Methodology based on linguistic protoforms for activity detection in patients with type 2 diabetes mellitus

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Abstract

Nowadays, activity recognition systems are a very hot topic with a high applicability in almost any field. These types of systems are capable of detecting human activities using Internet of Things devices that incorporate a set of sensors that allow us to collect events associated with such activities. This study presents a general methodology based on linguistic protoforms for human activity detection. This methodology approaches one of the main challenges of this type of systems, multi-occupancy, and for this purpose it incorporates an indoor localisation system. Furthermore, this methodology is applied in a real environment in patients affected by type 2 diabetes mellitus with the aim of enabling health care professionals to check the degree of compliance with the therapeutic contract. Finally, an analysis is conducted of the alignment of the Sustainable Development Goals with this research.

Keywords: Linguistic protoforms, Human Activity Recognition, Diabetes, Sustainable Development Goals

1. Introduction

The technology field has experienced unprecedented growth, with notable advances in various areas that have had a direct impact on the care and improvement of people's quality of life. Currently, a multitude of smart devices are available that analyse and provide knowledge to the user, and an example of this are activity wristbands (Bhat et al., 2020; Csizmadia et al., 2022). These devices incorporate sensors that collect data and transform it into knowledge, such as daily steps, calories burned or even the number of hours we have slept. In short, these devices are used to analyse us on a daily routine and improve our health (Bhattacharya et al., 2022).

Similarly, more complex systems aiming at detecting human activities or behaviour can be found in the literature (Gupta et al., 2022; Hussain et al., 2019; Kulsoom et al., 2022). These monitoring systems are a very hot topic and emerge to track and analyse the health status of the users.

In the last decades, researchers have developed such systems for multiple domains: surveillance, health, smart home, falls, among others (Gupta et al., 2022; Kulsoom et al., 2022). Moreover, these systems often differentiate in multiple aspects such as the underlying technology for data collection. However, one of the challenges of such systems is the problem of multi-occupancy. Currently, the proposed solutions are generally oriented towards a single person, but this is not applicable to a real environment.

The Internet of Things (IoT) and Artificial Intelligence (AI) has emerged as a solution to the challenge of human activity detection. On the one hand, IoT has become one of the most influential technologies in the field of healthcare. This interconnected network of physical devices, vehicles, sensors and software has enabled real-time monitoring and data collection, providing unprecedented insight into patients' health. Wearable devices, such as smartwatches and activity wristbands, have become ubiquitous, allowing individuals to monitor their heart rate, sleep quality, physical activity and more. On the other hand, AI is also instrumental in the transformation of healthcare. Through machine learning algorithms and large-scale data processing capabilities, AI systems can analyse large amounts of medical information, identify patterns and generate accurate predictions.

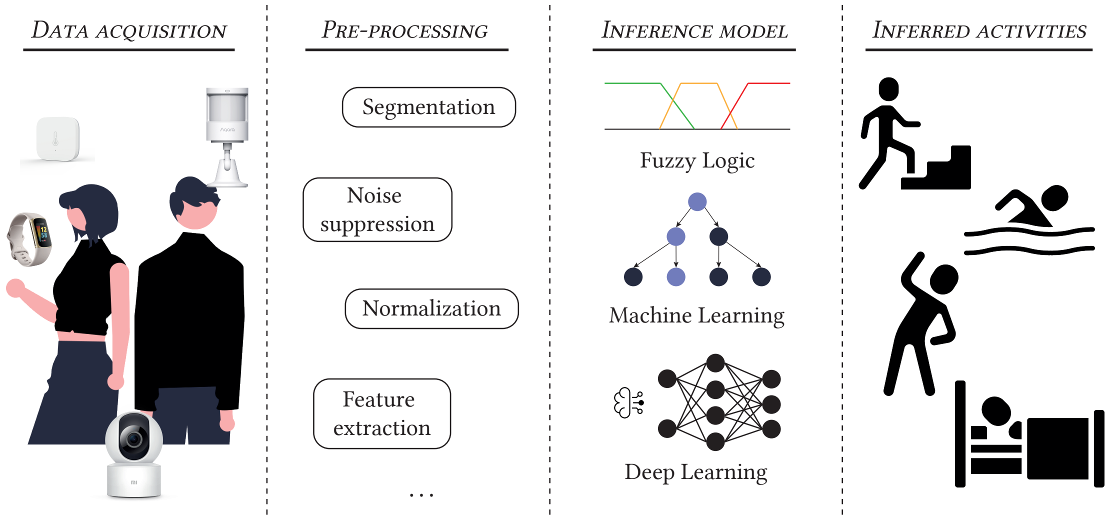


Figure 1. General stages established by HAR systems.

