Human Presence Detection to Support Contextual Awareness in Ambient Assisted Living Scenarios

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***Abstract*—Assistive technologies and ambient assisted living (AAL) environments promote independence and safety at home, especially to vulnerable users such as older adults or people who are recovering after a hospital stay. To support these technologies, we present an approach to detect the presence of people in individual locations of the University of Hertfordshire's Robot House, a four-bedroom residential house with smart sensors and robots. Specifically, our method provides contextual information to assistive services, enabling tailored support based on the specific location within the home. We assess the combined affordances of a series of low-resolution sensors in contributing to the ambient assisted living scenarios as an active part of a pipeline dedicated to developing personalised service provision at home. Moreover, we used lower-level features and combined sensory data to identify activities of daily living and gain insights into residents' habits. Our studies reveal that combining two or more sensors contributes significantly to the accuracy of presence detection, as individual sensors can lead to incomplete or biased information. The information we derive from a combination of sensors can be beneficial when ambient assistive technologies are used in the context of virtual wards to tailor a proactive, personalisable and predictive AI-powered observation deck to support patients in their homes.**

***Index Terms*—Assistive Technologies, Sensors, Smart Homes, Ambient Assisted Living, Virtual Wards**

I. Introduction

Smart living environments leverage technology to enhance the quality of life and save time and energy. Smart homes are becoming more common in today's tech-driven world, offering solutions to improve people's quality of life. Especially people who rely on care, for example, patients who are released to their homes after heart failure, can benefit from smart technologies such as ambient assisted living (AAL) environments [1]. AAL can thereby potentially improve the quality of home care and reduce hospital readmissions while offering cost-effective, efficient and convenient healthcare. However, any solution has to remain cost-effective, privacy-preserving, and context-aware.

One important aspect of delivering an effective assistance function is to identify *where* people are to be able to provide contextual awareness that can support various tasks such as lights and illumination, air conditioning, and heating control, as well as appliances and utilities. Despite promising advancements in human localisation, however, existing approaches often rely on expensive hardware, or wearable technology or invade the privacy of users [2]. Moreover, many methods for person localisation have not been evaluated in realistic home environments [3].

To address these challenges, we present an approach to human presence detection that maintains privacy and ethical standards as much as possible. We recorded and analysed a single person's activity in a home-like environment for five days, solely relying on low-cost and privacy-preserved movement sensors, pressure sensor mats and status sensors on appliances, doors, drawers, and cupboards instead of cameras or microphones. All data is collected in the University of Hertfordshire Robot House, a fully furnished, four-bedroom home dedicated to research studies for human-robot interaction, providing a real home environment for research to bridge the gap between laboratory research and practical applications.

We use the obtained data to enable a person presence detection approach that, at the same time, supports the detection of activities of daily living (ADL) and thus contributes to medical care and social well-being within the smart environment. Our approach of using sensor data and tools can be extended to monitor behaviours or observe patterns to identify abnormalities to facilitate the generation of notifications, for example, reminders about medication or exercise. More specifically, we have identified the presence of a person in the six most occupied areas of the home, clustered the data into various groups using the Density-Based Spatial Clustering of Applications with Noise (DBSCAN), and then applied some contextual rules to glean insights into their daily routines. Specifically, we have extracted information on 16 activities, including work, cooking, using the toilet, leisure activities, sitting in the bedroom, sleeping, food preparation, listening to the radio, reading in the living room, miscellaneous hygiene tasks, staying in bed, preparing hot drinks, actively watching TV, having meals, and being away from the house.

In the remainder of this paper, we will first introduce related work on person localisation in home environments (Sect. II) before we delve into the specific methodology of our data collection and analysis in Section III. We then present and discuss the results of our data analysis in Section IV before we conclude the paper.

