Longitudinal Data Acquisition for AI Services in Long-Term Care Facilities for Older Adults

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Keywords: Nursing Homes, Data Collection, Video Recording, Data Analytics, Geriatric Assessment, Long-Term Care, Video-Assisted Techniques and Procedures, Machine Learning, Image Processing, Decision Tree.

Abstract: Data is essential for analysis, processing, feature extraction, and machine learning models, serving as a cornerstone for developing patient-centered digital health technologies for older adults. Most datasets in older adult applications are collected in controlled laboratories, with fewer from natural environments. Data collection and processing in natural settings is challenging, often yielding both usable and unusable data. This paper focuses on collecting data from older residents in long-term care facilities using sensor boxes installed in resident rooms. The sensor box, equipped with a depth sensor, captures depth images around the clock. We collected continuous 24-hour depth images from 45 older residents in nursing homes over 15 months. We describe the ethical, social, and technical conditions for collecting on-site data from depth sensors in nursing homes. We propose a pipeline to process depth images and classify them into different room states and corrupted frames using machine learning models, achieving 93% accuracy in occupied room classification. Using this dataset, we aim to develop AI services such as fall detection, activity monitoring, gait analysis, sleep position monitoring, and bed exits in long-term care facilities. These insights advance digitally enabled care solutions for older adults, paving the way for innovative, sustainable strategies.

1 INTRODUCTION

1.1 Motivation

Falls are a critical event for an individual over the age of 65 years, which has considerable consequences, including health, cost (Saß et al., 2016) and loss of independence (Blumenberg et al., 2013) for the person. The fall introduces physical and psycho-social stress to the affected person and the nursing staff who witness a fall event (Scheel et al., 2020; Gruss et al., 2004). Falls happen in old age (Görres, 2018; Li et al., 2023) due to many factors like limited mobility, medication, and depression (Strutz et al., 2020). Fall detection could identify a fall, and thus aid could be sent as soon as possible. The older population is constantly rising, while the number of available staff working in long-term care is declining. Staff shortage leads to increased workload and can result in overtime work and high staff turnover. In Germany, high standards for sound nursing documentation and quality of care in ambulatory and stationary long-term care are enshrined in book eleven of the German social code (SGB, 2024). In combination with an increased workload, and organizational procedures during and after a fall event, it can result in heightened physical and psycho-cognitive stress for nurses (Krankenkasse, 2019).

Mobility and balance assessment tests provide a clear indication of the balance and frailty of an individual and their risk of experiencing a fall event. Re-

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Paul, R. E., Kock, P., Hartmann, Y., Ball, E., Seibert, K., Liu, H. and Schultz, T.
Longitudinal Data Acquisition for AI Services in Long-Term Care Facilities for Older Adults.
DOI: 10.5220/0013403900003911

In *Proceedings of the 18th International Joint Conference on Biomedical Engineering Systems and Technologies (BIOSTEC 2025) - Volume 2: HEALTHINF*, pages 1099-1110
ISBN: 978-989-758-731-3; ISSN: 2184-4305

search proves the effects of these tests of which Tinetti in (Chawan et al., 2022; Dubois et al., 2021), Timed Up and Go (TUG) in (Kroll et al., 2022; Hellmers et al., 2018; Pedrero-Sánchez et al., 2023; Dubois et al., 2021), and Short Physical Performance Battery (SPPB) in (Guralnik, 1994) are being used worldwide in geriatric medicine and nursing care. Permanent sensors for continuous monitoring of nursing home residents and automating assessments to predict frailty could assist in establishing precautions to ensure the safety of an individual. Automating routine activities at nursing homes has the potential to support staff and reduce workload (Evans et al., 2018). The activity monitoring, gait analysis, and mobility assessment are beneficial in frailty indication and in early detection of gait-based diseases such as Parkinson's disease (Balaji et al., 2020; Cicirelli et al., 2021). Sleep position monitoring is helpful for bedridden adults, where the position change and duration could be monitored, providing the caregiver indication for a position change and to avoid bed sore (Wong et al., 2020). The bed exit model could predict an exit by monitoring the series of activities beforehand, thus notifying the caregiver and avoiding a fall. This is advantageous for older adults who often fall when standing from the bed, due to balance or medication, but forget to call a caregiver for assistance.

Although these services are significant, collecting and processing data from the natural environment brings its own challenges. Data from a substantial number of individuals is necessary for enhanced Artificial Intelligence (AI)-services, but this increases the sensor installation costs. Usable sensor types are limited due to participant acceptability concerns. Secure and lossless data transfer from on-site to laboratory storage is crucial. Additionally, data will contain artifacts and uncontrollable variations due to numerous factors (eg. network issues, and interaction with other equipment). Natural environment data collection eliminates the constraints of controlled lab setups, providing a stress-free setting where residents usually behave. This is particularly beneficial for gait analysis, as it avoids the altered performance that may result from the awareness of being observed in a controlled environment. The controlled setup often fails to capture the comprehensive and varied nature of activities of daily life (ADL) (Beaudart et al., 2019). Our study collects depth data over an extended period, enabling residents' gait monitoring for 15 months. The data collected could be utilized to develop Machine Learning (ML) models for fall detection, activity monitoring, gait analysis, mobility assessment, sleep position monitoring, and bed exit.