These capabilities have significantly improved the early diagnosis of diseases, the identification of risk factors and the personalisation of treatments.

AI establishes a type of mathematical logic applied in multiple domains and is referred to as fuzzy logic. This logic is based on the concept that variables can have values that are not strictly true or false, but can be in an intermediate state. This feature makes it possible to deal with complex and ambiguous problems, such as the evaluation of activities performed by people with chronic diseases.

Today, diabetes is an increasingly common disease that millions of people suffer from in healthcare. Diabetes is a chronic disease that requires careful management and constant monitoring of daily activities such as food ingestion, physical exercise and medication administration. To improve the quality of life of patients with diabetes, therapeutic contracts are defined and must be followed if they are to improve their health status. To check the degree of compliance with the contract, patients are manually monitored by health and social care professionals through interviews and surveys. A very costly, tedious and error-prone procedure.

This research aims to resolve some of the limitations of the current systems. Firstly, it proposes a general methodology that can be applied in different closed spaces in multi-occupancy contexts. Furthermore, this methodology is based on fuzzy logic, freeing the system from context dependencies and previous training. Finally, a system capable of detecting daily activities in people with diabetes is proposed in order to study their daily life and thus help health and social care professionals to check if patients are performing the indicated daily routine. Therefore contributing to the Sustainable Development Goals (SDGs), e.g. by providing a new service to the healthcare system.

Consequently, in this work, a new general methodology based on fuzzy logic through protoforms and linguistic membership functions is established for the detection of human activities in patients affected by type 2 diabetes mellitus. This type of detection aims to determine the degree of compliance with the therapeutic contract established between the patient and the social-healthcare professionals.

The following sections have been defined in order to conduct the work. In Section 2 a review of the most recent literature on the works related to this research is performed. Below, Section 3 establishes the general methodology where the framework, the architecture, the devices and the definition of the general linguistic protoforms are specified. Next, Section 4 establishes a case study to define a fuzzy logic model applying the general methodology to recognise human activities in patients affected by type 2 diabetes mellitus.Subsequently, an analysis of the alignment of this research with the SDGs is presented in Section 5. Finally, Section 6 discusses future work and the conclusions drawn.

2. Related works

In the following, a brief bibliographical review will be carried out on the works related to the research established in this document.

Generally, Human Activity Recognition (HAR) systems establish four stages Gupta et al., 2022: *i*) data collection, *ii*) data pre-processing, *iii*) model inference and *iv*) human activity detection. These stages are summarised in Figure 1.

The first stage consists of collecting data from the sensors and devices deployed. In this stage the type of data collection is differentiated by the type of interaction that the user performs with the system. In total, there are four different groups(Hussain et al., 2019; Raeis et al., 2021): wearable device-based ones (Bhat et al., 2020; Csizmadia et al., 2022), object-tagged ones (Du et al., 2019), device-free ones (Damodaran et al., 2020; Shi et al., 2022) and hybrid ones (López et al., 2023; López-Medina et al., 2020) that use the advantages of each of these approaches. The most commonly used in real environments is the device-free based system, as it frees the user from interaction with the system and makes it totally invisible.

In this type of system, it is essential to discern in multi-occupancy environments who is carrying out the different activities detected. This challenge is often solved by the incorporation of Indoor Location Systems (ILS) which allow to discern where the inhabitant is. For example, in the work of López Ruiz et al., 2023 a system is implemented that is able to detect the relevant areas in which an inhabitant is located within an enclosed space.

The second stage of this general methodology for HAR systems is the pre-processing of the data from the previous stage. The aim is to clean and process the data to provide quality data for the inference models. This type of cleaning depends on the nature of the data. One of the most commonly used techniques for sensor data is time windowing (Espinilla et al., 2018) applied to time series. Another example is the use of image segmentation (Sharma et al., 2022) in camera-based systems.