II. Related Work

There is significant progress in the field of human presence detection and localisation. Various methods relying on

Bluetooth or Wi-Fi signals or speaker identification have shown promising results for human presence detection [3], [4]. One study, for instance, has achieved accuracies of 99.2% using Bluetooth technology, 98.6% relying on Wi-Fi signals, and 92.7% when identifying the speaker [5]. Likewise, novel models utilising data from sensors embedded in smartphones and smartwatches have outperformed the existing systems in intelligent localization and recognition of human activities [6]. One approach [7] detected human presence in the smart home utilising an infrared sensor and introduced an adaptive method that distinguishes between the presence and absence of a person using a k-nearest neighbour (KNN) model, and updates the learning parameters of its classifier over time. While this method is effective in detecting presence if tested in real-home scenarios, it may face challenges in adapting to changing environments and false alarms. Another study [8] introduces an information entropy-based method based on using signal strength samples for indoor human presence detection. Unlike Passive Infrared (PIR) sensor methods that detect presence in motionless scenarios by relying on heat emitted by moving objects, this method achieves better accuracy in such scenarios by using variations of radio signal strength, highlighting its potential for enhancing presence detection in specific contexts. However, the practicality of these approaches during daily activities in home settings remains a challenge as these sensors cannot be comfortably worn [9].

Furthermore, innovative frequency domain analysis-based device-free approaches are proposed for human presence in wireless sensor networks [10], achieving good results even with the changed layout of furniture and without human-worn transceivers. Such systems emphasise the need for adaptable systems in real-world settings. Another study [11] employed signal strength indicator (RSSI) data to detect the presence or absence of humans. Such cost-efficient and easy-to-install setups can be integrated into low-processing power gadgets and existing smart homes, but require careful consideration of environmental factors. Moreover, studies investigated the use of CO2 in indoor environments to detect the presence of humans [12], and their method has proved effective for indoor human presence detection over traditional motion sensors. However, this method requires specialised sensors and can be influenced by factors such as ventilation or occupancy by pets.

Microphones in smartphones, paired with applied deep learning models achieved promising accuracy in detecting human presence during emergencies such as earthquakes [13]. Similarly, sensors embedded in smartphones and smartwatches have demonstrated significant performance in intelligent localization and recognition of human activities [6]. Real-world deployment poses challenges to the previously mentioned approaches where furniture and room layouts, ecological conditions and unexpected user behaviours have negative effects on the accuracy of the approach [14], [15]. Privacy preservation is another critical concern for the systems relying on smartphone sensor data, cameras or other intrusive data collection techniques [3], [6].

Many studies lack real-world data and testing in actual homes [16], [17]. Extensive validation of human presence algorithms is required in real-world deployments [7]. Ethical, legal, and societal aspects of AAL technologies, such as those related to General Data Protection Regulation (GDPR), necessitate privacy-preserving tools and techniques [18]. Such challenges currently prevent the adoption into AAL technologies and highlight the need for presence detection solutions that can be generalised to different environments, are context-aware, low-cost and respectful of user privacy.

III. Experimental Setup

In a single-user experiment, we collected sensor data in a smart AAL environment, to which we then applied our person-detection approach. We analysed individual and combined sensor data to understand the effectiveness and accuracy of presence detection.

Data collection was performed in the University of Hertfordshire Robot House[1], a four-bedroom British residential home, whose ground floor has been adapted to conduct research studies for human-robot interaction in AAL scenarios. The Robot House provides an ideal setting for our experiments, offering a realistic home environment with typical furniture layouts and kitchen appliances, and natural lighting conditions to enable user behaviours of normal daily activities. Figure 1 shows the layout of Robot House's ground floor. The entire ground floor was available during the experiment but due to the non-sensorised nature of the conservatory and office, mostly the bedroom, bathroom, kitchen, and living room were used during the runtime of this experiment. The living room can be further compartmentalised since it serves as both a TV lounge and dining area so we ended up with the dining area and sofa area in the living room, hall entrance, kitchen, bathroom, and bedroom as the six locations for our experiment. There are more than 60 smart home sensors placed throughout the Robot House, including pressure mats, brightness, movement, temperature, water flow, power consumption and plug status sensors. We restricted the data recording to motion sensors, pressure mats, and status sensors used in this experiment which can provide essential functionality while maintaining a low to medium level of privacy exposure. These sensors primarily rely on signals and detect the presence and movement of individuals, without capturing any personal details. This approach helps to preserve user privacy while enabling efficient monitoring and automation within the home. We have specifically used the below-mentioned sensors in our experiment:

- **Movement Sensors** (7) positioned in each room, indicated by a purple, radar-like shape on Figure 1. These sensors detect people's presence in the area they are deployed in.
- **Status Sensors** installed at every door (4 sensors, depicted as quarter-circles), drawers (10), wardrobes (3), kitchen cabinet (6), fridge door (1), and toilet seat lid (1)

[1] https://robothouse.herts.ac.uk

Figure 1: Robot House ground floor with smart home sensors indicated by icons in their respective location.

