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Fuzzy cloud-fog computing approach application for human activity recognition in smart homes

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Abstract. Fog Computing is an approach involving smart devices. These devices carry out data processing to provide collaborative services to reach a common goal, usually, in the cloud. In the fog computing paradigm, uncertainty and vagueness are inherent to the data processing due to the limitations of computational and communication capabilities of the smart devices. Fuzzy logic and protoforms represent a powerful tool to model and compute imprecise data presented within the fog-computing paradigm. In this paper, we present a fuzzy cloud-fog approach based on fuzzy temporal windows and fuzzy aggregation. The innovations of this paper are: i) to model the uncertainty involved in fog nodes linguistically, ii) to compute and distribute relevant linguistic information (protoforms), and iii) to publish the computed protoforms in the cloud to generate complex protoforms, which reach the common goal. This new fuzzy cloud-fog approach is applied to the problem of activity recognition in smart homes. In this context, the smart devices in a smart home are represented by fog nodes, which cooperate for activity recognition using a fuzzy cloud-fog computing approach to provide solutions in ambient-assisted living. Finally, to demonstrate the effectiveness of the proposal in handling situations/environments where multiple and heterogeneous devices are involved (such as UWB beacons, smart objects and smart wearable devices), a case study of the proposed fuzzy cloud-fog approach is implemented in the smart lab of the University of Jaén. So, the results obtained with the proposed approach in the case study are compared to the results obtained with a non-fuzzy approach with the aim of showing the advantages of the fuzzy methodology.

Keywords: Fuzzy fog computing, fuzzy cloud computing, smart devices, UWB technology, activity recognition, protoforms, fuzzy temporal windows, fuzzy aggregation

1. Introduction

The Internet of Things (IoT) is a paradigm that has emerged as an integral part of our daily lives by enabling any object around us to generate, process, connect, and transfer data via network technologies [12, 15].

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This IoT paradigm includes sensing and computing nodes, smart devices, which are responsible for collecting data, reasoning, reporting, and reacting to a specific sensed phenomenon or user interactions. So, each makes decisions according to the data processing in this node or other nodes within the network. The main advantage is that communication in the IoT is machine-to-machine (M2M) between nodes, without human intervention [16].

In addition, cloud and edge computing architectures support the IoT paradigm to achieve the

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following important tasks: reduce costs, manage resource consumption, enhance performance, and connect the IoT nodes more effectively [3].

Although both cloud and fog computing offer similar resources and services, the latter is characterized, specifically, by offering a new range of applications and services closer to the end user [7]. The main features that define the Fog computing paradigm are: a) low latency and location awareness; b) wide-spread geographical distribution; c) mobility; d) a large number of nodes, e) the predominant role of wireless access, f) a strong presence of streaming and real time applications, g) heterogeneity [4].

In the IoT paradigm with a cloud–fog approach, the cooperation between smart devices opens many opportunities to make intelligent decisions or predictions in multiple and heterogeneous contexts [25]. This includes applications such as medicine and healthcare [10] or smart cities [3].

The accuracy of such decisions depends on the reliability of the generated sensor data, which contain uncertainty due to resource constraints of the sensors such as battery power, computational and memory capacities as well as communication bandwidth [2, 29–31, 33]. In addition, these sensors could be deployed in an unprotected way, causing malfunction [5]. Therefore, sensor data streams contain uncertain information with noise, missing and redundant data that should be modeled in an appropriate way.

In order to solve this problem, we extend the IoT paradigm based on a cloud–fog approach with a fuzzy approach so as to model and process the uncertainty and heterogeneity in an adequate way. In this paper, a methodology to model and aggregate sensor data streams based on protoforms is proposed. In this new fuzzy fog-cloud computing approach, fog nodes compute relevant linguistic fuzzy expressions, protoforms, from the sensor data stream generated in each smart device (nodes). These protoforms are distributed to other fog nodes, which fuse the protoforms for a common aim in the cloud. To process sensor data in fog nodes, fuzzy temporal windows and fuzzy quantifiers are used to compute fuzzy sensor data streams by means of aggregation fusion methods [19, 20].

Protoforms were proposed by Zadeh [36, 38] as a useful knowledge model for reasoning [37], summarization [14] and aggregation [35] of data under uncertainty, which are modelled by fuzzy sets whose degree of truth to fuzzy sets is defined by membership functions.