1.2 Related Work

Literature with similar scientific research purposes exists but is limited. In Zouba et al.'s study data was collected from older participants using heterogeneous sensors such as video camera, pressure sensor, and temperature sensor, among others, to recognize daily activities (Zouba et al., 2010). In this study, an experimental apartment with a kitchen, living room, bedroom, and bathroom was used with nine volunteers. Another study by Yang and Hsu focused on a home-based system for remote monitoring of an older adult using Passive Infrared and Electrical Current Transformer sensors that provide quick emergency responses (Yang and Hsu, 2012). They described a natural environment setup with sensors placed inside different rooms in a home. The sensors are recorded once every ten minutes to summarize the time a person spends in each room by detecting the person passing the sensor. Even though this study was conducted in a natural environment, in contrast to our approach, it does not use 24-hour recording and cannot distinguish between the older adult, nurse, or visitors. Survey in (Momin et al., 2022), included various older adult monitoring systems using depth sensors, but the majority of these systems are trained on data collected from laboratory with younger adults. Furthermore, other sensors such as RGB camera, internal sensor, and keypoint sensors on participant's joints for Motion Capture were combined with the depth sensors during the data collection. The (Skubic et al., 2016), describes a long-term fall detection using a webcam and depth sensor, where the model was trained extensively with stunt actors imitating falls. Data was not collected here; the fall detection algorithm was implemented for two years in multiple older adults' apartments. The home-based system proposed in (Maskeliūnas et al., 2023), evaluates the exercise and monitor progress during rehabilitation with depth sensors, and 14 key sensors for Motion Capture data combined with Virtual Reality. Dataset in (Baruch et al., 2021) captured real-world indoor scenes using RGB-D (color and depth) sensors and utilized them for object detection. A one-month long study using fitness trackers, measuring heart rate, activity, and sleep data for Mild Cognitive Impairment detection in (Xu et al., 2024) was conducted with 20 participants. The study in (Manning et al., 2024) conducted mobility assessments on older adults three times during the 12 months to evaluate the physical functioning concerning physical activity.

There have been studies on monitoring older adults, but most have been short-term based. A continuous 24-hour manner for about 15 months, is the novelty this paper brings in. Also, most studies used wearable sensors and RGB-D sensors for data collection, here we only use the partial privacy-protecting depth sensors collected from a natural environment without bounds. This ensures that residents are not identifiable by their faces, enabling stress-free data collection. Most data collections are conducted in a controlled environment, often using wearable sensors, and typically involve fewer individuals. Compared to wearables, limited battery life and storage capacity, electrode abrasion, wearing discomfort, and the risk of being forgotten by older adults, our approach allows uninterrupted data capture using depth sensors.

1.3 Research Question and Paper Structure

We designed this data collection as part of a project where the goal is to develop AI services for repetitive rule-based activities and digitize documentation in long-term care facilities, to reduce staff workload and enhance quality of care. Our research question is: Can frailty be assessed fully automatically, reliably, and over time for older residents in long-term care facilities using low-cost, minimally invasive, partially privacy-preserving sensors that are market-ready and work efficiently with the existing long-term care facility infrastructure? In this paper, we report on the hardware setup, collected data, and processing as the foundation for AI-services in long-term care facilities. The hardware and network setup used in this data collection is described in Section 2.1. Section 2.2 addresses ethical considerations, information exchange, preparations, and social aspects concerning the community at a long-term care facility. Section 3 explains the data collection and initial data analysis. Section 4 reports the processing and statistics of the collected data. Section 5 concludes our work and provides future research prospects. We collected data using depth sensors installed in 45 older resident rooms in three long-term care facilities for 15 months.

2 METHODS

2.1 Sensor Technology and Infrastructure

2.1.1 Sensor Hardware and Placement

The sensor box from DHC [1] depicted in Figure 1 is mounted on the walls of resident rooms in long-term care facilities and comprises a depth sensor, microphone, loudspeaker, Wi-Fi accessibility, and Raspberry Pi processor. All residents reside in these single-rooms within the nursing homes. The box has limited memory; hence, it cannot store the depth data over the entire duration. The sensor box is connected to the nursing home network via Wi-Fi. The sensor box depth data is transmitted to a central location within the nursing home network. All status information regarding the box is available online using a customized web interface, the Graphical User Interface, within the nursing home network. The sensor box can be used as a standalone system as in (Lukas et al., 2021). Most of the system configurations, software updates, and technical issues can be examined from outside the room using a Secure Shell connection to the sensor box, preventing interference with residents' daily activities.

Figure 1: Sensor box from DHC mounted on a wall in the rooms.

The placement of the sensor box was determined through inspection and discussion. We considered that the residents should not be at risk anyway, avoid accidental switching off and changing the rotation angle, avoid interference with the normal operation of equipment in the room, minimize the reflections from windows, and provide a maximum view of the person from head to toe. The general position of the sensor box in a room was about two meters high and near a corner of the room. Figure 2 outlines the position and the sensor box field in one of the rooms. Few rooms have slightly different placement positions due to specific characteristics such as furniture or an obstacle in the field of view (fov).

