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Research article

Human activity mining in multi-occupancy contexts based on nearby interaction under a fuzzy approach

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A R T I C L E I N F O

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A B S T R A C T

Multioccupation encompasses real-life environments in which people interact in the same common space. Recognizing activities in this context for each inhabitant has been challenging and complex. This work presents a fuzzy knowledge-based system for mining human activities in multi-occupancy contexts based on nearby interaction based on the Ultra-wideband. First, interest zone spatial location is modelled using a straightforward fuzzy logic approach, enabling discriminating short-term event interactions. Second, linguistic protoforms use fuzzy rules to describe long-term events for mining human activities in a multi-occupancy context. A data set with multimodal sensors has been collected and labelled to exhibit the application of the approach. The results show an encouraging performance (0.9 precision) in the discrimination of multiple occupations.

1. Introduction

Monitoring activities of daily living (ADL) plays a crucial role in various domains, including healthcare, smart homes, and assisted living. Accurately tracking and analysing ADLs within indoor environments has significant implications for improving healthcare outcomes, ensuring safety, and enhancing the overall quality of life [1]. With sensor-based technologies, such as binary and vision sensors, and advances in ultra-wideband (UWB) technology, indoor location tracking has seen remarkable progress, including machine learning and sensor data fusion [2] and improving performance to mitigate errors and signal interference [3,4].

In Human Activity Recognition (HAR), binary sensors, widely used in activity recognition systems because of low cost and privacy preservation, detect the presence or absence of a person in a particular area. Despite the strengths, they provide limitations in accurately identifying and tracking ADLs in multioccupancy contexts [5].

Distinguishing ADLs in multi-occupancy smart environments remains challenging, as most ambient sensor devices cannot differentiate between individuals or identify the specific person who develops an activity [6]. This limitation hinders the accurate tracking and analysis of ADLs in such settings. Consequently, research in multi-occupancy ADL monitoring is a challenging goal due to the limited capabilities of low-cost devices, privacy concerns and the complexity of human tasks.

In this work, we integrate UWB technology, which has gained significant attention to improve indoor location tracking [7,8]. UWB enables precise positioning and ranging capabilities by utilizing Time Difference of Arrival (TDoA) and Received Signal Strength Indicator (RSSI) techniques [9]. Additionally, indoor environments are commonly multioccupied, which adds complexity to ADL monitoring. UWB enhances Real-Time Location Systems (RTLS), which are employed to implement indoor tracking solutions that

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allow high-precision localization, tracking, and monitoring of individuals in real time. These systems have been widely adopted in healthcare settings, enabling continuous monitoring of patients' activities, fall detection, and emergency response [8,10].

On the other hand, fuzzy logic has been proposed as a paradigm of high influence to describe activities in smart environments using a knowledge-based approach [11]. Clearly, fuzzy logic provides sensor fusion capabilities [12] and the mining of daily activities from sensor streams [13].

This work aims to bridge the gap in knowledge regarding ADL monitoring and smart environments, providing a model for describing activities in multi-occupancy contexts. It is based on the nearby interaction of UWB, which provides user location with high privacy and non-invasive devices. The findings of this study will assist researchers, healthcare practitioners, and system designers in making informed decisions regarding the selection and integration of sensor technologies and RTLS systems for accurate ADL monitoring in multi-occupancy environments and improved healthcare outcomes. Additionally, the research results will address critical privacy concerns associated with multi-occupancy ADL monitoring, paving the way for developing privacy-preserving solutions in this field.

The remainder of this paper is organized as follows. Section 2 presents related studies related to HAR and multioccupancy RTLS in intelligent environments with multioccupancy. In Section 3, we detail the proposed fuzzy model for mining human activities based on the nearby interaction of sensor activation. In Section 4, we describe the case study and experimental setup developed in this work to evaluate and present the use of the methodology in a real-life context and an in-depth description of the methods used. Section 5 presents the results and discussion on the data collected in the case study developed. At the end, we present the conclusions and ongoing work in Section 6.

2. Related works

Human Activity Recognition (HAR) uses interconnected devices to monitor individual daily tasks and recognize their activities based on sensor data [14]. The collected data takes the form of temporal sequences/data streams that capture specific (and uncertain) values or transitions between different states [15]. These data are instrumental in extracting knowledge related to Activities of Daily Living (ADL), which can raise notable privacy concerns [16]. Consequently, binary sensors and wearables have emerged as the prevailing technologies in this domain due to their comparatively unobtrusive nature [5]. However, achieving HAR within smart homes poses a significant challenge due to the inherent complexity and variability of human activities, which can vary daily and among different occupants, each characterized by distinct behavioural patterns and capabilities [17].

Multi-occupancy smart environments present persistent challenges in effectively distinguishing Activities of Daily Living (ADLs) [18], and most devices cannot provide individual-specific information or identify the specific individual who triggered the sensor [6].

Recent investigations in multi-occupancy environments have prioritized using environmental, wearable, and vision sensors. Within an unsupervised framework, many PIR (passive infrared) sensors strategically positioned within residential premises have been employed to discern the presence of visitors, as documented in [19]. By analysing PIR sensor data and employing entropy measurements, researchers have established a threshold that indicates the presence of a visitor based on occupancy data's standard deviation and entropy metrics such as Approximate Entropy, Sample Entropy, and Fuzzy Entropy. Many scientific contributions have adopted similar methodologies utilizing PIR sensors to derive occupancy-related insights within indoor environments [20–23].

However, most research efforts in this field focus on detecting visitors within single-occupancy households or trying to determine the count of individuals within a given environment. The challenge lies in establishing a definitive association between the data obtained from environmental sensors and a specific inhabitant. Although vision sensors present enhanced precision, this approach engenders concerns about privacy [24] and identification.

To tackle this quandary, recent investigations have explored the utilization of low-resolution thermal cameras [25–28]. Using thermal vision sensors supported by CNN is common. In [25], authors detect falls with multiple occupants by employing a thermal vision sensor and a decomposer to identify users. The CNN then individually determines if a fall has occurred, outperforming systems without multi-occupancy. Furthermore, [29] tracks multiple occupants by analysing the difference between consecutive frames using a computer vision algorithm combined with a 19-layer CNN. Fusing results through sliding windows yields highly accurate tracking of occupants' paths. Other approaches include [30], which employs a LiDAR sensor and a clustering-based method to separate point clouds for each person. This system, trained on real-time and open-access datasets, performs well after applying domain adaptation techniques.

Typically, methods to determine the identity of people participating in activities or triggering sensors are based on location-based approaches. Consequently, several studies mentioned earlier incorporate the tracking of individuals within the environment. However, the accurate tracking of indoor locations continues to present challenges, as existing systems and devices frequently generate false positive activations [31]. Real-Time Location Systems (RTLS) enhance and support sensors to identify users [7,32]. RTLS leverages techniques such as the time difference of arrival (TDoA) and the received signal strength indicator (RSSI) to accurately calculate positions based on the signals received by the anchors from the tags [33–35]. Using multiple anchors allows the system to achieve high-accuracy positioning [36,37]. Middleware plays a crucial role in the functioning of RTLS by processing raw data, performing filtering and position calculations, and seamlessly integrating with other systems [38,39]. Monitoring and visualization software facilitates real-time tracking and visualization by presenting the processed location data through user interfaces. RTLS finds wide-ranging applications in healthcare, manufacturing, logistics, retail, and security, contributing to enhanced operational efficiency, improved safety, and data-driven decision-making [8].