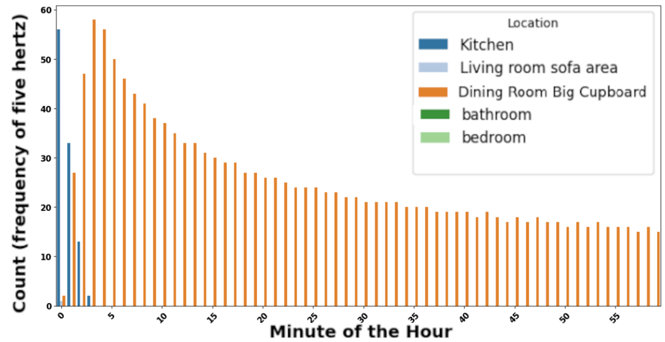

Figure 2: Results of the presence detection for one example hour when only relying on motion sensors. Each minute of the hour is displayed on the X-axis. The Y-axis shows the sensor activation count. Most sensor activations can be observed near 'Dining Room Big Cupboard' and some in the 'Kitchen' area.

to indicate their open/close status. These latter sensors are depicted as rectangles with a handle at the side

- **Pressure Mats** on the sofa seats (5, depicted as armchairs) and the bed (1) to identify the occupancy.

Details of data cleaning and reasons for selecting these specific sensors are provided in Section III-B and Section IV-A.

A. Experiment Procedure and Participant

For our data collection, we involved one participant living in the Robot House for five days. The participant spent 12 hours each day, performing typical daily life activities including sleeping, using the toilet, preparing food, making coffee, sitting on the sofa, using gadgets, moving around the house for daily chores and checking at the door if the doorbell rings. The participant's activities were continuously recorded by sensors, marking each data point with a timestamp. It is noteworthy that the occupant is not an actual resident of this house, but resides there only for data collection. The participant arrived at the Robot House at 7 AM and left at 7 PM every day. They spent five days living in the Robot House, excluding the overnight stay. While our goal is to have actual residents sleep in the Robot House, for this experiment, we have simulated typical sleeping patterns within the Robot House environment. We manually designated the time frame between 10 PM and 6 AM as representative of sleep, aligning with the participant's documented sleep schedule.

As a baseline for comparison, we asked the participant to manually document their routine in Robot House. For the first two days, the participant had some interaction in the bathroom and kitchen after arriving and then took a nap in the bedroom. They woke up between 10 and 11 AM to start their home office work. On the other days, the participant did not sleep in the bedroom which is also reflected in our analysis. The participant mostly worked on a laptop, sitting on the sofa or at a desk in the office or bedroom, from 10 AM to 5 PM, with breaks during the day.

B. Data, Preprocessing, and Cleaning

Our data was collected at a frequency of five hertz in all locations. Each entry data included all sensors, recording the higher level status of the sensor (i.e. open, closed, off, present, absent), the value of the sensor, and its coordinates (as X and Y position in metres) within the house. The person's presence was to be determined based on ample sensor data for each timestamp. Our data cleaning process involved several key steps to ensure the quality and relevance of presence detection. The initial data, obtained from Robot Operating System (ROS) and stored in JSON files, was cleaned to remove unnecessary plug readings, and sensor information including brightness, radiators, temperature, water pipes, and lights sensors, focusing on motion, pressure, and status sensors only. We removed irrelevant locations like the upstairs hall, garden, and garage from our data. The filtered data was processed to annotate presence at different locations.

IV. Results and Discussion

To detect a person's presence and gain insights into their daily habits using the sensor data, We first analysed the individual sensors and then performed a combined sensor analysis. Section IV-A provides detailed information on our findings on the combination of sensor readings and their impact on presence detection for AAL scenarios. We then describe the use of DBSCAN and rule-based methods for clustering and identifying context-aware activities.