The third stage establishes the inference model which detects the defined activities. There are many different HAR systems in the literature, although the most widely used models are those based on machine learning (ML), deep learning (DL) and fuzzy logic. Systems based on ML (Csizmadia et al., 2022; Kulsoom et al., 2022; Manivannan et al., 2022) use algorithm-based classifiers to solve the challenge of human activity detection. These types of models are characterised by being very lightweight and are able to provide real-time output. Also, systems based on DL (Bhattacharya et al., 2022; Gumaei et al., 2020) models are found in the literature. These types of models are much more complex and usually have a much longer training and response time. In addition, in both cases (ML and DL) a labelled dataset is required to be trained. The third major group is fuzzy logic based systems (López-Medina et al., 2020; Susmitha and Ganapathy, 2019). This type of logic defines membership functions and linguistic protoforms guided by expert knowledge. Fuzzy logics are very simple models, with a fast response and without any previous training.

Finally, the fourth stage is the output generated by the inference models. Two main groups have been found in the literature (Gupta et al., 2022). The first group establishes the detection of activities carried out by a single person. Within this group we find the detection of behaviours, gestures, Activity of Daily Living (ADL) and Ambient Assistive Living (AAL). The second group establishes the detection of activities carried out by multiple people by detecting their interaction and the number of people.

HAR systems are a hot topic and have a wide applicability. Currently, these systems are used in different fields (Gupta et al., 2022; Kulsoom et al., 2022) such as health care, abnormal behaviour and falls, home, sports and exercise or even crowd surveillance.

In this work, as opposed to others, it is able to perform a detection of daily activities in a multi-occupancy context through fuzzy logic. This methodology does not require complex models that are trained on datasets and that in some cases can hardly be deployed in real-time environments due to their response time and hardware cost. Also, the aim is to approach the monitoring of the disease of diabetes in a very different way from the other research through their daily life (Rodriguez et al., 2021). In contrast, other research focuses on monitoring using intrusive sensors that give direct information on interstitial glucose, without monitoring lifestyle habits.

Lastly, this type of research lacks (Espinosa et al., 2021) an analysis of the alignment of the SDGs with the proposed system. In the same way that effectiveness analysis is conducted using traditional metrics (Verdejo et al., 2022), it is also necessary to conduct analysis to establish how our research contributes to the SDGs. This is essential to understand how we are impacting positively on society from a sustainable point of view.

3. Methodology based on linguistic protoforms for activity recognition

The proposed general methodology for the detection of activities in patients with type 2 diabetes mellitus is defined below.

3.1. HAR framework

First, the special features of the HAR system presented in the study are defined:

- An interior space S is defined in which the activities are detected. This interior space is bounded by an Axis-Aligned minimum Bounding Box (AABB) B_{main} defined by two points $B_{main} = [p_1, p_2]$. The points of the AABB lie in the two-dimensional Euclidean space $\mathbb{R}^2$ such that each point is defined by two coordinates $(x, y) \in \mathbb{R}^2$. The point p_1 is coincident with the Cartesian coordinate origin O.

- Within this space, a set of relevant locations $\{L_1, ..., L_j, ..., L_J\} \in S$ are defined and used to determine who is carrying out the detected activity.
- Each relevant location L_j is defined by an AABB $B_j \in B_{main}$.
- A set of inhabitants $\{P_1, ..., P_k, ..., P_K\} \in S$ is also established and monitored.
- Each inhabitant P_k has a unique and non-transferable therapeutic contract C_k associated with it. Moreover, depending on the contract C_k, a set of inferred activities $\{A_1, ..., A_k, ..., A_K\} \in C$ is defined.

3.2. Architecture

In this section, the elements of the system are proposed as well as the communication set up to generate the data flows to compute the linguistic protoforms.

First, the elements related to indoor localisation are defined:

- Each relevant location L_j has an associated set of anchor devices $\{W_1^1, ..., W_u^j, ..., W_U^J\} \in L_j$. Each device is only associated with one location $L_i \cap L_j = \emptyset$.
- Each inhabitant P_k has an associated tag device T_k used to locate it within a closed space S.

Then, the devices related to the recognition of human activities are established. All these elements are associated with a single relevant area L_j:

- A set of open and close sensors are deployed in the monitored space $\{soc_1^1, ..., soc_l^r, ..., soc_L^R\} \in S$.
- Also, a set of motion sensors are deployed in the monitored space $\{sm_1^1, ..., sm_l^v, ..., sm_L^V\} \in S$.
- A temperature and humidity sensor sth_u is included for each shower.