These fuzzy techniques have been successfully applied to deal with the uncertainty and vagueness of data generated by sensor devices in multiple areas such as an intelligent multi-dose medication controller for fever [21] and predicting the urgency demand of COPD patients from environmental sensors within smart cities [22] and cardiac rehabilitation using wrist-worn heart rate devices [23].

In this paper, the fog nodes within the proposed fuzzy cloud-fog computing approach have been designed to collaborate for real time activity recognition (AR) [6] in a smart home from a set of smart devices [1, 18]. The inhabitant in the smart home wore a smart wearable device, which generates protoforms that describe the movement of the inhabitant as well as receiving the computed protoforms from other nodes to identify the activity. This is achieved in real time.

The scope of application of this paper, AR in real time, is directly related to the proposed fuzzy cloud-fog computing approach because AR systems have the ability to detect human actions and their goals. Real-time refers to the recognition of activities: (i) when they are being undertaken [34], (ii) while new sensor data are being recorded from multiple devices, and (iii) with the processing of data to produce results within an acceptable period of time [18].

Additionally, the proposed fuzzy cloud-fog approach is suited to this scope of application for three crucial reasons. The first reason is that the problem of AR targeted by this work represents a reputable and challenging research topic for supervising older adults and aiding them in living independently and with the best quality of life for as long as possible [27]. For this reason, AR is considered as a critical component in smart homes to address some of the problems associated with supporting the ageing population in ambient-assisted living [28]. The second reason is that fuzzy linguistic models have been successfully proposed for managing uncertainty and vagueness in an interpretable way, which is key in obtaining high performance in AR [24]. Finally, the third reason is that activity recognition can be computed with protoforms linguistically and efficiently, which enables activity recognition in a central node with computed protoforms. Third, complex contexts can be easily extended and customized using protoforms, such as, user adaptation and multi occupancy AR in smart environments [9, 26].

The key points of the proposed fuzzy cloud-fog approach in this paper are defined as follows:

- The use of fuzzy temporal windows and linguistic quantifiers to process the sensor data stream in each fog node to manage uncertain sensor data generated.
- Each fog node is modelled to transmit relevant linguistic information defined by protoforms, which linguistically summarize the sensor data stream from each smart device. Thus, raw data are not sent– only relevant data, which has been processed linguistically.
- In the fuzzy cloud computing approach, complex protoforms are computed and distributed to other fog nodes to offer a new and intuitive linguistic representation of highest-level information.
- The proposed fuzzy cloud-fog approach is applied to AR. This area of application is a challenging research topic in an uncertainty context in which the advantages of the new fuzzy cloud-fog computing approach are evidenced to achieve the objective of recognizing the activity in real time.

Finally, this paper not only presents a theoretical proposal for the use of fuzzy logic in the fog-computing paradigm–we also develop and integrate the new fuzzy cloud-fog computing approach in the Smart Lab of the University of Jaén [8] to recognize activities of an inhabitant from heterogeneous devices to demonstrate the effectiveness of our proposal. The obtained results are compared with the results obtained with a non-fuzzy approach in order to show the benefits of fuzzy processing.

The remainder of this paper is structured as follows: Section 2 reviews fuzzy concepts to compute fuzzy sensor data streams using protoforms. Section 3 presents a novel fuzzy fog computing approach that uses fuzzy linguistic temporal windows and fuzzy aggregation methods to generate, connect, and transfer data via network technologies. Section 4 introduces a case study to show the utility and applicability of the proposed model for AR in a smart environment. Finally, in Section 5, conclusions are discussed.

2. Computing fuzzy sensor data stream using protoforms

In this section, a fuzzy modeling of the sensor data stream generated by smart devices in an uncertain context is reviewed [19, 20].

A smart device D generates sensor data by means of a pair $\bar{s}_i = \{s_i, t_i\}$ where s_i represents a given value according to the nature of the sensor and t_i is the timestamp. So, the sensor data stream of the smart device is defined by $S_D = \{\bar{s}_0, ..., \bar{s}_i, ..., \bar{s}_n\}$.

A fuzzy value term, VD, can be associated with a smart device D, by means of a fuzzy membership function $\mu\mathrm{VD}(s_i)$.