The prevailing method for indoor location employs Bluetooth Low Energy (BLE) due to its affordability and ease of deployment. Both [40,41] utilize BLE beacons and scanners with fingerprinting techniques. The distinction lies in the second proposal, which combines fingerprinting with triangulation results derived from Received Signal Strength Indicator (RSSI) measurements. However, the latter primarily achieves area accuracy (e.g., kitchen, bedroom) without specifically distinguishing the precise location within a room. Moreover, the variability of the BLE signal and the presence of obstacles necessitate the installation of a high density of beacons. In [42], the authors present an empirical experiment on office occupancy detection using BLE beacons and power meters, achieving an F-measure of 90% for occupancy inference based on aggregated power consumption.

In recent years, the incorporation of Ultra-Wideband (UWB) technology has witnessed a notable surge within the scientific and industrial realms, predominantly driven by its increasing cost-effectiveness and proliferating popularity [10]. UWB represents a wireless communication modality characterized by its utilization of significantly broad spectral bandwidth and fleeting radio pulse durations. Diverging from conventional wireless technologies, such as Wi-Fi or Bluetooth, which operate within narrower frequency confines, UWB capitalizes on an expansive frequency range spanning from a few megahertz to several gigahertz. Owing to its concise pulse durations, UWB enables the meticulous measurement of signal time-of-flight, thereby endowing the capability to ascertain device coordinates with an astounding degree of centimetric exactitude [8].

Several recent works have explored indoor positioning techniques. In [43], DS-TWR and Particle Filter are employed for UWB positioning and BLE signal processing, respectively, achieving 2–3 cm accuracy after optimizing the EKF algorithm. Che et al. [44] utilize UWB radar and NB algorithm to classify LOS and NLOS environments with 4 anchors and 1 tag. Ambrose et al. [45] combine DWM3000EVB boards with nRF52840-DK (UWB+BLE) and trilateration for indoor positioning, achieving an error of 344 mm in a small square pattern with 1 tag and 3 anchors. Efendi et al. [46] employ EWINE UWB technology with decision tree learning, achieving 90% accuracy in detecting LOS and NLOS cases across indoor environments. The proposal by Volpi et al. [47] utilizes the Qorvo MDEK1001 kit with DWM1001 module for trilateration-based positioning. Laboratory tests using 4–6 anchors and 1–3 tags achieve sub-meter accuracy [47]. In [48], the authors compare RSSI signal strength and ToF transit time measurements using the DW1000 module. In [49], Decawave DWM1000 and the AI-EKF algorithm handle NLOS conditions, achieving an RMSE of 0.53 with 5 anchors and 1 tag. In [50], energy-saving route mapping is performed using 2 tags and 8 anchors, but details are limited. In [51], multi-static antennas and the Newton–Raphson method are employed with 3 anchors and 1 tag for destination localization. In [52], an indoor positioning system utilizing UWB technology and RTOF measurement is proposed, employing the LSETaylor method. The system in [53] uses the DecaWave DW1000 module and the TWR algorithm, achieving an average accuracy of 0.59 m. In addition, integrating UWB in home contexts and dynamic paths has been demonstrated to be limited by:

- Poor performance in buildings with walls and furniture [54].
- Increasing error and uncertainty due to passive localization system. needs to be very stable with low jitter and high signal [55].
- Location affected by the position of body wearable sensor [56].

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Regarding the combination of UWB and HAR, the DW1000 module, trilateration algorithms, and non-linear least squares were used to achieve localization and activity recognition in an indoor environment in [57]. The recognized activities included sitting, standing up, standing, and walking. Average activity recognition accuracies of 87.2% and 80.2% were achieved using SVM in different configurations. In [58], a UWB radar system was used for recognizing activities of daily living (ADLs). Deep learning models such as Stacked LSTM, CNN-LSTM, and ResNet were utilized to classify activities based on data captured by the radars. The recognized activities included drinking, sleeping, putting on a jacket, doing household chores, cooking pasta, making tea, washing dishes, brushing teeth, washing hands, reading a book, eating, walking, putting on shoes, taking medication, and using a computer. A precision of 94% was achieved using the CNN+LSTM model. In [59], Pozyx technology was used, which consists of mobile sensors (tags) and stationary anchors for 3D positioning through UWB communication. The TDOA and TWR algorithms were employed for positioning. A CNN was implemented to recognize physical activities, achieving a training accuracy of 97.5% and a testing accuracy of 94.7%. The recognized activities included pull-ups, squats, and dips.

In a related study [60], authors propose a methodology that shares similarities with our approach, combining indoor location tracking and activity recognition using machine learning techniques. They employ Bluetooth Low Energy (BLE) technology through a wearable device placed on the waist, beacons, and scanners to measure Received Signal Strength Indicator (RSSI) levels. The authors utilize random forest and support vector machine (SVM) algorithms as activity and location classifiers. However, this study also highlights the limitations of BLE systems and the restricted range of recognized activities, including sitting, lying down, walking, falling, and standing. Furthermore, sub-activities are associated with the identified activities depending on the specific area within the environment. For example, if the subject stands in the kitchen, their activity is classified as cooking. In [61], the authors detail a methodological approach that is easily replicable as it is well-detailed. MoSen uses a Machine Learning-based approach to infer the location and recognize people's activities in a domestic environment where multi-occupancy may be present. The system was evaluated in a domestic environment, but limitations include limited generalizability, lower accuracy in complex environments, difficulty distinguishing similar activities, and computational costs. In [62], a knowledge-based reasoning approach is employed to analyse contextual data and selectively exclude activities from the probability distribution obtained through activity recognition that does not align with the given context. They propose that MICAR could potentially leverage these technologies to achieve reliable data association.

Based on all these proposals, in this work, we present an approach for multi-occupancy context: (i) to model uncertain in areas of interest in dynamic paths and real-home deployments, (ii) to discriminate sensor-event interactions, and (iii) to model rules of human activity using a knowledge-based approach from IoT non-invasive sensors.

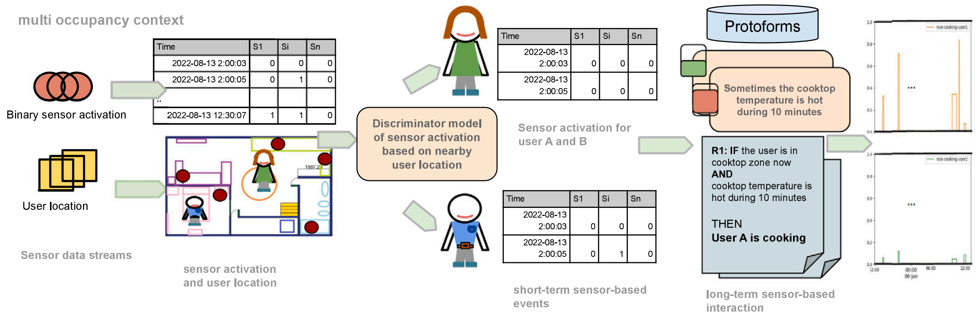

Fig. 1. Architecture of components which configure the proposal. The sensor activation and user location are collected from sensor data streams to compute short-term activation and long-term events for each user.

3. Methods

In this section, we formally describe the proposed fuzzy model for mining human activities based on the nearby interaction of sensor activation and user proximity. The work mainly focuses on describing and discriminating two daily processes from human activity tasks: (i) *sensor-based events*, which are related to short-term activation of binary sensors, and (ii) *activities*, which are related to long-term events from sensor activation and user location. In Fig. 1, we detail the architecture of components which configure the proposal.

A flowchart of the approach of this work is presented in Fig. 2. First, the sensor activation and user location are collected from sensor data streams. Second, short-term activation of binary sensors is discriminated for each user. For this purpose, a degree of user interaction is computed for each region of interest associated with each sensor. When there is an activation of a sensor, it is discriminated which user has performed the interaction based on the highest degree of interaction. Third, long-term events defined by protoforms describe long-term events from sensor-based activation. For this purpose, the sensor streams are transformed to fuzzy data streams that enable computing expert knowledge in a spatio-temporal way by means of protoforms. These protoforms configure IF-THEN rules and compute activation time intervals. Finally, the region of interest of each rule determines which users performed the activity.