A. Combination of Sensor Readings

For the separate analysis of sensors, we found that any sensor alone was insufficient to determine the presence, as they can often provide false and biased information. For example, a motion sensor can detect movement in the living room when a person is passing through on their way to the bathroom.

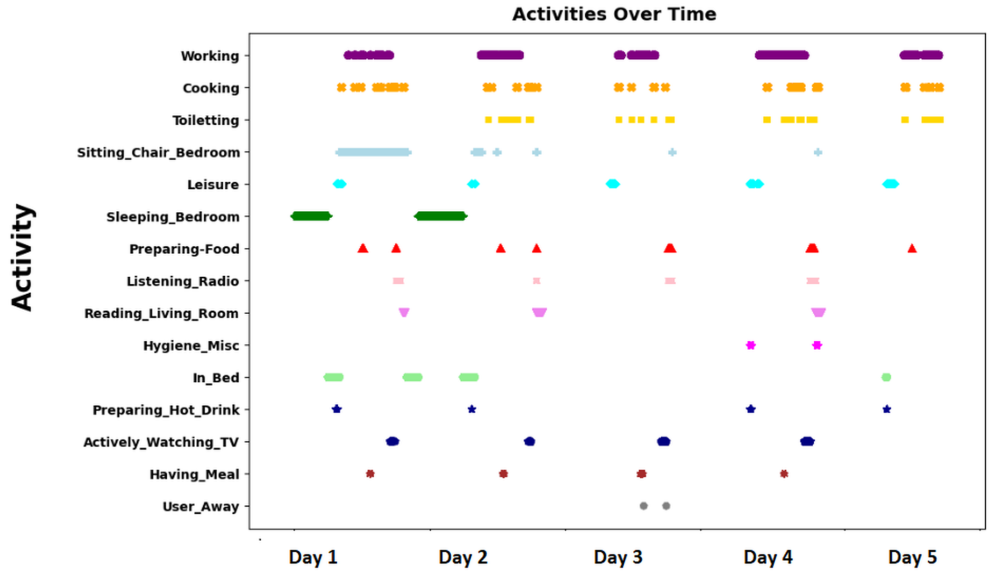

Figure 3: Overview of detected activities over the course of five days.

In such cases, the actual presence was in the bathroom and sensor data could inaccurately identify the person in the living room. Figure 2 depicts a motion sensor activations of one hour. As opposed to participant annotations, reporting activity mainly in the sofa area, kitchen, and bathroom, these sensors mostly detected activities in the dining area of the living room. Such sensor readings attest to a large influence of the sensor mounted on top of the large cupboard in the dining room indicating that the sensor covers a very wide and central area of the house and movement around this area is frequently triggered. Similarly, for the status sensors, mere opening and closing of doors or usage of kitchen appliances is not sufficient to indicate a person's presence. For instance, leaving the door open accidentally, or putting the food in the microwave and then returning to the living room while the food is reheating, are not insufficient to conclude that the person is in that location. Therefore, combining data from different sensors is necessary to determine the exact location.

Using an unnecessarily large number of sensors can also lead to false results for various reasons. For instance, brightness sensors may vary based on the time of day or the use of artificial lighting, not necessarily indicating presence. Similarly, readings in temperature sensors might vary due to environmental changes rather than human presence. Sometimes, energy sensors can also be misleading; for example, a TV might be on while the person is in the kitchen preparing coffee, or a laptop might be charging without the person being present. Hence, the contextual rules are vital in these scenarios to precisely determine the presence and absence of a person.

We combined all three types of sensors - pressure mats, motion, and status sensors - to find out the presence of a person at a location. We consider evidence from at least two sensors (regardless of type) to be necessary for detection, though this is considered weak. For strong presence detection, we required three or more sensors supporting the presence of a person at that location. The rationale behind distinguishing between 'strong' and 'weak' is to minimise false positives. When classifying the presence between the strong and weak, we favoured the strong presence.

