitchen/Bathroom/Outside 11:16-11:16 → Kitchen/Bathroom/Outside 12:47-12:47 → Kitchen/Bathroom/Outside 13:00-13:06 → Bedroom 13:12-13:13 → Kitchen/Bathroom/Outside 13:52-14:26 → Kitchen/Bathroom/Outside 14:32-19:05 → Kitchen/Bathroom/Outside 19:26-19:54 → Kitchen/Bathroom/Outside 20:16-20:26 → Bedroom 21:03-21:38 → Bedroom

Figure 5: Analysis results of continual monitoring

5. Conclusion

In this deliverable, we presented a complete, end-to-end RF-based home monitoring system tailored for elderly and terminally ill patients. Through the integration of multi-radar sensing, real-time point-cloud processing, multi-target tracking, patient-specific data extraction, and a practical cloud-based interface, the system demonstrates strong feasibility for long-term, privacy-preserving in-home health monitoring.

Our deployment across six real households confirms that the system is robust to varying home layouts and daily living conditions. The collected data—ranging from spatial trajectories to long-term activity trends—shows clear potential for supporting digital-twin-based health assessment, early anomaly detection, and caregiver decision support.

The results highlight not only the technical strength of the system but also its human-centric value: enabling patients to stay comfortably at home while still benefiting from continuous, unobtrusive monitoring. This deliverable therefore establishes a solid foundation for future clinical collaboration, large-scale studies, and more advanced health analytics built upon RF sensing.

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