In the next sections, we describe modelling fuzzy data streams from user nearby interaction and ambient sensors. Subsequently, we present the short- and long-term sensor-based events discrimination from user-nearby under a fuzzy approach.

3.1. Modelling fuzzy data streams from user nearby interaction of region of interest

A location area u_i of a user u for each time-step t_i is defined by geometrical space, such as a point a, a circle, an ellipse or a bounding box (rectangle). The geometrical space which defines the user location determines an approximated measurement with uncertain and imprecision. The data streams are defined in points of time $t_i = \{t_0, t_0 + \Delta + \cdots + t_N - \Delta + t_N\}$ defined in a given time interval of interest $[t_0, t_N]$ whose time-step is Δ. In this way,for a given user u is traced by a location stream $\vec{u} = \{u_0, \ldots, u_i\}$.

Second, a region of interest r is defined by one or several interaction location areas $L(r) = \{l^r_0, \ldots, l^r_i\}$. Each area l^r_i is described by an interaction degree $\overline{l^r_i}$ to determine multiple areas with different interactions flexibly. The interaction degree between the region of interest r and the user location u_i in the time stamp t_i is computed aggregating the intersection of location areas $\bigcup_{l^r_j}^{L(r)}$ weighted by their interaction degree $\overline{l^r_j}$ as:

$$L(r)^u_i = L(r) \cap u_i = \bigcup_{l^r_j}^{l^s_j \in L(r)} (\overline{l^s_j} \otimes l^s_j \cap u_i) \tag{1}$$

The interaction is defined by a degree $L(r)^u_i \in [0, 1]$ whose semantic relates the spatial intersection between user location u in the region of interest r in the timestamp t_i. In this way, From the location stream of a user and a region of interest r, we are able to compute a fuzzy data stream over time $\overline{L(r)^u} = \{L(r)^u_0, \ldots, L(r)^u_i\}$.

3.2. Modelling fuzzy data stream of ambient sensors

A sensor stream $\vec{s}$ from a sensor s is composed of a set of measures $\vec{s} = \{s_0, \ldots, s_i\}$. A measure s_i is collected in a time-stamp t_i, defined in the time interval of interest $[t_0, t_N]$ whose time-step is Δ. Under a linguistic approach [13], we describe a sensor data stream $\vec{s}$ using fuzzy terms v to describe the measures of the sensor in an interpretable way. A membership function $\overline{v(s_i)}$ for the term v defines a membership degree $\overline{s^v}_i \in [0, 1]$ for each measure s_i. For example, binary sensors are straightforwardly related to the terms *active, inactive*, and temperature sensors to *low, medium, high*. So, from a sensor stream $\vec{s}$ and a linguistic terms v, we compute a fuzzy data stream $\overline{s_v} = \{\overline{s_{v0}}, \ldots, \overline{s_{vi}}\}$.

Fig. 2. Flowchart of the proposed fuzzy model for mining human activities based on nearby interaction.

3.3. Discriminating short-term sensor-based events from user nearby interaction

This section describes the methods to discriminate short-term sensor-based events in activity recognition from user-nearby interaction. Mainly, short-term events are related to the activation of binary sensors located in the ambient, which collect the user interaction with household appliances or door openings.

Short-term events occur at a point of time t_i where a given sensor s is activated $\overline{s_{active_i}} > 0$.

For relating the event to a spatial context, we define a sensor interaction area $L(s)$ for each binary sensor s of interest. We compute the interaction degree $\overline{s^u_{active_i}} = L(s) \bigcap u_i$ in time t_i to generate a sensor-activation stream for each user u and sensor s where $\overline{s^u_{active}} = \{\overline{s^u_{active_0}}, \dots, \overline{s^u_{active_i}}\}$. We note this sensor-activation stream enables separately discriminating the user activity.

So, the interaction degree $L(s)^u_i > 0$ of a user u in a region $L(s)$ when a sensor activation $\overline{s_{active_i}} > 0$ occurs and determines the spatial–temporal relation with the user based on the next rule:

$$R : \text{IF } L(s)^u_i \text{ and } \overline{s_{active_i}} > 0 \text{ THEN } \overline{s^u_{active_i}}$$

However, several users may interact in the sensor area when the sensor is active in time t_i, so we apply an exclusive single-user interaction, where only one user may have interacted with the sensor. In this case, the interaction is uniquely related to a higher user degree defined by the operator sup, which is represented as maximum in this work:

$$\overline{s^u_{active_i}} = \begin{cases} L(s)^u_i \quad if \quad L(s)^u_i = sup(L(s)^{u_j}_i), \forall u_j \in U \\ 0 \qquad\qquad otherwise \end{cases} \tag{2}$$

Other policies of multiple interactions [63] have been previously described and included in the next section for long-term sensor-based events.

3.4. Discriminating long-term sensor-based events from user nearby interaction

Using fuzzy logic, high-level information related to long-term events in activity recognition can be mined from sensor activation and user interactions. In this section, we detail the use of *protoforms*, which integrate an interpretable, rich, and expressive approach that models the expert knowledge to extract information from data streams. We propose the next protoforms for sensor streams, which have been successfully integrated into other proposals [64,65], whose shape is as follows:

$$Q \quad V \quad T$$

where are Q s_v T are identifiers of the following linguistic terms:

- V determines the fuzzy data stream of the sensor or location sources.
- T defines a fuzzy temporal window (FTW) $\overline{T}$ where the fuzzy data streams s_v are aggregated in the temporal domain $s_v \bigcap T$.
- Q is a quantifier that filters and transforms the degree of aggregation of $\overline{Q}(s_v \bigcap T)$.

So, a protoform $P = QVT$ defines a new fuzzy data stream whose degree $\overline{P_i} = \overline{Q}(\overline{V_i} \bigcap \overline{T})$ for each timestamp t_i is related to the temporal relevance of the source data stream in the temporal window (FTW) transformed by the fuzzy quantifier. Appendix I describes the aggregation of temporal windows and quantifiers to fuzzy data streams. An example of protoform is *most of the time the oven is hot for more than 20 minutes*, where Q =' *most of the time* V =' *the oven is hot* T =' *for more than 20 minutes'* where s ='oven' and t ='is hot'.

To compound high-level activities interrelating protoforms, we fuse protoforms and discriminate the user who develops the activity using an ad hoc IF-THEN shape rule. First, we join protoforms using the t-norm *AND* for modelling the antecedents, which define the time intervals where the degree of protoforms is true. Next, the consequent computes the interaction degree for each user in these time intervals to determine who develops the rule.

A rule R is in the shape of:

$$R : \text{IF } A^1 \dots \text{ and } A^j \text{ in } T_R \text{ THEN } Q_R(\text{User u R })$$

where antecedents $A^1 \dots$ and A^j in T_R define time intervals, which are computed as follows:

- An antecedent A^j corresponds to a protoform previously described. The operator AND is applied to compute a unification of antecedents that generate a fuzzy data stream $\overline{R_i} = \overline{A_i^1} \cap \overline{A_j^1}$ for the rule R for each timestamp t_i.
- A fuzzy temporal window T_R concatenates antecedent degree $\overline{R_i}$ during the time. It is key for interpretability to reduce the number of time intervals, concatenating those *close* to each other. The FTW $\overline{T_R}$ defines the temporal proximity to the join intervals. The Appendix describes the method of concatenating a fuzzy data stream by a FTW.
- Antecedents provides time intervals $\Delta_R = \{(t_0^-, t_0^+), \dots, (t_i^-, t_i^+)\}$ defined by initial t_0^- and ending point of time t_0^+. They are calculated based on a degree $\alpha - cut > 0$ which identifies the timestamps t_i of the time intervals (t_i^-, t_i^+) where $\overline{R_i} > 0 \forall t_i, t_i \in (t_i^-, t_i^+)$.