B. Analysis using DBSCAN and Rule-Based Methods

To determine the presence of individuals in specific locations, we analysed the preprocessed and cleaned sensor data. We then annotated weak and strong detections of presence in various areas of the home, depending on whether at least two or at least three sensors met certain criteria.

1) DBSCAN Clustering: We organised the obtained presence results into clusters according to their identified locations using DBSCAN, a popular clustering algorithm in data mining and machine learning [19]. This algorithm groups the data points that are closely packed, based on their density in the data space. This algorithm does not require the number of clusters in advance and is robust for noisy data. We set the parameters $eps = 0.5$ so that it considers activities to be neighbours if they occur within a 0.5-unit distance from each other, and $min\_samples = 10$ to ensure that a cluster contains at least 10 points to be considered significant. This method proved more efficient in our experiment, as it processes a smaller subset of sensors, leading to quicker computation times.

2) Rule-Based Filtering for Context-aware Activities: After making the clusters, we applied rule-based filtering to identify the context-aware activities. We labelled the activities according to different times of the day. Activities in the bedroom between 11 PM and 06 AM were labelled as 'sleeping', while the rest of the bedroom activities were labelled as 'resting'. Similarly, the presence in the kitchen, and interaction with kitchen objects during the typical morning, evening, and meal

TABLE I: Activity Counts Across Different Locations in Robot House

Activity	Location	Count
Cooking	Kitchen	4552
Leisure	Living Room Sofa Area	26960
Preparing Meal	Kitchen	6629
Resting	Bedroom	64193
Sleeping	Bedroom	50371
Toileting	Bathroom	10740
Working	Living Room Sofa Area	59338

times lasting more than 10 to 15 were labelled as 'meal preparation', 'preparing_Hot_Drink' and further classified as 'cooking' if lasting for half an hour or more. Bathroom activities involving open toilet lid, combined with motion sensor and door status data were labelled as 'toileting'. When the toilet lid was closed but the other values remained, the activity was labelled as 'hygieneMisc'. 'Leisure' was identified as any activity occurring in the 'Living Room Sofa Area' outside typical working hours (after 5 PM). This implies that during these times, the activity is more relaxed and less structured.

Table I shows the counts of various activities in different locations within the Robot House. Out of the total 222,785 activity counts, there were only two instances with no clear patterns and could not be included in any cluster. The rest of all activities were categorised into distinct clusters based on common patterns. It can be observed that the bedroom had a high frequency of 'sleeping' and 'resting' activities. The most dominant activity for the kitchen was 'meal preparation' and 'preparing_Hot_Drink', reflecting the participant's typical daily routine. The living room had a mixture of 'working' and 'leisure' activities in the sofa and dining areas, while the bathroom mostly indicated 'toileting'. Figure 3 represents the overall density of activities over five days, at different times of the day. There are 16 different activities, each represented by distinct symbols and colours, across multiple days. The x-axis represents the days, while the y-axis lists the different activities. It can be observed that between 9 AM and 5 PM, there was high activity in the living room and frequent activities in the kitchen and bathroom for breaks, meals, and toileting. The 'Working' activity declined after 5 PM, followed by an increase in relaxing and leisure activities during the last two hours of the day.

Figure 4 compares the results from our rule-based method relying on sensor data in part 4a (including unclassified instances), compared with manual notes provided by the participant in part 4b. Both graphs show peak activity time between 8 AM and 12 PM and between 5 PM and 7 PM. Activities such as 'Leisure/Relaxing' and 'Resting' are prominent in the same hours in both graphs. 'Sleeping' appears in the early hours in both graphs.

V. Conclusion and Future Work

The analysis of our approach demonstrates the effectiveness of using low-level sensors to gain insights into high-level activities. The combination of low-resolution sensors such as motion, status, and pressure mats can provide cost-effective and accurate presence detection of a person in smart homes. The combination of DBSCAN and rule-based techniques proved to be a superior approach for getting insights into a resident's daily habits. In follow-up work, we will explore hybrid approaches to balance simplicity and accuracy and integrate adaptive filtering techniques to dynamically select relevant sensors. We also suggest testing the system in different homes with multiple occupants, various population groups, diverse home layouts, and over extended periods. This will help to more accurately detect patterns and anomalies in human behaviour and to generalise the findings.