Finally, a main element denominated fog node sbc is defined. This element is in responsible for establishing the broker for communication through the MQTT protocol. In addition, it includes all the logic associated with the model and finally sends the inference obtained to a server in the cloud.

All sensors, as well as one of the anchor devices of the localisation system, send the generated samples via the MQTT protocol..

For communication with the sensors, the Zigbee protocol is proposed due to its specific characteristics. Although there are other communication protocols available, such as WiFi and Z-Wave, Zigbee is chosen for several reasons. In the case of WiFi, the large number of devices that can be connected to this network can generate interference and congestion, which would affect reliable and efficient communication with the sensors. On the other hand, the Z-Wave protocol has limitations in terms of device availability and its specification is not completely open, which restricts the options for customisation and development of tailor-made solutions. In this sense, Zigbee is a low-power, short-range wireless communication standard designed especially for IoT applications. Its ability to form mesh networks allows for greater flexibility in connecting multiple devices, which is especially useful in environments where interaction with numerous sensors distributed over a large area is required.

However, to enable communication between the compute node and the Zigbee devices, the integration of an adapter is required. In this context, the Conbee II adapter presents itself as a convenient option as it acts as a bridge between the compute node and the Zigbee devices.

The whole architecture can be observed in Figure 2.

3.3. Devices

Each of the devices used, their utility and the type of data sent are described below.

UWB anchors First, anchor devices based on Ultra-WideBand (UWB) technology are used for the IPS system. This system relies on multilateration to locate an inhabitant through Time Difference of Arrival (TDoA). For this purpose, a set of anchor devices are deployed throughout the space and a tag element is associated to each inhabitant. One of the anchor devices is in responsible for transforming all this data into a 2D point $(x, y) \in \mathbb{R}^2$. The coordinates of this point are expressed in metres relative to the origin point O of the monitored space.

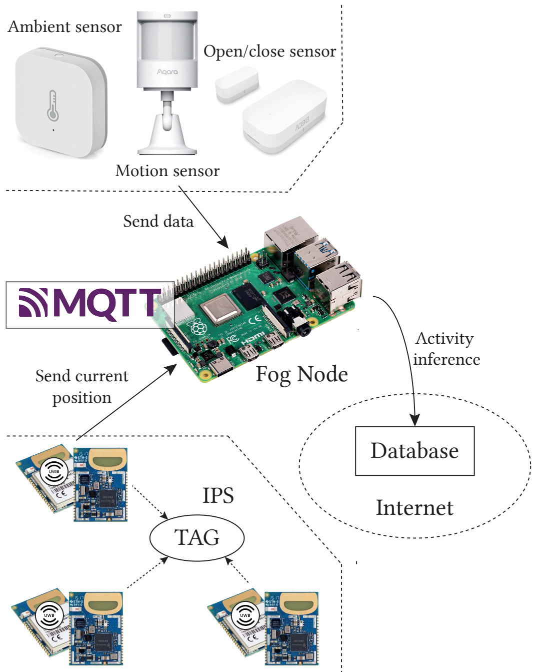


Figure 2. Architecture of the proposed HAR system.

Binary sensors Also, a set of binary sensors are used to collect events that allow us to identify the activity being carried out by the user. In total, two types of binary sensors have been used: motion sensors and open/close sensors. These sensors can only send two possible values: 0 or 1.

Motion sensors are capable of detecting movement within a viewing angle and distance through infrared technology. These sensors are usually adjustable and the detection distance and sampling rate can be defined. In this case, the device sends a 1 when it detects motion and 0 otherwise. In the proposed system, these sensors are used to determine an inhabitant's presence within a limited area of action, e.g. the shower.

In this group, there are also opening and closing sensors. This type of sensor consists of two parts and relies on magnetism to detect if a door is open or closed. When the two parts are separated, it means that the door is open and therefore a 1 is sent out. These sensors allow to determine the actions of the inhabitant on certain elements such as the medicine drawer.