Once we obtain the time intervals (t_i^-, t_i^+) where the degree of compounded protoforms is true, the consequent computes the interaction degree for each user to determine who develops the rule R. The interaction degree of a user u and the rule R is computed as follows:

- Each rule R is related to a region of interest $L(R)$.
- In long-term events, we enable multiple user interactions where several users may have developed the event. In this case, the interaction degree in the time-interval (t_i^-, t_i^+) of a user u is computed by aggregating the interaction degree of the user with the region of interest $\overline{R_i} \cap u_i$ based on the timestamps t_i from time-interval:

$$R_{(t_i^-, t_i^+)} \cap u = \bigcup_{t_i}^{t_i \in (t_i^-, t_i^+)} L(s)_i^u \otimes \overline{R_i} \tag{3}$$

- We note that several users are able to be related with the rule R sensor and in the same time interval $R_{(t_i^-, t_i^+)} \cap u_A > 0$, $R_{(t_i^-, t_i^+)} > 0 \cap u_B, u_A \neq u_B$.
- Finally, a quantifier Q_R is applied to the interaction degree of the user $\overline{Q_R}(R_{(t_i^-, t_i^+)} \cap u)$ to determine a minimum and rectify the final interaction degree based on expert criteria.

4. Case study and experimental setup

In this section, we describe the case study and experimental setup developed in this work to evaluate and present the use of the methodology in a real-life context. The case study was conducted in a kitchen where two inhabitants (71-year-old man and 70-year-old woman) carry out their daily activities in an ordinary living space. The interaction of the two adults with kitchen

Table 1
Spatial–temporal discrimination of sensor activation for users 1 and 2 (Setup dataset).

Inhabitant	Fridge	Cutlery	Microwave	Cookware
User 1	49	54	6	5
User 2	37	50	7	10
None	0	2	0	0
Total	86	106	13	15

Table 2
Spatial–temporal discrimination of sensor activation for users 1 and 2 (Evaluation dataset).

Inhabitant	Fridge	Cutlery	Microwave	Cookware
User 1	66	41	21	10
User 2	36	50	9	7
None	1	1	0	1
Total	98	92	30	18

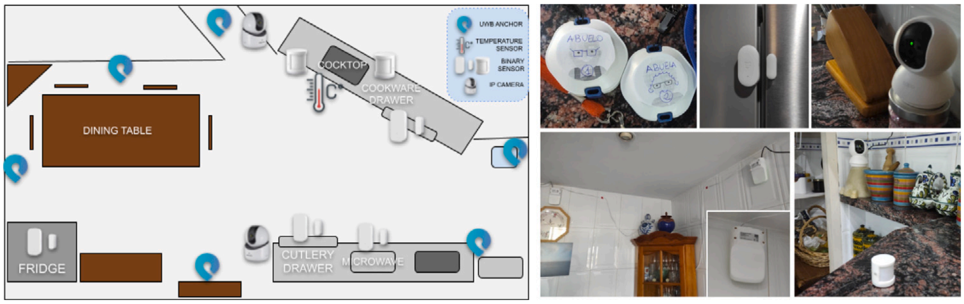

Fig. 3. (Up) Floor plan of the kitchen, (Bottom) Deployment in a real-kitchen environment including cameras UWB and ambient sensors.

appliances/furnishings (cutlery, fridge, microwave, and cookware) was monitored using UWB (ultra-wideband) and ambient sensors. The kitchen has been selected as a relevant and challenging space where inhabitants at home develop multi-occupancy daily activities.

The data, method implementation, and results of this work are available at https://github.com/AuroraPR/AMALTEA-IoT.

4.1. Description of case study

The case study took place in a 29 m^2 kitchen. Six UWB anchors, four open/close sensors, two presence sensors and two IP cameras were deployed to cover the environment (see Fig. 3). We collected data for obtaining two datasets:

- Setup dataset. A setup dataset is collected to define the interaction areas and behaviour from observable data in the case study separately from the evaluation dataset based on the description of the nearby location, sensor activation and camera-pixelated images. It encompasses two days, from 20/12/2022 at 15:00 a.m. to 23/12/2022 at 15:00 a.m., to include breakfast, cooking, lunch, and dinner. 220 interactions from open/close sensors were collected, detailed in Table 1.
- Evaluation dataset. To evaluate the methods described from the sensor interaction areas defined in the setup dataset, a non-observable dataset by human experts for evaluation purposes is collected. It encompasses two days, from 04/01/2023 at 12:00 a.m. to 06/01/2023 at 12:00 a.m., to include breakfast, cooking, lunch, and dinner. 238 interactions from open/close sensors were collected, detailed in Table 2. Regarding UWB location data, 114.559 samples were collected from user 1 and 110.254 from user 2.

The IP cameras collected camera-pixelated images every 3 s to tag the data collected by the sensors from an external observer, whose labelling for discriminating user activation is described in Tables 1 and 2.

4.2. Ambient sensors deployment

Ambient sensors were deployed to monitor the interaction of the inhabitants with appliances/furniture in the kitchen. Specifically, Xiaomi Aqara open/door and temperature sensors (https://www.aqara.com/) were used and integrated into the Home Assistant platform (https://www.home-assistant.io/), an open-source tool that allows the integration of multiple devices and sensors for smart home monitoring. Real-time data collection was performed using the MQTT protocol, a lightweight and efficient communication protocol for real-time data transmission between IoT (Internet of Things) devices. The sensors were placed on key appliances/furniture items (see location in Fig. 3), which includes the fridge, microwave, cookware drawer, cutlery drawer and cooktop.

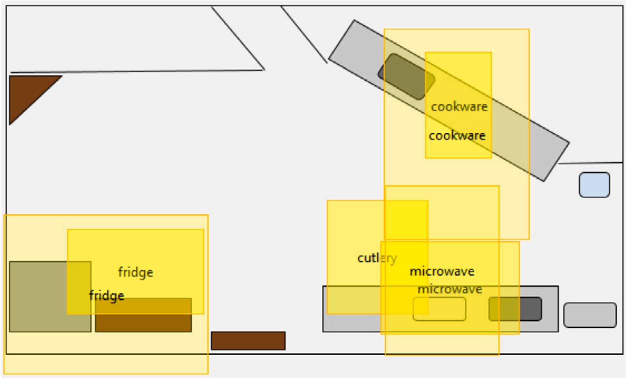

Fig. 4. Interaction location areas related to fuzzy rules and location.

4.3. UWB real-time location system for nearby-interaction

A Real-time Location System (RTLS) is a technology used to track and identify the real-time location of objects or people within a specific area. It provides accurate and continuous positioning information, enabling organizations to monitor and manage their assets or personnel effectively. The core components of an RTLS typically include: (i) tags, which are small devices that are attached to or carried by objects or individuals that transmit signals containing unique identification information and location data; (ii) anchors, which are ambient infrastructure devices strategically placed throughout the coverage area.

In this case study, the locations of the kitchen inhabitants were tracked using UWB proximity sensor technology https://www.pozyx.io based on UWB. Four anchors were placed in the kitchen walls to provide the 2D location (x,y) of the inhabitants, who wore a UWB wearable tag (see Fig. 3). The platform provides trilateration estimation in real time using the MQTT protocol.

4.4. Implementation of user nearby interaction of region of interest based on UWB location system

Based on the formal description detailed in Section 3, in this section, we detail the implementation of methods for UWB Real-time location system and ambient sensors deployed in this case study.