A fuzzy temporal window (FTW) can be computed to model the sensor data in order to generate weighted fuzzy linguistic terms based on fuzzy temporal linguistic terms and provide flexibility in the presence of uncertainty. A FTW is described in a simple manner according to the distance of the current time t_0 to a given timestamp t_i as $\Delta t_i = (|t_0 - t_i|)$. So, a fuzzy temporal term, TD, can be associated with a smart device D, by means of a fuzzy membership function $\mu\mathrm{TD}(\Delta t_i)$.

The relevance of a pair $\bar{s}_i$ in a fuzzy value term VD, in a linguistic temporal term TD, of smart device D, is defined by an intersection operation to fuse both degrees of membership by means of Equation (1).

$$V \cap T(\bar{s}_i) = \mu VD(s_i) \cap \mu TD(\Delta t_i) \in [0, 1] \quad (1)$$

The relevance of a sub-set of measures in the sensor data stream that are associated with the FTW associated to TD, i.e., $\mu TD(\Delta t_i) > 0$ are aggregated using the union operator in order to obtain a single degree of the degrees implied in a fuzzy value term in a linguistic temporal term by means of the Equation (2).

$$V \cup T(S_D) = \cup(V \cap T(\bar{s}_i)) \in [0, 1] \quad (2)$$

Next, Q defines a fuzzy quantifier to evaluate the impact and fulfillment of the linguistic term V within the temporal window T. A fuzzy quantifier applies the following transformation:

$$\mu Q([0, 1] \rightarrow [0, 1] \quad (3)$$

to the aggregated temporal degree $\mu Q(V \cup T(S_D))$.

From the fuzzy value term V, the fuzzy linguistic temporal window T and, finally, the fuzzy quantifier Q, the concept of *ad-hoc* protoform P_0 is defined by:

$$P_0(S_D) = QVT(S_D) = Q(V \cup T(S_D)) \quad (4)$$

in order to integrate an interpretable and rich-expressive approach to model the expert knowledge linguistically.

Finally, protoforms can be combined using fuzzy logical operators to increase the linguistic capabilities of the model. We briefly review the following basic operations, which could be easily increased with advanced fuzzy operations in other contexts [32]:

- Fuzzy negation operator, which is represented as the complement $\neg$ in the following fuzzy function $\neg P_0(S_D) = 1 - P_0(S_D)$
- Fuzzy union operator, which is represented by the t-norm $P_0 \cup P_l(S_D) = P_0(S_D) \cup P_l(S_D)$. The semantic function proposed for the fuzzy union operator is *min*: $P_0 \cup P_l(S_D = \min(P_0(S_D), P_l(S_D))$.
- Fuzzy intersection operator, which is represented by the co-norm $P_0 \cup P_l(S_D) = P_0(S_D) \cap P_l(S_D)$. The semantic function proposed for the fuzzy intersection operator is *max*: $P_0 \cap P_l(S_D = \max(P_0(S_D), P_l(S_D))$.

3. Fuzzy cloud-fog approach in a smart environment for activity recognition

In this section, the fuzzy model for fuzzy processing of the protoforms in smart fog nodes is proposed, as well as its architecture.

3.1. Fuzzy framework

The aim of this new fuzzy framework is to define the components required for AR in a smart home in which fog nodes and smart devices have been deployed to publish a linguistic summary for the central model in order to compute complex activity protoforms.

The following notions and terminology are presented in the proposed fuzzy framework for multi occupant AR with wearable devices.

1. A smart home in which a set of activity classes exist is defined as $A = \{A^1, ..., A^i, ...A^{AI}\}$.
2. A set of smart devices, fog nodes, is defined as $D = \{D^1, ..., D^j, ...D^J\}$, that is associated with a set of objects or areas, respectively. For each smart device D^j, the following elements are defined:
   - 2.1 A fuzzy value variable with a set of fuzzy value terms and its membership functions: $V^j = \{V^j_0, ..., V^j_k, ... V^j_k\}$.
   - 2.2 A fuzzy temporal variable with a set of fuzzy linguistic temporal terms and its membership functions: $T^j = \{T^j_0, ..., T^j_h, ... T^j_H\}$.
   - 2.3 A fuzzy quantifier variable with a set of quantifiers and its membership functions: $Q^j = \{Q^j_0, ..., Q^j_r, ... Q^j_R\}$.
   - 2.4 A set of relevant protoforms for the set of activities defined by $PQ^j_X(S_{Dj}) = Q^j_r V^j_k T^j_h(S_{Dj})$, which computes the sensor data stream of the devices to publish a linguistic summary for a central node.
3. A central node (CD) is defined as the main coordinator which is subscribed to all predefined protoforms from the fog nodes $SCD = \{PQ^j_X(S_{Dj})\}$. This central node combines the protoforms in order to generate complex activity protoforms PA^i. Each activity A^i is computed by a set of protoforms from fog nodes which are fused by applying fuzzy operators, to obtain a degree of the activity in real time.