2.1.2 Network and Server Setup

Adding a hard drive in the sensor box makes it bulkier. If the depth data is stored within the box, it requires a technician to retrieve data at regular intervals, which would intervene in the residents' daily activities. In this data collection, we send depth data from several sensor boxes to a central storage location with larger memory, labeled as cloudnode from now onward. Cloudnode is similar to a PC, which can store

[1] DHC Digital HealthCare-Systems GmbH.

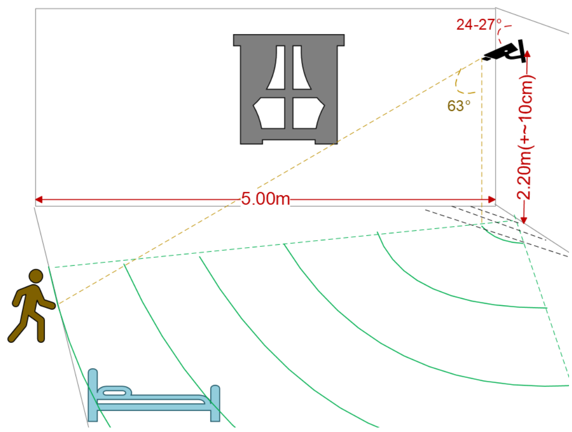


Figure 2: The position and fov of the sensor box installed in a room. The green lines indicate the fov of the depth sensor, and the black dotted lines indicate the area below the depth sensor outside fov.

data, has Wi-Fi connectivity, and has a processor. The cloudnode serves a dual purpose: one side allows the nursing home to upload data, while the other enables our laboratory to download it. The data from each sensor box is uploaded to the cloudnode over the nursing home Wi-Fi. The entire nursing home network is protected from the public internet using a security system such as a firewall (security system). The sensor box and the cloudnode are within the nursing home and the data transfer between them is well protected so that no one outside the network can access those data.

2.2 Study Design

2.2.1 Ethical Considerations

In this study, we developed a study protocol to address all potential ethical issues. The study protocol included all research questions to be answered, the general study design, relevance to the research, justification of the requirement to include participants from long-term care facilities in the study, and the requirement to store data for machine learning models. The protocol also addressed the issue of data privacy. The collected data had to be stored in a way that the participants were pseudonymized. In the protocol, we stipulated that the data would only be collected until the end of the project. The study protocol included the inclusion and exclusion criteria for the targeted participants, the type and form of data collected, the duration of data collection, and potential risks involved and their preventive measures. Data protection included in the study protocol detailed how a person is anonymized, how the data is securely stored so that direct third-party access is not possible, and how it will be deleted after the retention period. The data must be stored and handled only by the responsible study team, and cannot leave the hard drives and processors of the respective groups. The collected data involved resident depth images, audio, and personal information such as name, age, gender, height, weight, diagnostic codes, and previous fall events. Personal information is needed in the backend to trace back the information deduced from the AI system to each resident, and a record is kept at the nursing home. This information is useful in long-term monitoring of the residents' condition and documentation. Personal data is anonymized using a lookup table, and an identifier is assigned to distinguish individual residents. The ethical approval for the study was granted by the German Society of Nursing Science.[2]

2.2.2 Participant Recruitment Process

In the first step, staff at the nursing homes were informed about the project, the proposed changes to the physical environment and care processes, the types of data recorded by hardware, and the potential uses of the data. Staff members were informed about the system's needs and benefits, and the rights and measures of data protection with the help of work councilors at the facilities. As per the study protocol agreement, the depth data collected during the project is not permissible for use in legal actions against any individuals. The participant recruitment process overview in each nursing home is pipelined in Figure 3. The staff suggested residents who have some degree of mobility as suitable participants. They were residents who could walk with or without aid, were prone to falls, were active, and would walk around in their rooms, these include the requirement check. From a list of suitable participants, the project officer at each nursing home contacted each resident on the list. Each resident and their family or legal guardians were explained about the project, voluntary participation, benefits, and other possibilities by a research team member. Written consent was obtained from residents who agreed to participate in the project or their respective legal guardians. During this information exchange stage, all the questions and concerns of staff and residents were clarified by the project officer responsible for the nursing facility, who remained responsible for all additional questions. The next step was the installation of hardware in the rooms of the interested participants. The technician in the nursing home installed the sensor boxes with the residents' permission and with minimal disruption to their daily

[2] Application number: 22-015.