- The user location is defined by a bounding box $u_i = \{(x_i^-, y_i^-), (x_i^+, y_i^+)\}$ in a timestamp t_i. The bounding box which determines the user location is computed using the min–max aggregations from the 2D locations (x_i, y_i) estimated by the indoor location system in the time step t_i for each user u, $u_i = \{(min(x_0, \dots, x_i), min(y_0, \dots, y_i)), (max(x_0, \dots, x_i), max(y_0, \dots, y_i))\}$.
- The interaction degree $(r)^u_i i$ in a timestamp t_i between the bounding boxes of location areas l^r_j and the bounding boxes of the user location u_i is defined from the metric of intersection over union $J(A, B) = \frac{A \cap B}{A \cup B}$. We modify it to weight the intersection metric only with the user location area $J(l^r_j, u_i) = \frac{l^r_j \bigcap u_i}{u_r}$:

$$L(r)^u_i i = \sum_{l^r_j}^{l^r_j \in L(r)} \overline{l^r_j} \cdot \frac{l^s_j \bigcap u_i}{u_i} \tag{4}$$

4.5. Discriminating kitchen opening-door activities from user nearby interaction

The methods described in Section 3.3 in this case study enable discriminating the user interaction of short-term sensor-based events, such as opening-door. First, user nearby interaction is defined by sensor interaction areas $L(s)$ for each opening-door sensor s. Fig. 4 details the sensor interaction areas defined by human expert criteria from the observable data from the setup dataset.

Based on the interaction areas, next, we apply the next fuzzy rule to compute the interaction degree $L(s)^u_i > 0$ for each user u in a region $L(s)$ when a sensor activation $\overline{s_{active_i}} > 0$ occurs:

$$R : \text{IF } L(s)^u_i \text{ and } \overline{s_{active_i}} > 0 \text{ THEN } sup(\overline{s^u_{active_i}})$$

In this case study, the given users are $u = \{u_1, u_2\}$, where u_1 is the man and u_2 the woman, and the sensors $s = \{\text{cutlery}, \text{refrigerator}, \text{microwave}, \text{pot cabinet}\}$.

Table 3
Protoforms and rules for long-term kitchen activities of this case study.

Id	Protoform	Q V T		
P1	Sometimes the cooktop temperature is hot during 10 min	Q = Sometimes	V = 'the cooktop temperature is hot'	T = 'at least 10 min
P2	Sometimes the cooktop presence is active during 10 min	Q = Sometimes	V = 'the cooktop presence is active'	T = 'at least 10 min
P3	The user u is in cooktop zone now	$Q = \emptyset$	V = 'the user u is in cooktop zone'	T = 'now'
P4	Mainly the user u is in table zone around 20 min	Q = Sometimes	V = 'the user u is in cooktop zone'	T = 'now'

ID	Rule	Antecedents
Cooking	User u is cooking	P1 AND P2 AND P3 around 5 minutes
Sitting	User u is sitting at the table	P4 around 5 minutes

Term	Membership function
Sometimes	$\overline{Q} = L[0, 0.5](x)$
None	$\overline{Q} = L[0, 1](x) = x$
Mainly	$\overline{Q} = L[0.25, 0.75](x) = x$
Temperature is hot	$\overline{v} = R[21^{\circ}, 25^{\circ}](x)$
During 10 min	$\overline{T} = T[-5\ m, -3\ m, 3\ m, 5\ m](t)$
Now	$\overline{T} = T[-15s, 0, 0, 15s](x)$
Around 20 min	$\overline{T} = T[-10\ m, -8\ m, 8\ m, 10\ m](t)$

4.6. Implementation of long-term kitchen activities from user nearby interaction

Based on the methods of Section 3.4, we detail the use of protoforms and user-nearby interaction to describe long-term kitchen activities. The expert uniquely observed the setup dataset to define rules, protoforms and interaction areas based on human expert criteria from data of the nearby location, sensor activation and camera-pixelated images.

In this case study, we extracted the following long-term activities: *cooking* and *sitting at the table*. The rule *cooking* is activated when the cooktop temperature is hot, the sensor of cooktop presence is active, and the user is in the cooktop zone. The rule *sitting at the table* is activated when the user is in the table zone for around 20 min.

For modelling these rules, we have straightforwardly defined the protoforms and membership functions described in Table 3. Please, note that the membership functions are defined with the left, right and trapezoidal functions $\overline{R, L, T}$, detailed in Appendix. In addition, the region of interest of each rule and the representation of membership functions are shown in Fig. 5.

5. Results and discussion

This section presents the results and discussion on the data collected in the case study developed from user nearby interaction in kitchen daily activities. We detail the discrimination of short-term opening/closing-based and long-term sensor-based activities.

The data were labelled using the camera deployed in the kitchen for an external observer. To ensure user privacy, the resolution of the collected cameras was reduced, and the image was pixelated, which has been proven a suitable method in literature [66–68], to uniquely distinguish the user and the action/location of the inhabitants. Fig. 6 shows an example of frames collected during the case study. Short-term opening/closing-based and long-term sensor-based activities were labelled by the observer, determining the user who developed them and the point of time when they occurred. Data obtained from the proposed fuzzy model and the labelled event activities by the observer are evaluated in the next sections. The time-step was set to $\Delta = 15$ s, which determines the aggregation of locations in the bounding-box areas and the coarse-granularity of activation of binary sensors.

5.1. Results on user discrimination of open/close sensor-based events

This section describes the results of discriminating open/close sensor-based activities in a kitchen case study in naturalistic conditions. First, we note two datasets were configured: (i) a setup dataset for defining interaction areas and rules from expert criteria, and (ii) an evaluation dataset with non-observable data for evaluation purposes.

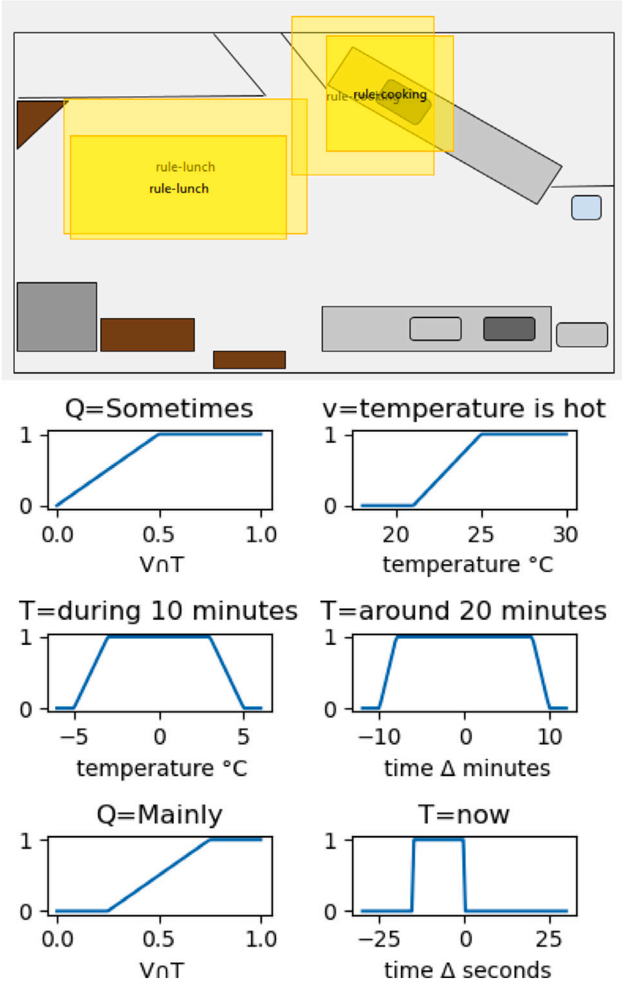

Fig. 5. (Up) region of interest of each rule and (bottom) representation of membership functions for linguist terms.

Fig. 6. Example of camera collection and labelling of the observer.

Table 4
Precision, recall and f-score of user 1 and 2 for open/close sensor activities (Setup dataset).