3.2. Architecture of the fuzzy cloud fog approach

In this section, we present the architecture of the proposed fuzzy cloud-fog approach based on the fuzzy framework.

First, each smart device D^j, is associated to a smart fog node, which collects the data from its sensors in order to compute the membership degree of its own protoforms $PQ^j_X(S_{Dj})$.

The protoforms are previously defined linguistically with a fuzzy value term V^j_k, a fuzzy temporal window T^j_h, and a fuzzy quantifier Q^j_r. The membership degrees and description of the protoforms are computed and spread using a publish/subscribe protocol with MQTT[1]. Under this architecture, any subscriber, as a central node for AR, can receive changes in the membership degrees and the linguistic description of the protoforms in real time. The central node CD fuses the protoforms using fuzzy operators to compute the complex activity protoforms which describe the AR at the end of the processing in real time.

Figure 1 illustrates the architecture of the proposed fuzzy cloud-fog computing in the human activity of "drink".

In Fig. 1 of the architecture, two smart devices are involved which are related to two fog nodes. There is a central node, for example a mobile device, which is subscribed to the protoforms of these two fogs. The first fog node is the wearable device that generates acceleration data streams and computes two proto-

[1] http://mqtt.org/

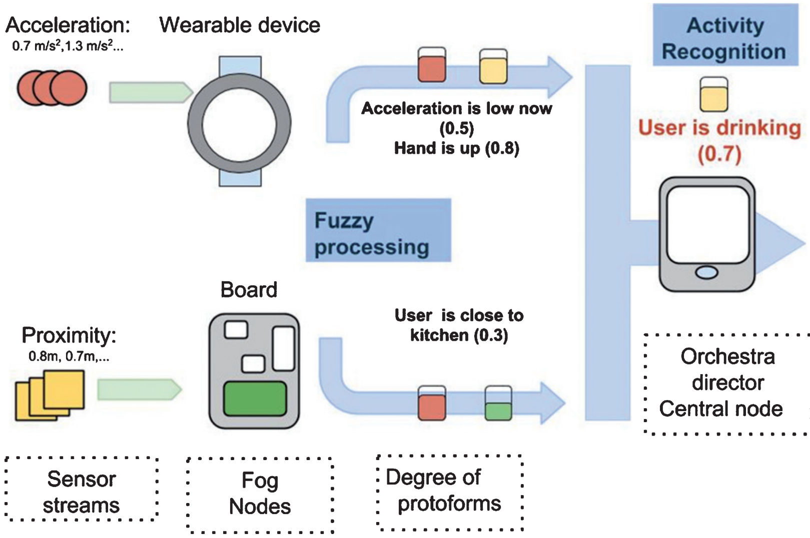

Fig. 1. Proposed fuzzy cloud-fog approach to recognize the activity "drink" in real time.

forms. The second fog node is a low cost computer (Raspberry pi) with indoor location technology in the kitchen that generates location data streams.

In real time, membership degrees of protoforms are spread to subscribing nodes using a publish/subscribe protocol. The mobile device fuses the subscribed protoforms in real-time to compute the degree of the developed activity.

4. Human activity recognition in a smart lab

In this section, we develop and integrate the new fuzzy cloud-fog computing approach in the smart lab of the University of Jaén to recognize the activities of an inhabitant in a real scenario to demonstrate the effectiveness of the proposal in this paper.

To do so, we first describe the scene of the case study, as well as the Smart Lab and smart devices that are involved in the scene. Second, the protoforms computed by the smart devices in fog computing are described. Complex protoforms computed in cloud computing are then presented. Finally, the results of the real scene following the proposed approach are presented and discussed.

4.1. Scene in the UJAmI smart lab

The case study includes a popular set of six human activities in the context of ageing population in ambient-assisted living: sleeping, brushing teeth, drinking, watching TV, making a phone call and leaving home. One inhabitant undertook these activities sequentially in the UJAmI smart lab described below.