Temperature and Humidity sensors On the other hand, there are environmental sensors. This type of sensor measures the temperature and even the relative humidity of the environment. In this case, the chosen sensor is capable of both measurements. The temperature is reflected in degrees Celsius ($°C$) and is sensitive to between $-20°C$ y $50°C$. As for relative humidity, it is possible to measure values between $[0, 100]\%$. In this case, this type of sensor can help to discern if the user is taking a shower due to a large change in temperature and humidity.

Single-board computer Finally, Single-Board Computer (SBC) devices are also used to perform computational tasks. In our system, this type of device is used to include all the fog node logic. Among its main tasks are to establish a broker to perform the communication through MQTT, collect and pre-process all the data, establish the fuzzy logic model and, finally, send the detected activities to store them persistently in the cloud.

An overview of this type of devices can be seen in Figure 3.

Figure 3. Summary of devices used in the system.

3.4. General linguistic protoforms

Fuzzy linguistic protoforms are a theoretical tool developed by Zadeh (Zadeh, 1975) to deal with uncertainty and imprecision in natural languages. These protoforms allow to represent fuzzy degrees of membership in categories or concepts, in contrast to conventional linguistic forms that assign binary labels. Fuzzy linguistic protoforms integrate fuzzy variables to represent imprecision, fuzzy temporal windows to model evolution over time, and fuzzy quantifiers to express linguistic quantities. In addition, fuzzy operators are used to combine and manipulate fuzzy membership degrees.

After meetings with the social and health care professionals, a set of activities are established that must be detected in order to check whether the patient is complying with the therapeutic contract.

The activities established are as follows:

- Eating activity.

- Activity take medicines.
- Sleeping activity.
- Toothbrushing activity.
- Showering activity.
- Exercise activity.

This definition of activities is used as the basis for proposing a set of general protoforms for the different activities defined above:

Eating activity High movement during meal times and presence of the user most of the time in the usual eating area.

Activity take medicines Medication sensor now active and user detected in the relevant location where the sensor is located.

Sleeping activity High movement during sleeping hours and presence of the user most of the time in the bedroom.

Toothbrushing activity High movement in the washbasin area and presence of the user most of the time in the toilet.

Showering activity High movement in the shower area, presence of the user most of the time in the bathroom and high humidity change.

Exercise activity No user presence.

4. Case of study

In this section, a case study is established through which we apply the IoT and fuzzy logic based HAR system to determine the degree of compliance with the therapeutic contract in patients affected from type 2 diabetes mellitus.

The case study is divided in two parts: the contextualisation of the dwelling, and the approach to the linguistic protoforms for the monitoring space.

4.1. Contextualisation

The monitoring environment is a dwelling of approximately 46.72 m^2 (7.3 x 6.4 m). This space has four rooms: bedroom, bathroom, kitchen and living room, and hall. Two users live in this space, one of them affected by diabetes.

The patient with diabetes has the following therapeutic contract:

- Sleep a minimum of 7 hours.
- Eat 3 meals a day.
- Brush teeth after every meal.
- Take the medicine once daily.
- Shower once daily.
- Leave the house to exercise for at least half an hour.

Therefore, the following devices are deployed:

- Motion sensors:
  - a sensor oriented to the shower area to detect showering activity.
  - a sensor oriented to the washbasin area to detect toothbrushing activity.
  - 2 motion sensors for the bed area (one for each inhabitant).
- an open/close sensor placed in the medicine drawer.
- a temperature and humidity sensor oriented towards the shower to detect the showering activity.
- ILS system:
  - 7 UWB anchor devices to identify the user's location.
  - 2 tag devices associated with each of the inhabitants.
- 1 fog node located in an area in the middle of the dwelling.

The complete deployment of devices as well as the floor plan of the house is illustrated in Figure 4.

For each of the relevant areas detected, a set of AABB's have been defined and these are the following:

- AABB associated to the dwelling: [(0, 0), (7,3, 6,4)].
- AABB associated with the bathroom: [(0, 0), (2,36, 1,75)].
- AABB associated with the bedroom: [(2,36, 0), (7,3, 3)].
- AABB associated with the kitchen: [(0, 3), (2,36, 6,4)].
- AABB associated with the living room: [(2,36, 3), (7,3, 6,4)].