	Inhabitant	Precision	Recall	f1-score
Fridge	1	0.96	0.96	0.96
	2	0.97	0.95	0.96
Cutlery	1	0.95	1.00	0.97
	2	1.00	0.94	0.97
Microwave	1	1.00	1.00	1.00
	2	1.00	1.00	1.00
Cookware	1	0.83	1.00	0.91
	2	1.00	0.90	0.95
Total	1	0.95	0.98	0.97
	2	0.99	0.94	0.97
	avg	0.97	0.96	0.96

Table 5
Precision, recall and f1-score of user 1 and 2 for open/close sensor activities (Evaluation dataset).

	Inhabitant	Precision	Recall	f1-score
Fridge	1	0.94	0.94	0.94
	2	0.91	0.86	0.89
Cutlery	1	0.92	0.83	0.87
	2	0.89	0.82	0.85
Microwave	1	0.88	1.00	0.93
	2	1.00	0.67	0.80
Cookware	1	0.91	1.00	0.95
	2	1.00	0.86	0.92
Total	1	0.92	0.94	0.93
	2	0.89	0.86	0.88
	avg	0.92	0.88	0.90

On the setup dataset, in Table 4, we describe the precision, recall and f-score of users 1 and 2 when developing open/close activities for the furniture fridge, cutlery, microwave and cookware. The global performance is 0.96 on average, with low dispersion in precision and recall.

Second, on the evaluation dataset, in Table 5, we describe the precision, recall and f-score of users 1 and 2 when developing open/close activities for the furniture fridge, cutlery, microwave and cookware. The global performance is 0.9 on average, with low dispersion in precision and recall. The differences between metric discrimination are similar for users 1 and 2 (0.92 and 0.89, respectively). We observe an encouraging performance in non-observable data from the setup configuration defined by expert criteria.

In Fig. 7, we detail the confusion matrix for each item of furniture, which provides a significant difference in daily use but not significant variances in user discrimination performance of the proposed model. Moreover, in Fig. 8, we detail the activation of open/close events and the discrimination developed for each user, representing the outcome of the proposed model described here (see Fig. 7).

In Table 2, we detail some special cases detected while the case study (related to *none* row): (a) in cutlery, 1 false positive sensor activation, (b) in the fridge, 1 false sensor activation, (iii) 4 sensor activations where the inhabitant did not wear the tag, and (iv) in cookware, 1 false sensor activation. As an additional comment on the encouraging performance metric, we note some cases where both inhabitants could develop activation due to close proximity (for example, at 2023-01-06 11:52:30, which correspond to (B) frames of Fig. 6).

In addition to our proposal, we have evaluated two different models for discriminating short-term event interaction:

- *Min-distance*. This approach focuses on user identification using the nearest neighbour approach, which calculates the distance between User 1 and User 2 relative to the activated sensor. The minimum distance between users and home appliances is computed by the Euclidean distance. In this case, it does not require a learning phase, so the performance is straightforwardly computed on the evaluation dataset, yielding 0.86 accuracy.
- *BB-classification*. This data-driven approach uses the signal from a positioning system to discriminate the user activity. It is based on the proposal of authors [60], where RSSI is computed by Support Vector Machine (SVM) and Random Forest (RF) to discriminate user interaction. In the context of the nearby interaction of this work, the bounding boxes of user location from UWB compose the input of the model. We evaluated the following configurations:
  - First, we train and test the approach on the evaluation dataset, with a 20% test and 80% train data split. The SVM results were 0.82 accuracy, and RF results were 0.87 accuracy. However, it is worth noting that there exists partial overfitting when assessing this dataset solely because of its specific context and its restricted size (238 events).

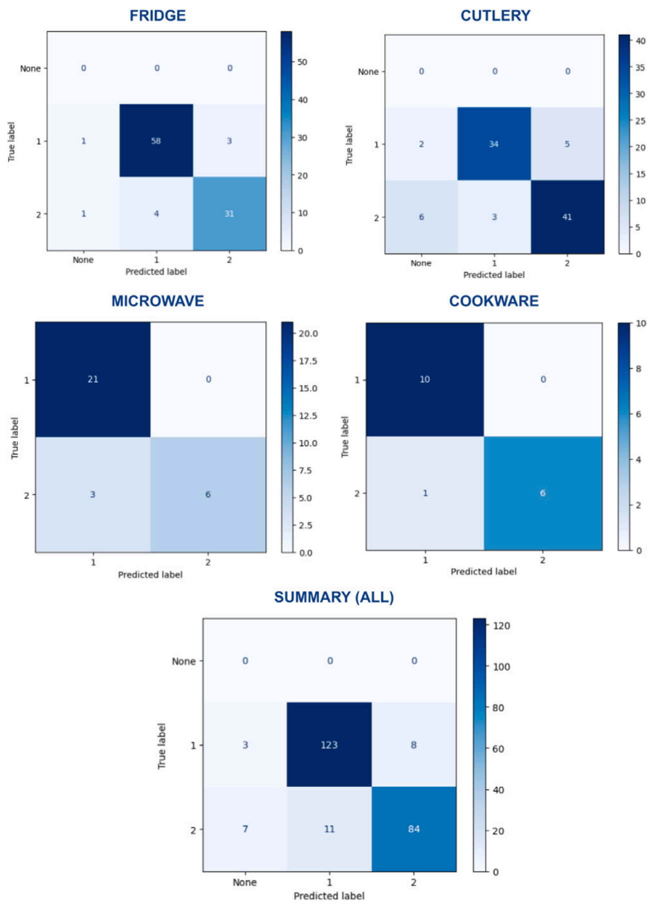

Fig. 7. Confusion matrix of binary sensors in evaluation dataset.

Table 6
Precision, recall and f1-score of bounding boxes and SVM (BB+SVM), bounding boxes and Random Forest (BB+RF) and min-distance (on evaluation dataset).

		BB+SVM			BB+RF			min-distance		
	user	**precision**	**recall**	**f1-score**	**precision**	**recall**	**f1-score**	**precision**	**recall**	**f1-score**
cutlery	1	1,00	0,33	0,50	0,67	0,86	0,75	0,88	0,68	0,77
	2	0,67	1,00	0,80	0,90	0,75	0,82	0,66	0,87	0,75
fridge	1	0,91	1,00	0,95	0,88	1,00	0,94	0,94	0,92	0,93
	2	1,00	0,78	0,88	1,00	0,60	0,75	0,86	0,89	0,87
microwave	1	0,83	0,62	0,71	1,00	1,00	1,00	0,95	0,87	0,91
	2	0,00	0,00	0,00	1,00	1,00	1,00	0,67	0,86	0,75
cookware	1	1,00	0,60	0,75	0,75	1,00	0,86	1,00	0,83	0,91
	2	0,33	1,00	0,50	0,00	0,00	0,00	0,71	1,00	0,83
total	1	0,92	0,72	0,80	0,83	0,97	0,89	0,93	0,82	0,87
	2	0,65	0,89	0,75	0,93	0,68	0,79	0,74	0,88	0,80
	avg	0,82	0,78	0,78	0,87	0,86	0,85	0,86	0,84	0,85

– Secondly, we train the approach using the configuration dataset and next evaluate the test dataset. The results were below the performance of our system, with SVM achieving a maximum accuracy of 0.57 and RF achieving 0.49.

In Tables 6 and 7, we present a summary of the performance of various methods explored in literature applied to our problem. The difference in performance between approaches of BB+SVM and BB+RF in Tables 6 and 7 lies in the varying of activities and context among users in the scenes which configure the two datasets. Defining regions of interest enables straightforwardly modelling the interaction and discrimination of users in a more flexible and adaptive manner to data-driven models, which are tailored to the specific context of trained domains.