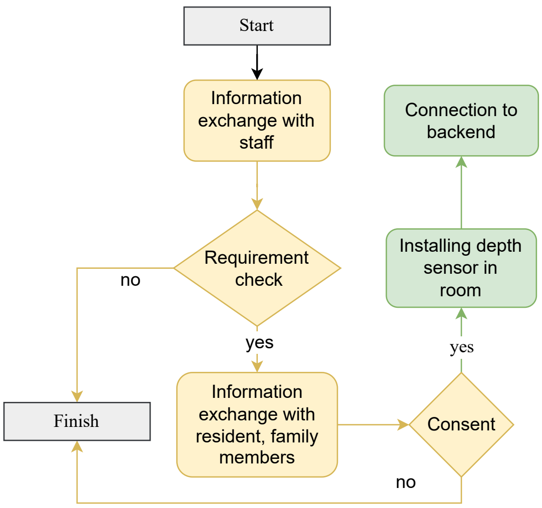


Figure 3: Steps in the participant recruitment process for data collection at the nursing home; hardware-related (in green) and person-related (in yellow).

routines. Once the sensor boxes were installed, the rotation angle was adjusted and the sensor box was calibrated to the floor. Then it was connected to the software backend and the staff would receive notifications or alarms from the sensor boxes in the corresponding frontend. Training sessions were held to guide the staff on the frontend operations and handling sensor box situations.

2.2.3 Social Aspects

One of the nursing homes had previous experience with an earlier version of the sensor box. The new system for staff and residents led to mixed acceptance among staff, and measures were taken to enhance acceptability. While some staff members and residents were comfortable using the system, others chose to ignore it. During the initial phase, several interactions and workshops were conducted to explain the system and data security. The way and what data will be recorded, who has access to it, what will be done with it, and how it will be helpful in everyday nursing care later was clearly explained. As many residents do not engage much in conversation due to their cognitive state, we decided against obtaining voice recordings, which would have contained mostly the voices of the nursing staff. Residents were also concerned that voice recording would discourage visitors and external service providers from interacting with them. Hence, the microphone in the sensor box was permanently turned off. Anecdotal evidence suggests that many residents expressed happiness and pride in participating in the study, highlighting their appreciation for contributing to a project that serves society. The nursing staff welcomed the opportunity to use new digital devices to support their daily work.

3 DATA COLLECTION

3.1 Recording Site

Data were collected in three nursing homes owned by non-profit healthcare providers in Germany. The sensor box continuously streamed data in the residents' rooms until it was manually turned off. The sensor box sends recorded data ceaselessly to the cloudnode. The sensor box data are collected on the nursing home side of the cloudnode. The depth data from each sensor box at every hour is compressed using lossless compression. At the beginning of every hour, the compressed data from the previous hour is uploaded to the laboratory side of the cloudnode.

3.2 Collection Site

As stated above, the data collected from the sensor box remains within the long-term care facility network. However, the data must be downloaded to our laboratory in a remote location outside the nursing home network for further processing. To allow data flow to our laboratory, we created a secure window in the nursing home network firewall while ensuring that there is no possibility of a leak in the public Internet. With an established Virtual Private Network (VPN) connection, we downloaded the depth data from the laboratory side of the cloudnode to a dedicated Personal Computer (PC) in our laboratory. The entire network structure of the nursing home, the public, and the laboratory is overviewed in Figure 4, and the secure VPN channel through the public network represents the window between the long-term care facility and the laboratory networks.

The cloudnode has limited memory: It stores up to a few hours of data from all sensor boxes. Hence, the data must be transferred to a permanent storage location. Data is collected from two–ten sensor boxes around the clock for 15 months. We initially used hard drives, later replaced by a file server with about 160 TB of memory, to store the data collected during the research. The data flow from the sensor box to the file server using Wi-Fi is delineated in Figure 4. The file server is easily manageable, and we have connected it to our processors in the laboratory for later processing. The access and use of data follow all the data protection procedures. We have a dedicated PC for downloading every hour, connected to the laboratory side of the cloudnode using VPN access. We use *Windows* Operating System and *WinSCP* with the credentials given to download from cloudnode. For the repetitive hourly downloading task, we used the *Task Scheduler* application of the *Windows* Operating system. A task is created to download data using *WinSCP*, which is activated every hour at a given time and automatically executes the task and records the details in a log file.

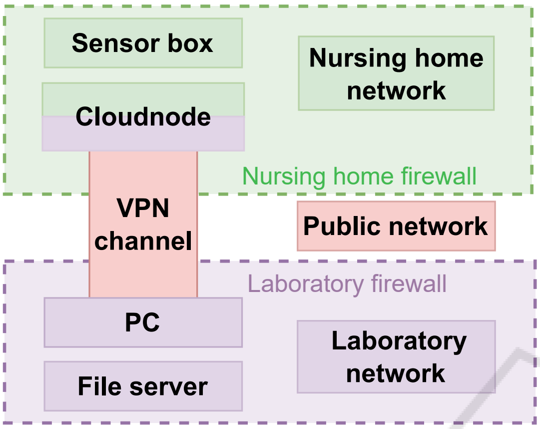


Figure 4: Connection over sensor box, cloudnode, and local machine; within the nursing home network (in green), within the laboratory network (in purple), and through a secure VPN channel (in red).