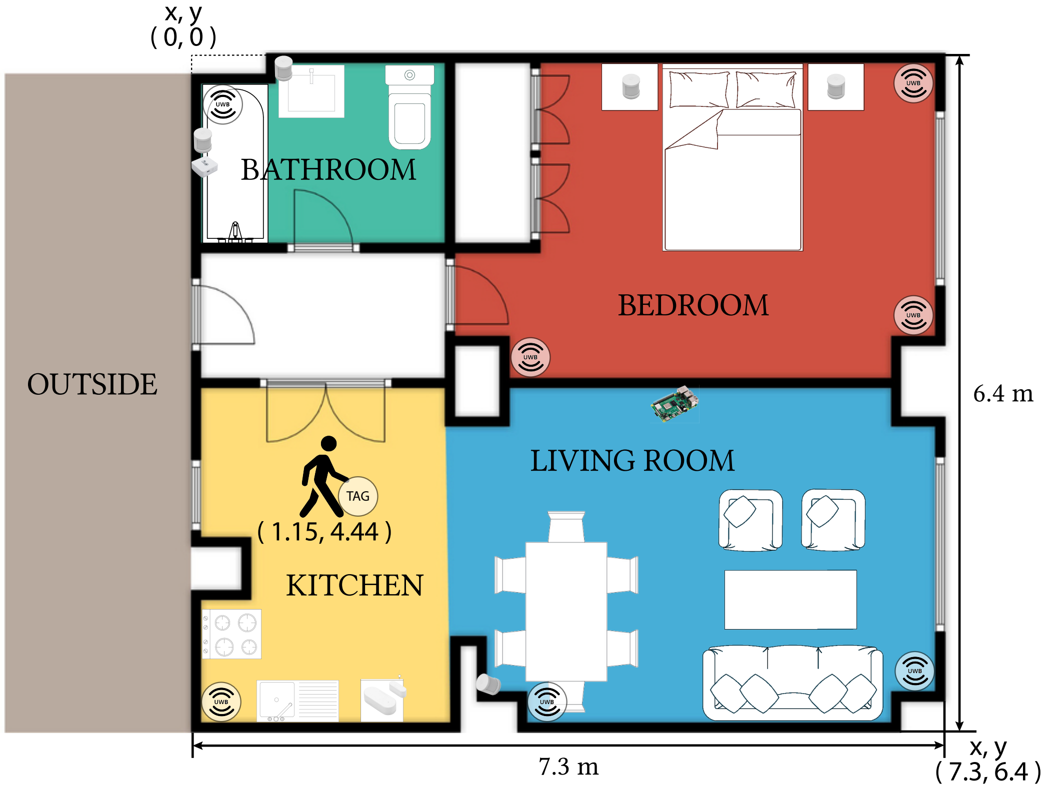


Figure 4. Floor plan of the dwelling with each of the relevant areas established and devices deployed.

These AABB's are a simplified version of the relevant area, as they can be composed of architectural elements such as a column. An example of an AABB box applied to the living room is illustrated in Figure 5.

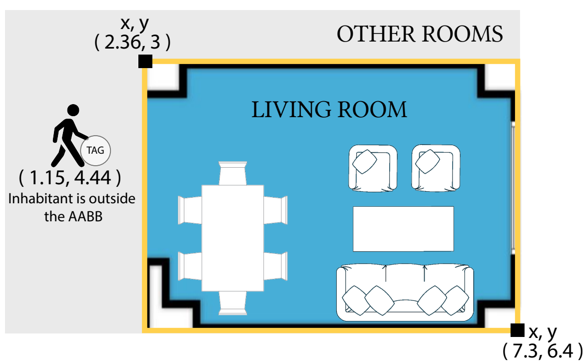


Figure 5. Example of AABB applied to the living room area.

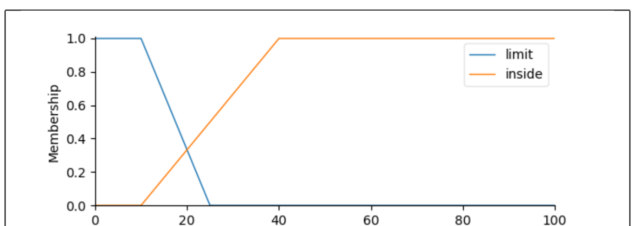
4.2. Linguistic protoforms

The membership function values have been defined through testing and expert knowledge. Additionally, therapeutic contracts provided by healthcare personnel have been employed in the definition of certain activities, such as sleep.