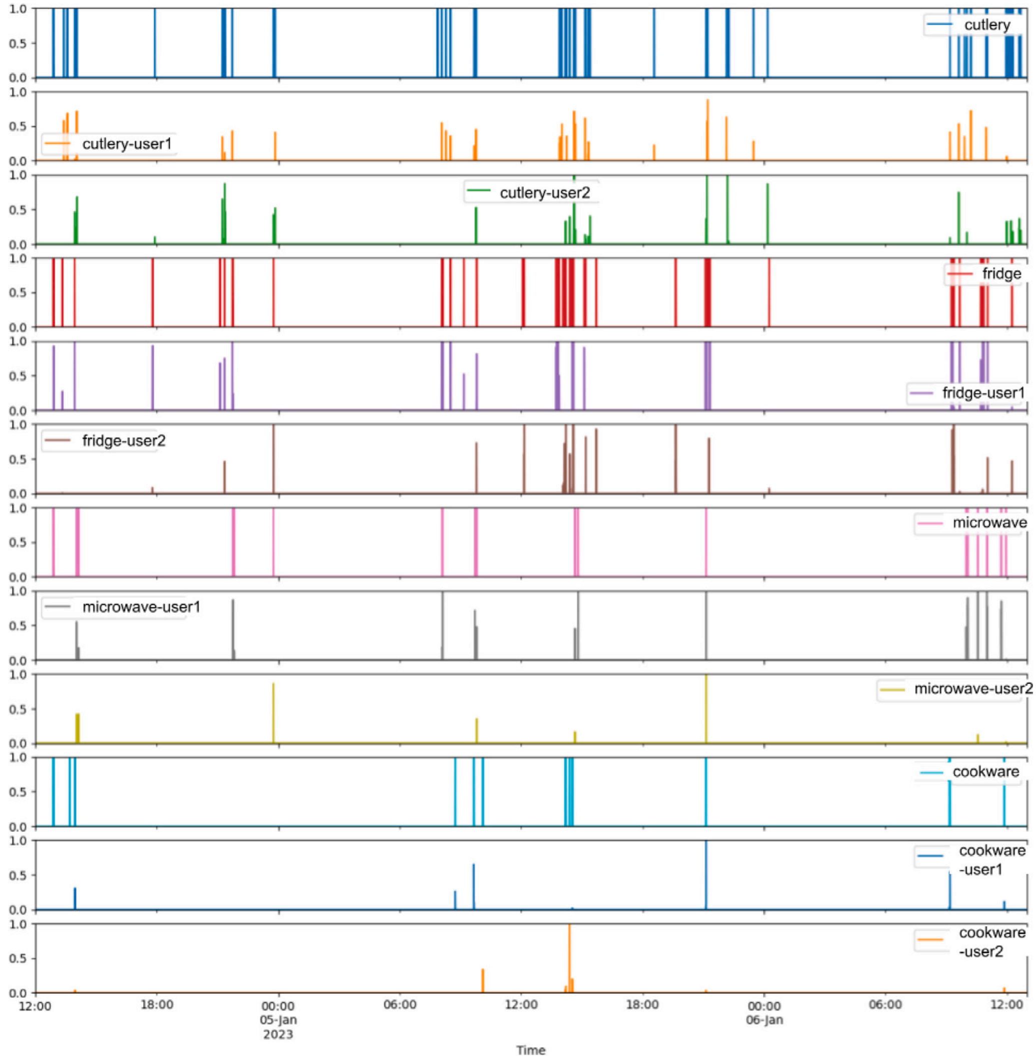

Fig. 8. For each sensor activation, we have raw activation, interaction degree of user 1 and user 2, computed from the spatial–temporal discrimination method.

Table 7
Precision, recall and f1-score of bounding boxes and SVM (BB+SVM), bounding boxes and Random Forest (BB+RF) (on setup dataset as training and evaluation dataset as test).

		BB+SVM			BB+RF		
	user	**precision**	**recall**	**f1-score**	**precision**	**recall**	**f1-score**
cutlery	1	0,06	0,02	0,03	0,27	0,34	0,30
	2	0,45	0,66	0,54	0,33	0,26	0,29
fridge	1	0,73	0,84	0,78	0,77	0,58	0,66
	2	0,63	0,47	0,54	0,49	0,69	0,57
microwave	1	0,75	1,00	0,86	0,00	0,00	0,00
	2	1,00	0,22	0,36	0,74	0,81	0,77
cookware	1	0,00	0,00	0,00	0,00	0,00	0,00
	2	0,41	1,00	0,58	0,50	0,60	0,55
total	1	0,63	0,55	0,59	0,55	0,54	0,55
	2	0,50	0,58	0,53	0,42	0,40	0,41
	avg	0,57	0,56	0,57	0,49	0,48	0,49

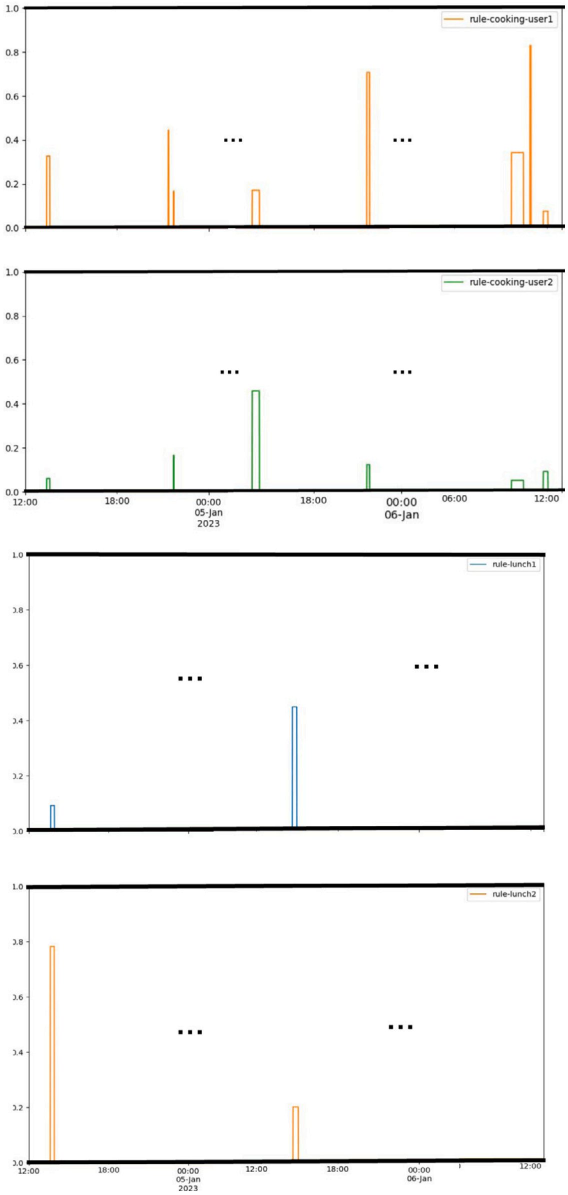

Fig. 9. For each interval (cooking and sitting for lunch), we have the interaction degree of user 1 and user 2, computed from the spatial–temporal discrimination method.

5.2. Results on long-term sensor-based events from user nearby interaction

In this section, we describe the results of mining long-term sensor-based events based on the rules of cooking and sitting, which are defined in Section 4.6.

In Tables 8, 9 and Fig. 9 we describe the time intervals obtained by the models in the evaluation dataset, which describe for each user the degree calculated based on the nearby interaction for the related region of interest. First, cooking is related to the concurrent activation of the presence sensor and high temperature on the cooking surface in the middle term. Users 1 and 2 can interact concurrently in action, which has been labelled to obtain the active minutes by an external observer based on images of cameras. Second, sitting is related to a long-term presence in the table zone, which users 1 and 2 use for lunch after cooking. To generate an interpretable outcome of the user activation for each rule, the computed degree for each user and the cooking rule is defuzzied into the terms: none (degre==0), partial (degree< 1/3) and active (degree >=1/3) (see Fig. 9).