First, data is downloaded to a hard drive and then moved to the file server. The data could not be downloaded directly to the file server because the file server is within the laboratory network and the PC is connected to the VPN of the nursing home. The temporary hard drive has a memory of eight terabytes, which requires to be replaced once it is full. We established an automated memory check using a *Python* code to check the remaining hard drive memory and email the responsible person if it is below the given threshold. We checked whether the files were downloaded every hour to combat the situations of no upload to the cloudnode or no download by the dedicated PC. In the event of a malfunction, a redownload is initiated and an email is sent as a notification. We updated the *Python* code to check the size of the compressed file downloaded from the cloudnode, where a small size refers to a large loss that hour. This information helps us to trace back to the cloudnode and sensor boxes to discover the issue and to solve it quickly.

3.3 Depth Data and Challenges

The depth sensor captures images as depicted in Figure 5. These depth images form depth video and the pixel values represent distance from the sensor. The depth image is recorded with a header, including the date, time, IP address of the depth sensor, and resolution of the depth sensor in a binary format. The sensor box captures depth images with a resolution of 640×480 pixels at ten frames per second in 16-bit depth map format. Depth images offer the potential to extract various features for AI services, with joint keypoints being a primary feature. These keypoints can be obtained using pose estimation methods (Hartmann et al., 2024; Sun et al., 2017) and subsequently utilized in AI models.

Figure 5: Low visibility of lower body parts; specifics below the knees are not distinguishable in the depth image.

We noticed a decrease in the visibility of a person or specific human body parts while moving away from the sensor box, thus reducing the depth data quality. As described in Section 2.2.2, the sensor box is placed at a height of about two meters, so the diagonal distance between the sensor box and the foot of the resident is more than the upper body parts; thus, the foot has lower visibility, as exemplified in Figure 5. As the person moves further away, the clarity of the depth data decreases also proved in (Mejia-Trujillo et al., 2019).

Most resident rooms are larger, and the distance between the sensor box and the resident increases as the resident moves toward their bed, making it challenging to detect them. In smaller rooms, the clarity is better, but the foot remains difficult to distinguish. We did a quantitative analysis to check the data quality with the distance from the sensor box. The quality of the depth data could be noticed from the Standard Deviation (SD); the increased SD is due to the high variance or data fluctuations, which indicate deteriorated depth data. Here, we took a few points in the data that corresponded to different objects at different distances from the sensor box. Then we calculated the SD at those points over 100 frames. In Figure 6 the different objects are marked in a depth frame from one of the sensors installed in the nursing home. The objects in order of increasing distance are as follows: table, doorway, floor, bed, and side table. Figure 6 also shows the SD values corresponding to object distances. The closer the distance to the sensor box is, the lower the SD value is, which represents fewer fluctuations in depth data. This variance could be due to a person entering the room causing the change in the depth data. Therefore, we take the SD from an annotated empty room. Multiple sensors in the room at distinct locations could solve the issue of residents being far away from the sensor, thus enhancing the data quality; it could also capture other parts of the room outside the fov of the other sensor. However, this requires more bandwidth to transmit the data over Wi-Fi. We could not test due to these bandwidth limitations.

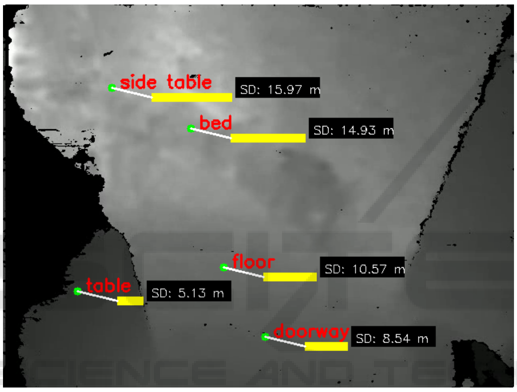
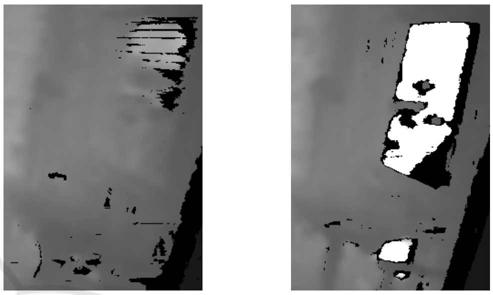


Figure 6: Different objects at various distances from depth images with their SD.

3.4 Data Recording Challenges

As we use the nursing home network to transfer between the sensor box and cloudnode, it has different access points, all part of the entire network used by staff, residents, and guests. We noticed a bandwidth bottleneck that limits the number of sensor boxes that can simultaneously send data to the cloudnode. We could stream between two–ten sensor boxes at a time according to the network conditions and network usage at a facility. There was also a data drop every hour from all the sensor boxes. In every hour, we could observe a loss of at least ten minutes of depth data from each sensor box. We noticed that the data drop was larger whenever there was high network usage. This could be improved by using a dedicated network for the sensor boxes and the cloudnode.

The Raspberry Pis' USB-2 bandwidth limitation influences the maximum resolution and frames per second that could be produced. The hardware must be selected according to the requirements, and the latest version could be used for better quality of depth data output. Depth sensors use infrared technology, so lighting conditions do not affect the images, although glass and mirrors can create artifacts. We noticed artifacts in the depth data due to the reflection of glass windows and mirrors, as illustrated in Figure 7. When the curtain is kept open, more artifacts are visible. During most of the daytime in care facilities, the curtain is kept open. During this data collection, we tried to install the sensor boxes to minimize this effect, i.e., by not installing them directly opposite the windows.