In terms of localisation, the real-time membership is calculated for each room. In this sense, the entries (x) for the membership functions of the different rooms are established as the sum of the percentage of separation in the x and y axes of the anchor position with respect to the AABB faces.

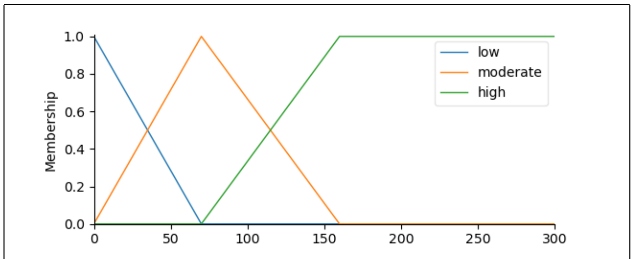
This application is limited only to walls adjacent to other rooms, as it is these that can present difficulties in determining whether they are located inside or on the boundaries of such an area.

Once the inputs are established, the boundary and outer fuzzy sets are defined.



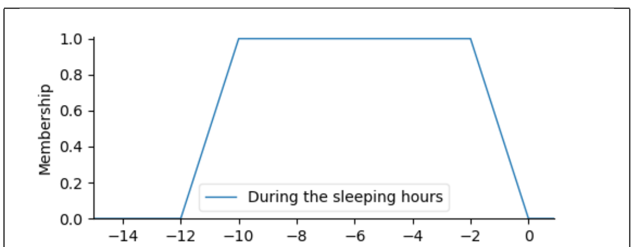
Summarizer	Membership function	Change
Limit	z-shape(10,25)	$(-\infty, 10)$
Inside	s-shape(10,40)	$(40, \infty)$

In the context of presence sensors, a different approach has been followed in the analysis. Calculations are performed based on 5-minute data windows to determine the total time the sensor has been activated within that time interval. Based on the total time (x), a number of fuzzy sets are defined to model the uncertainty associated with the motion. In this case, low, moderate and high fuzzy sets are proposed:



Summarizer	Membership function	Change
Low	z-shape(0,70)	0
Moderate	tri(0,70,160)	70
High	s-shape(70,160)	$(160, \infty)$

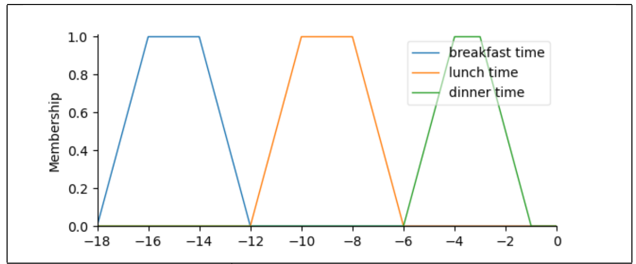
For the sleeping activity, a time window ”during the sleeping hours” defined by the following fuzzy set is used, taking into account that $t0$ corresponds to 10 am of the current day and $t-12$ to 10 pm of the previous day. Where t is the hour:



Temporal window	Membership function
During sleeping hours	trap(-12,-10,-2,0)

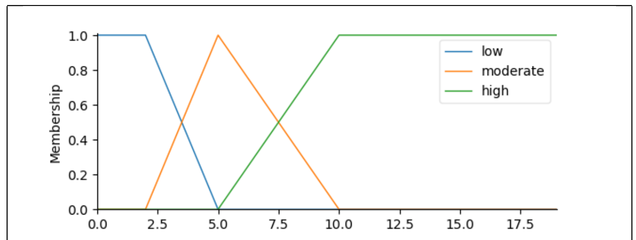
For the eating activity, the following fuzzy time windows are defined, taking into account that $t-1$ corresponds to 11 pm and $t-13$ to 11 am, where t is the hour:

The methodology used for humidity analysis involves considering the difference in humidity between two values separated by an interval of 5 minutes. It is important to highlight that the operation of this sensor does not allow a specific measurement interval to be defined. Instead, the sensor sends data when it detects significant changes in humidity. Therefore, in cases where accurate values are not available to calculate this humidity difference in the 5-minute interval, an attempt is made to find the closest value outside this time range.