Our approach aims to facilitate the provision of comfort, round-the-clock service, and cost reduction in comparison to (re-)hospitalisation. We postulate that integrating presence detection in ambient assisted living can provide significant benefits for virtual wards at home. In future work, we aim to demonstrate this working system in the care of heart failure patients. We combine the elements of essential care with the affordances offered by multiple sensors, as well as mobile robots and wearable technology, to tailor a proactive, personalisable and predictive AI-powered observation deck to support patients in their homes.

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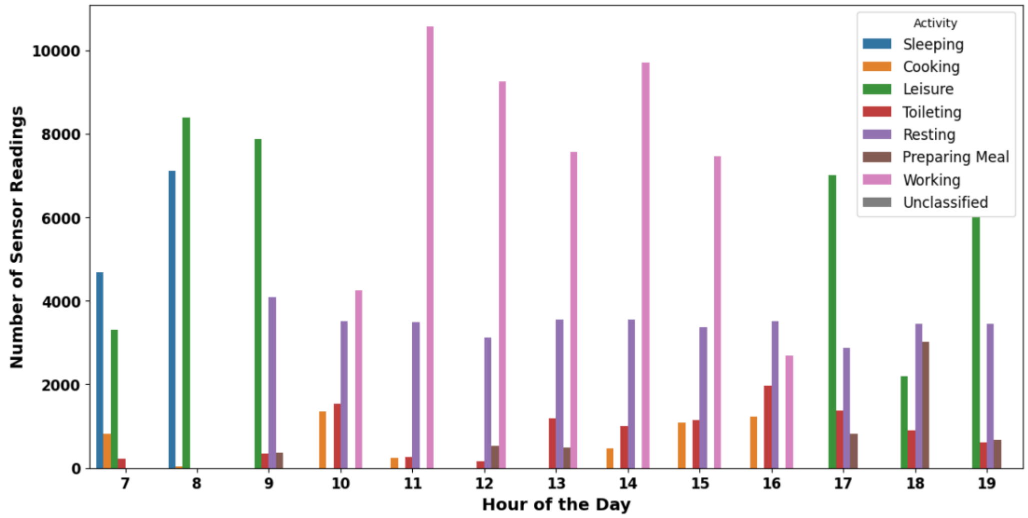
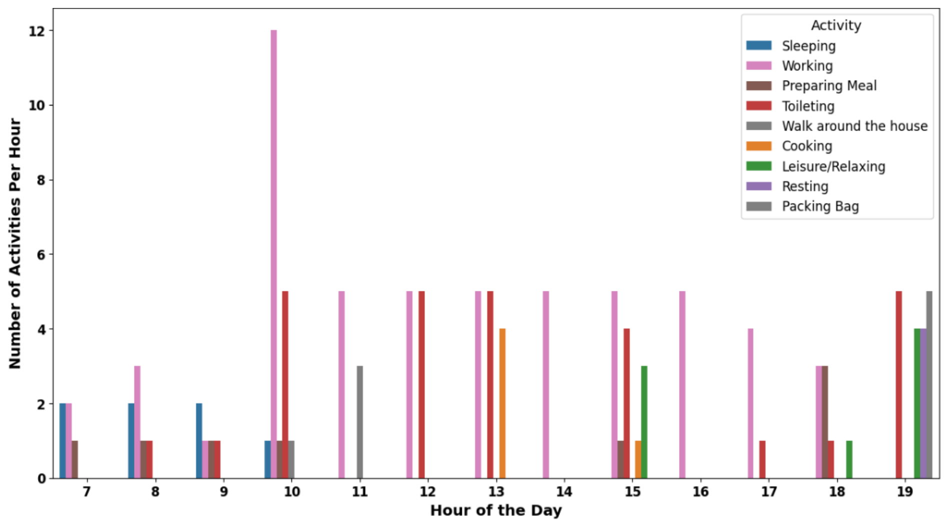


(a) Activity classification results given as the number of sensor readings.



(b) Manually annotated baseline by the participant given as the number of activities.

Figure 4: Participant activities between 7:00 AM and 7:00 PM. The Y-axis displays the amount of activity, separated by the hour on the X-axis.

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