(a) When curtain is closed.

(b) When curtain is opened.

Figure 7: Appearance of artifacts due to reflections from the glass window.

The automated download task in Section 3.2 would not be initiated under the following conditions: (1) if the previous task is still in progress; (2) if the upload is not completed at the given start time of the task. Hence, to ensure that the data is downloaded in the next hour, the cloudnode keeps the data every hour for three hours so that there are at least three chances of downloading before the data is deleted. Automated check with email notifications is also built as a scheduled task executed every hour. The dedicated PC is ensured to remain turned on, for downloading and sending notification emails every hour. However, unplanned power surges or system updates have not yet been detected. Data is missing during such events. For larger files, uploading the data to cloudnode and downloading it to the dedicated PC takes longer. This leads to a delayed download at the next hour, and continuous delays lead to data loss.

3.5 Corpus Statistics

The data collection is still in progress, and we have collected about 15 months of depth data from three long-term care facilities within Germany, as shown in Figure 8. We gathered a total of 58,037 hours, averaging 3,627 hours per month with a SD of 1,327

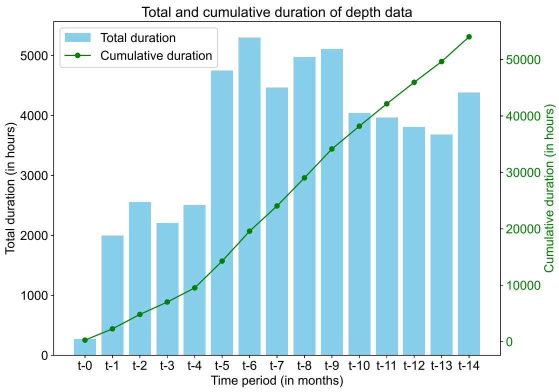


Figure 8: Data collection plot from all the long-term care facilities for 15 months.

hours. There are 45 distinct residents ($\geq$ 60 years old) in the data collected, recorded continuously for at least 24 hours. The total includes male and female residents. Eight percent are bedridden, 38% using walking aids like rollators and sticks, 20% relying on wheelchairs, and 30% classified as independent walkers. Four percent of the residents transitioned between independent walking and other categories, either temporarily or permanently, due to falls or medical conditions, while 3% passed away. Residents using aids or wheelchairs are also at risk of falling, particularly when transitioning from a wheelchair to a bed or sofa, or while using aids during such transitions. Few bedridden residents shift position in bed and this can be used for sleep position monitoring. Other details such as gender percentage and disease classification are unavailable due to the anonymous data. Even though sensor boxes are only installed in specific rooms, others who enter the room are also recorded in the depth sensor. Anyone other than residents included in the study is considered 'others,' including other residents not part of the study, staff, and guests. In the initial month, the number of sensor boxes installed was less, and it increased in the later months. We receive depth data from 15 sensor boxes installed at different facilities every hour. Due to bandwidth limitations as mentioned in Section 2.1.2, all the installed sensor boxes could not be streamed simultaneously; hence rotation of sensor boxes at regular intervals was introduced so we collected data from different resident rooms. During every change in the sensor box and network, we noticed a drop in data collected for a few hours before the network stabilized again.

4 DATA PROCESSING AND PILOT MACHINE LEARNING

The data is filtered for workable data. Workable data contains depth frames with a person in them; frames filtered out include empty and frozen frames. The frame is considered empty when the resident is out of their room and when the resident sleeps in a room where the visibility is low and far away, as mentioned in Section 2.1.1. We noticed that sometimes the entire frames in the data are without any change and are considered frozen frames. The downloaded data is a *zip* file contains stacked files from several sensor boxes. For every sensor box, we get a *bin* file with a header followed by the depth image as explained in Section 2.1.1. The files were processed from the *zip* archive without fully extracting the *zip* file, and then only the workable data was stored, saving memory. The data preparation for manual annotation is to convert the raw file into a video in *MP4* format. The contrast and brightness of *MP4* videos are adjusted for better visibility during annotation. Annotators use these videos for ground-truth preparation for all machine learning models. The frames are extracted as *npz* files and used as training, evaluation, and testing datasets of machine learning models.

4.1 Processing Pipeline

The data processing pipeline depicted in Figure 9 includes all the steps introduced above at the collection site, involving *zip* file downloading, *bin* file extraction, occupied and frozen frames check, and final *MP4* video archiving. An *MP4* video is not archived if its entire frames are identified as empty or frozen. If partial frames are identified as empty or frozen in the whole depth data at an hour, the entire video is still saved, and empty frames are annotated. Archiving of full video instead of key snippets of the occupied portion preserves contextual information, which facilitates a better understanding and quick annotation of the depth video. The marked empty frame makes it easier to find the occupied portions. A *csv* file is also saved for subsequent statistical analysis. This pipeline was executed through depth data collected from different facilities at different hours. We organized the data into various folders for later easier access, enabling running, pausing, and restarting the pipeline execution.