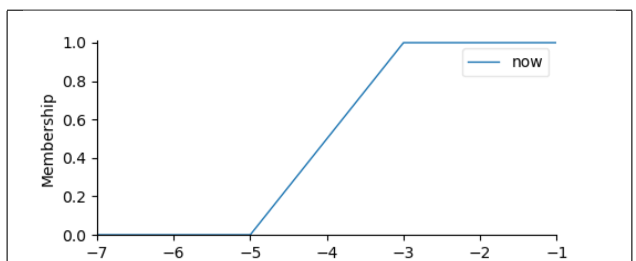
Temporal window	Membership function
Breakfast time	trap(-18,-16,-14,-12)
Lunch time	trap(-12,-10,-8,-6)
Dinner time	trap(-6,-4,-3,-1)

For the uncertainty representing the humidity difference, the following fuzzy sets are proposed: low, medium and high, where x is the humidity difference:



Summarizer	Membership function	Change
Low	z-shape(2,5)	$(-\infty, 2)$
Moderate	trim(2 5,10)	5
High	s-shape(5,10)	$(10, \infty)$

Due to the fact that the binary sensor corresponding to the medicines only indicates whether it is open or closed, it is necessary to use a fuzzy time window. It is proposed to use the fuzzy time window now, being defined by the following values, expressed in seconds:



Temporal window	Membership function
Now	s-shape(-5,-3)

Finally, for the exercise activity, an approximation is proposed. Because there is no opening and closing sensor on the main door, the exercise will be determined by the absence of the user on any of the defined locations for a period of more than half an hour.

5. Alignment with Sustainable Development Goals

The United Nations (UN) built the 2030 Agenda in 2015 (United Nations, 2015) as an urgent call to action for all nations. This agenda has 232 indicators, 169 objectives, and 17 SDGs. Consequently, it is crucial to assess this activity from a sustainable viewpoint. The following is an analysis of those SDGs, targets and indicators that we consider our research contributes to. This analysis is summarised, as a full and comprehensive analysis is beyond the scope of this manuscript.

Firstly, this research is primarily concerned with SDG 3: "Ensure healthy lives and promote well-being for all at all ages". In this case, there are several studies that indicate that people with diabetes suffer from a deterioration in their mental state. Our system is used to improve the lifestyle of people affected by diabetes by improving their mental state and well-being. Therefore, the work is aligned with objective 3.4 and indicators 3.4.1 and 3.4.2.

On the other hand, this research establishes a new health service oriented towards patient monitoring by social and health care professionals. In this way, the research is directly aligned with objective 3.8 and indicator 3.8.1.

The research also influences SDG 7: "Ensure access to affordable, reliable, sustainable and modern energy for all". Considering the deployment of the system with a minimum of energy efficient devices, this work contributes directly to target 7.1. However, studies focusing on energy consumption and system cost are essential.

Finally, it is important to highlight how to enhance the system to increase alignment with the SDGs. First, alignment with SDG 7 can be improved by powering the system with clean energy. Second, alignment with SDG 8 can be achieved by incorporating training for specialised professionals. Third, alignment with SDG 9 can be increased by promoting innovation in agencies and institutions using the system. Last, alignment with SDG 11 can be improved by implementing the platform in rural or disadvantaged territories, among others.

6. Conclusions and future work

The aim of this research has been to propose a methodology based on linguistic protoforms for activity detection in the context of patients with diabetes. For this purpose, the fuzzy logic has been used through general linguistic protoforms and commercial IoT devices.

In order to apply this methodology, a case study of a real home has been included to monitor patients affected by type 2 diabetes mellitus. This monitoring space defines the detection of activities such as eating, taking medication, showering, brushing teeth, sleeping and exercising.

However, the system has some aspects that could be improved:

- Although those activities requested by health and social care professionals have been included, the system does not incorporate other types of activities. For example, differentiation between the type of exercise: running, swimming, cycling, etc.
- The position of sensors and devices needs to be adapted according to the dwelling and factors such as AABBs, as the living space differs.

As future work, an experiment is proposed to evaluate the effectiveness of the HAR system presented using traditional metrics. In addition, the aim is to define more complex protoforms applied to the therapeutic contract in order to produce detailed reports for health and social care professionals. Also, the aim is to extend the activities detected by the system, exploring new possibilities and covering a wider range of situations. This work aims to improve the effectiveness and usefulness of the HAR system in the social and healthcare field. Finally, a study on how to further align with the SDGs, improving sustainability, is essential.

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