Based on the results, the sitting rule has been computed with a very high precision regarding ground truth. Time intervals and presence are closely aligned (0.94 of coverage). The degree activation is stable, accurate, concatenating, and aggregating by the

Table 8
Results of mining long-term sensor-based events based on the rules of cooking.

Cooking							
Ground truth				Model			
Start time	Duration (min)	min u1	min u2	degree u1	degree u2	u1	u2
2023-01-04 13:24:15	12	8	4	0,842	0,158	Active	Partial
2023-01-04 21:21:30	2	2	0	1	0	Active	None
2023-01-04 21:42:30	1,25	0,75	1	0,5	0,5	Active	Active
2023-01-05 14:16:15	26	3	10	0,273	0,727	Partial	Active
2023-01-05 21:14:15	10	10	7	0,853	0,147	Active	Partial
2023-01-06 9:42:15	46,75	25	2	0,887	0,113	Active	Partial
2023-01-06 10:54:30	4	4	0	1	0	Active	None
2023-01-06 11:46:30	18	18	11	0,455	0,545	Active	Active

Table 9
Results of mining long-term sensor-based events based on the rules of sitting-lunch.

Sitting - lunch							
Ground truth				Model			
Start time	Duration (min)	min u1	min u2	degree u1	degree u2	u1	u2
2023-01-04 13:37:15	19,25	16,5	18	0,857	0,935	Active	Active
2023-01-04 14:43:30	21,75	19,75	23,25	0,908	1,069	Active	Active

FTW model, the expert criteria. The cooking rule is more complex due to the presence sensor's sensing activation, which includes imprecise activation time. In this way, the users can interact partially, cooking or not, and interact or not in the related region of interest while the rule is active. The defuzzification in linguistic terms is key in this rule to highly the linguistic representation based on the uncertain and imprecision and provide a rich description describing each user's activation rule.

6. Conclusion and ongoing works

This work presents a fuzzy knowledge-based model for mining human activities, which addresses the challenge of multi-occupancy by utilizing nearby interaction based on UWB technology. Incorporating fuzzy logic in this model allows for the effective modelling of the spatio-temporal relationships between events and user locations. The paper presents both short-term and long-term event definitions, which enable an accurate description of human activities and facilitate the identification of users associated with each action based on proximity.

To demonstrate the practical application of the proposed approach, a dataset with multi-modal sensors was collected and carefully labelled using camera-pixelated images to ensure privacy. The obtained results exhibit a highly promising performance, achieving an accuracy of 0.9 in discriminating multi-occupancy situations.

As developed in this work, the fuzzy data stream generated from the activation of sensors and the corresponding activity profiles effectively resolved the complexity arising from multi-occupancy scenarios. This enabled the use of other activity recognition models originally designed for single occupancy contexts. Consequently, we expect this research will provide a solid foundation for preprocessing future multi-occupancy datasets, which can be further evaluated using classical single-model approaches.

Moving forward, our ongoing efforts will focus on two main areas. Firstly, we plan to integrate additional multi-sensor data to enrich the human activity recognition (HAR) system in various contexts. This expansion will allow for a more comprehensive understanding of human behaviours. Furthermore, an interesting avenue for further research lies in investigating the integration of more user-friendly devices into the proposed model. One such device with significant potential is Apple's AirTag, which incorporates the U1 chip compatible with DecaWave's DW1000 modules. By seamlessly integrating AirTag into the existing framework, we can enhance the usability and accessibility of the system. Integrating these devices can greatly benefit the fuzzy knowledge-based model for mining human activities, offering advanced capabilities for capturing spatiotemporal data related to human actions, thereby providing richer and more accurate information for activity recognition. Leveraging the compatibility of the U1 chip with the DW1000 modules, we can expand the data collection scope and improve the model's overall performance. Applications in smart homes, healthcare monitoring, and assisted living systems can greatly benefit from the ease of use and familiarity of such devices. Users can seamlessly integrate these devices into their daily routines, creating a more comprehensive and diverse data set for activity recognition. Finally, we aim to compare data-driven approaches with synthetic data to discriminate multi-occupancy situations and generate areas of interest and fuzzy rules without relying solely on human expert criteria. By exploring these avenues, we hope to enhance the effectiveness and versatility of the proposed model and contribute to the advancement of activity recognition in complex environments.

License

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data, method implementation and results of this work have been made openly available at https://github.com/AuroraPR/AMALTEA-IoT.

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Appendix. Sample appendix section

A dedicated appendix has been included to understand this work's mathematical principles and methods comprehensively. The appendix serves as a supplementary resource, presenting a collection of equations and expressions that are pivotal in supporting the theoretical framework of this study.

- $V \cup T$ Aggregation of a fuzzy temporal window T and a fuzzy data stream $V = s_v$. The membership function of the FTW is temporal defined from the distance $\Delta t_i^* = t^* - t_i, t^* > t_i$ from a current time t^* to other timestamps of the data stream t_i. For each timestamp t^*, we aggregate the degree of terms regarding the fuzzy temporal degree using the t-norm and co-norm operators:

$$V \cup T(t^*) = \bigcup_{(v_i,t_i)}^{V} \overline{v_i} \cap \overline{T}(\Delta t_i^*) \in [0,1] \tag{A.1}$$

  The weighted average for multi-modal is defined as aggregation functions for the aggregation of FTW in sensor streams [64].

$$V_r \cup T_k(t^*) = \frac{1}{\sum \overline{T}(\Delta t_i^*)} \sum_{(v_i,t_i)}^{V} \overline{v_i} \times \overline{T}(\Delta t_i^*) \in [0,1] \tag{A.2}$$

- Q Quantification. A quantifier applies a transformation employing a membership function $\overline{Q} : [0,1] \to [0,1]$ to transform and model the source degree $\overline{Q}(x)$. It determines a minimum $\alpha - cut$ and rectifies the target degree.
- $V \cap T$. Concatenating a fuzzy data stream V by a FTW T reduces closer time intervals (t_i^-, t_i^+) of the fuzzy data stream before applying an α-cut to obtain them. The main outcomes of the method are: (i) to concatenate the inner degrees of closer degrees $v_i > 0$, (ii) not extending the initial t_0^- and ending point of time t_0^+. To assess (ii) FTW $\overline{T}$ should be defined by a membership function with a shape left or right. Here, we suppose that the FTW T_t is a left shoulder function and $T_t(-1)$ is the symmetric right shoulder function. Concatenating is defined by joining the temporal windows $(V \cup T) \cap (V \cup T_t(-1))$, where $\cup$ is computed as the weighted average previously described, and $cap = min$.

- $T[l_1, l_2, l_3, l_4](x)$, $L[l_1, l_2](x)$, $R[l_1, l_2](x)$, are trapezoidal, left and right shoulder functions, respectively. $T[a, b, c, d](x)$ is a well-known trapezoidal membership function defined by a lower limit l_1, an upper limit l_4, a lower support limit l_2, and an upper support limit l_3 (refer to Eq. (A.3)). Left and right shoulder trapezoidal L, R are defined as $L[l_1, l_2](x) = T[l_1, l_2, l_2, l_2](x)$, and $R[l_1, l_2](x) = T[l_1, l_1, l_1, l_2](x)$, respectively.

$$T(x)[l_1, l_2, l_3, l_4] = \begin{cases} 0 & x \leq l_1 \\ (x - l_1)/(l_2 - l_1) & l_1 < x < l_2 \\ 1 & l_2 \leq x \leq l_3 \\ (l_4 - x)/(l_4 - l_3) & l_3 < x < l_4 \\ 0 & l_4 \leq x \end{cases} \tag{A.3}$$

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