4.2 Occupied Frame Detection

While we record data continuously, processable data with residents actively moving is limited. Therefore,

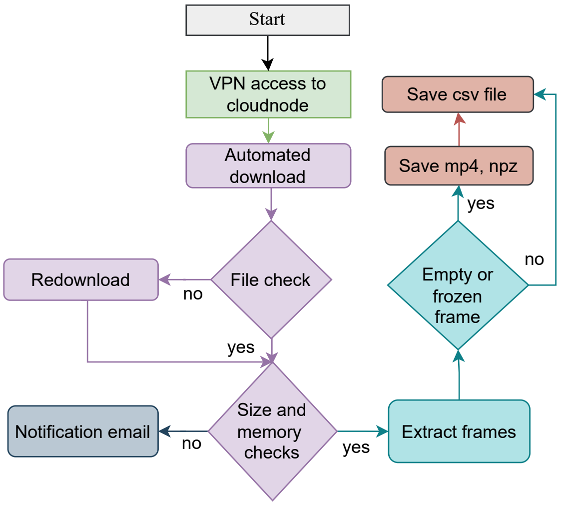


Figure 9: Data collection pipeline with download, extraction, frame classification, and conversion into final formats. The nursing home network (in green), the laboratory network and file checks (in purple), data processing (in turquoise), notifications (in grey), and final files (in brown).

we emphasize occupied room detection to extract relevant data for statistical analysis and further use in the models. Empty frames refer to frames capturing unoccupied rooms, containing only the furniture within them. During the initial months of data collection, we observed that there were a lot of empty room frames in the depth data. The sensors are placed in resident rooms where their daily routines are captured. Even though residents spend time in their rooms, the empty frames are present in the depth data whenever the resident leaves the room for breakfast, lunch, evening coffee break, and group activities with staff or other residents. Due to the low visibility of the distant bed as described in Section 2.1.1, the resident in the bed without movement is also considered an empty frame. It becomes difficult and time-consuming for the annotators to look through the entire video and discover the person to annotate. Hence, we introduced an occupied room classifier in the data preparation pipeline to classify a frame as empty or occupied.

A frame could be identified as empty or occupied by checking whether there was a change in the frame compared to adjacent frames (Karasulu and Korukoglu, 2012). We first performed the absolute subtraction between 15 consecutive frames, for the occupied room classification. Next, we found the heatmap contours in the pixels where there was a change. A *csv* file was created with the number of contours and the size of the largest contour. Ideally, in the subtraction heatmap between an empty and occupied frame, the contour will resemble the shape of a human silhouette, which should be the largest contour. But there could be more than one person in the room; Helping aids such as a rollator, wheelchair, and displaced furniture result in more contours in the subtraction heatmap. In the dataset, we noticed the appearance of artifacts and constant flickering in the depth data, adding to the number of contours in the subtraction heatmap. Therefore, we only used contours that were larger than a predefined threshold, which filtered out most of the small contours that do not refer to a person. The whole task of the occupied room classifier is shown in Figure 10.

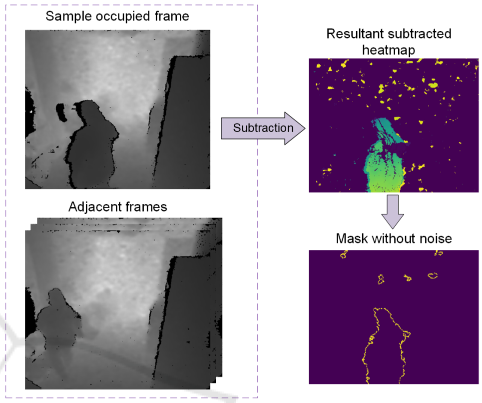


Figure 10: Empty and occupied room detection from depth frames using adjacent frame subtraction and resultant heatmap.

4.2.1 Results and Discussion

We used machine learning models Decision Tree and K-Nearest-Neighbor as classifiers. The input to the models was the contour count, the largest contour size, and the identifiers. The dataset we used included about 23 hours of data with 17 hours of empty data and six hours of occupied depth data. We achieved an accuracy of 93% with Decision Tree and 84% with K-Nearest-Neighbor, where the guess baseline accuracy was 75%. The resultant confusion matrices from both classifiers are shown in Figure 11.

There were cases where an occupied frame was misclassified as empty when the resident did not move from the previous position, resulting in smaller contours, and when the resident was far away from the sensor box as referred to in Section 3.3. Empty frames were misclassified as occupied, in cases of the sudden appearance of larger artifacts, as portrayed in Figure 7. We tried a slightly modified approach for occupied room classification. Here, we considered an empty frame as a reference background frame for each room, which, instead of the adjacent frames, was used in the absolute subtraction of the current frame (Yokoyama and Poggio, 2005). Such a classification results in an accuracy of 82%. The inaccurate recognition of slow

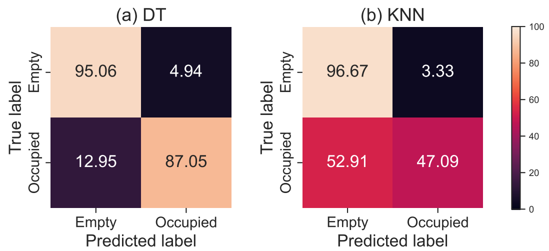


Figure 11: Confusion matrices of occupied room classifier based on Decision Tree and K-Nearest-Neighbor.

to no movement of residents in the previous algorithm was resolved. Nevertheless, the flickering and artifacts were misclassified as occupied, and the room with a person positioned far away was misclassified as empty. The threshold for occupied room detection needed to be varied for each recorded resident room, making this algorithm more complex.

4.3 Frozen Frame Detection

The key difference between empty frames and frozen frames lies in their cause: frozen frames are corrupted due to sensor or network issues, resulting in a single frame being repeated in the data instead of being updated with new frames. The depth data shows constant flickering, causing pixel values to change even when the room is empty. These slight changes enable frozen frames to be identified using absolute differences between current and previous frames. The classification can be based on the threshold of the sum of such differences, which is kept exceptionally low so that only the frozen frames are detected.

4.4 Distribution Statistics

Currently, we extract depth frames as *npz* file and use them in machine learning models; we plan to directly use the classified workable frames from the *zip* archive without fully extracting the *zip* file. We can also execute this pipeline as a recurrent task in the task scheduler to run after every download task. When this pipeline was executed on the dedicated PC, it slowed down the download task and resulted in a few hours of data loss. Figure 12 shows the distribution of frames after the pipeline described in Figure 9 was executed for 20% of the collected data from three long-term care facilities. Although only 33% of the 20% collected data is judged applicable, we have been collecting data continuously for up to 15 months to build a vast and reliable dataset.

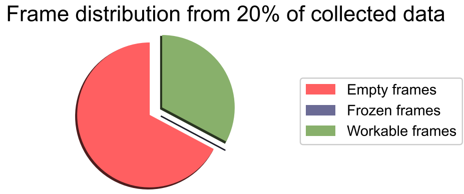


Figure 12: Pie chart with the distribution of empty, frozen, and workable frames on the 20% collected data based on pipeline referred in Section 4.1.

5 CONCLUSION AND FUTURE WORK

This paper outlines the ethical, social, and technical framework involved in long-term depth data collection from residents in long-term care facilities. We began with the study protocol, which addressed the ethical questions related to the study. It was emphasized that no data would be used to monitor or evaluate staff performance. Instead, all data would be utilized solely to enhance the quality of life for residents and reduce staff workload. The sensor box was easily installed and is standalone; therefore, the depth data was collected with minimum intrusion for residents. The images captured by the sensor box do not contain visible indicators of the person, ensuring privacy, which leads to higher acceptance. The depth data from each sensor box was collected at cloudnode and then transmitted to the file server over Wi-Fi. Over the course of 15 months, we collected 24-hour depth data from 45 older adults living in three nursing homes. We designed a pipeline that extracted depth images, checked for different room states and corrupted frames, saved data in various formats, and analyzed statistics of the data. Our study remarks on the feasibility of data collection from a natural environment with a substantial number of participants. This data collection will be a great contribution to several AI services for older adults such as fall detection, sleep position monitoring, gait analysis, movement monitoring, and bed exit detection.

As falls are a serious medical risk with high incidence rates among older adults, we aim to initiate experiments with fall detection systems coupled with notification mechanisms for caregivers. As the risk of falls could be identified from mobility assessment tests, such as Tinetti, SPPB, and TUG, we put initiate studies to automate these tests on the agenda. Furthermore, around-the-clock resident monitoring and gait parameter extraction help in determining the probability of falls and early detection of gait-related disorders. A caregiver or physician can provide tailored training to improve the gait and balance of older adults, which could reduce the likelihood of falls.

5.1 Future AI-services

Longitudinal data collection holds vast potential for advancing research in care support for individuals. In our study, depth data were collected, which could be leveraged to develop targeted applications to assist older adults. For example, a virtual assistant could be designed to help older adults with daily activities and physical exercises. By integrating additional sensors, such as microphones, these systems could evolve into conversational agents. However, we observed that the continuous use of a microphone was not ideal due to social concerns. As an alternative, a microphone could be activated when the individual is alone, allowing for voice-based assistance and interaction. This could enable applications such as voice agents that engage in conversations, assist with tasks, and support simple activities, providing valuable companionship and utility.

ACKNOWLEDGEMENTS

The research reported in this paper has been supported by the German Ministry of Health (BMG), as part of the research project ETAP - Evaluation von teilautomatisierten Pflegeprozessen in der Langzeitpflege am Beispiel von KI-basiertem Bewegungsmonitoring (etap-projekt.de/). We extend our heartfelt gratitude to the staff and residents of AWO Karlsruhe GmbH, Stift Tilbeck GmbH Havixbeck, and Ss. Fabian und Sebastian Rosendahl for their invaluable support and cooperation during the data collection. We acknowledge ChatGPT, an AI language model developed by OpenAI, for its assistance in this paper writing.

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