UJAmI Smart Lab[2] [8] is based in the University of Jaén, Spain. The lab was designed and deployed to replicate a real apartment that can sense, adapt and respond to human needs, habits, gestures, and emotions.

The UJAmI Smart Lab measures approximately 25 square meters, being 5.8 meters long and 4.6 meters wide. As shown in Fig. 2, it is divided into five areas: hall, kitchen, workplace, living room and a bedroom with an in suite bathroom, and has multiple and heterogeneous smart devices with sensors and actuators.

Figure 3 illustrates the set of smart devices involved in the scene of this case study based in the UJAmI Smart Lab.

The inhabitant wore a *smartwatch with acceleration sensors* in the Smart Lab. The model used in this scenario is the Polar M600[3] smartwatch with Android OS.

Additionally, *smart devices with acceleration sensors* are located in objects throughout the smart lab. In this case study, the following two smart devices are considered: the toothbrush in the bathroom and a cup (Fig. 4). To do so, two ESP8266 Wi-Fi development boards with an acceleration sensor where added to these items. Figure 4 illustrates the smart board that was attached to the cup and in the toothbrush to collect

[2] http://ceatic.ujaen.es/ujami/en/smartlab

[3] https://www.polar.com/es/productos/sport/M600-GPS-smartwatch

Fig. 2. UJAmI Smart Lab at University of Jaén.

the acceleration data as well as compute and publish its own protoforms.

These smart devices have been selected according to the nature of the activities to be recognized in this case study. An extended set of objects could be included to detect a broader set of activities.

Smart location beacons with UWB technology [11]. Three beacons are located in this Smart Lab, while the inhabitant wears a tag with this UWB technology. The Raspberry Pi 3 was used with modules for UWB technology to facilitate this (see Fig. 5). Each smart accurate beacon provides the distance from its location to the location of the inhabitant's tag.

Finally, *smart binary devices*. These are the simplest kind of smart device. In spite of their simplicity, however, these devices allow the system to discriminate interactions within the environment in a simple way. In this case study, the following three smart binary devices are considered: the TV remote, the phone and the exit door.

Among these devices, a supervisor fog node is modelled as the main coordinator, receiving the fuzzy processing of the protoforms, which are computed within the fog nodes of smart devices. These are then fused to recognize the activity that is being carried out in real time.

4.2. Protoforms in fog computing

In this section, the description of the protoforms that are computed in each smart device is presented.

4.2.1. Location of the inhabitant

The location of the inhabitant is generated by analyzing the collected values based on distances from three smart location beacons with UBW technology (B1, B2 and B3).

As shown in Fig. 1, B1 is located in the bedroom, B2 is located in the living room and B3 is located in the kitchen.

Each smart location beacon broadcasts its signal; if the tag is in the range of a beacon, the beacon obtains an indicator in order to calculate the distance of the tag, which is measured in meters. The following fuzzy sets are defined over the indicator of distance, expressed in meters (m).

CloseBX (m): TS (1, 1, 0.2, 0.4).

MiddleBX (m): TS (2, 3, 4, 5).

FarBX (m): TS (0, 0, 3, 5).

VeryFarBX (m): TS (0, 0, 4, 5).

A fuzzy temporal window is defined, considering the current time t_0 with a trapezoidal membership function, the universe being represented in seconds (s).

From3s5 s (Δt)*: TS (2, 3, 5, 6).*

Regarding the sensor data in the fuzzy temporal windows, a Quantifier, Qm, is applied, which represents "most" that is defined by the following trapezoidal membership function.

Qm (x): TS (0, 0, 0.5, 1).

According to the fuzzy sets defined previously, the following complex protoforms in the Tag (PTBX) are computed, considering the smart beacon BX:

PTCBX: Most of the Distance Is CloseBX From 3 s to 5s→ Qm CloseBX(m-BX) From3s5 s(t_0)*.*

PTMBX: Most of the Distance Is MiddleBX From 3 s to 5 s → Qm MiddleBX(m-BX) From3s5 s(t_0)*.*

PTFBX: Most of the Distance Is FarBX From 3 s to 5 s → Qm FarBX(m-BX) From3s5 s(t_0)*.*

PTVFBX: Most of the Distance Is VeryFarBX From 3 s to 5 s → Qm VeryFarBX(m-BX) From3s5 s(t_0)*.*

For simplicity, the following equivalences are defined:

Location is bedroom: PTCB1 and PTFB2.

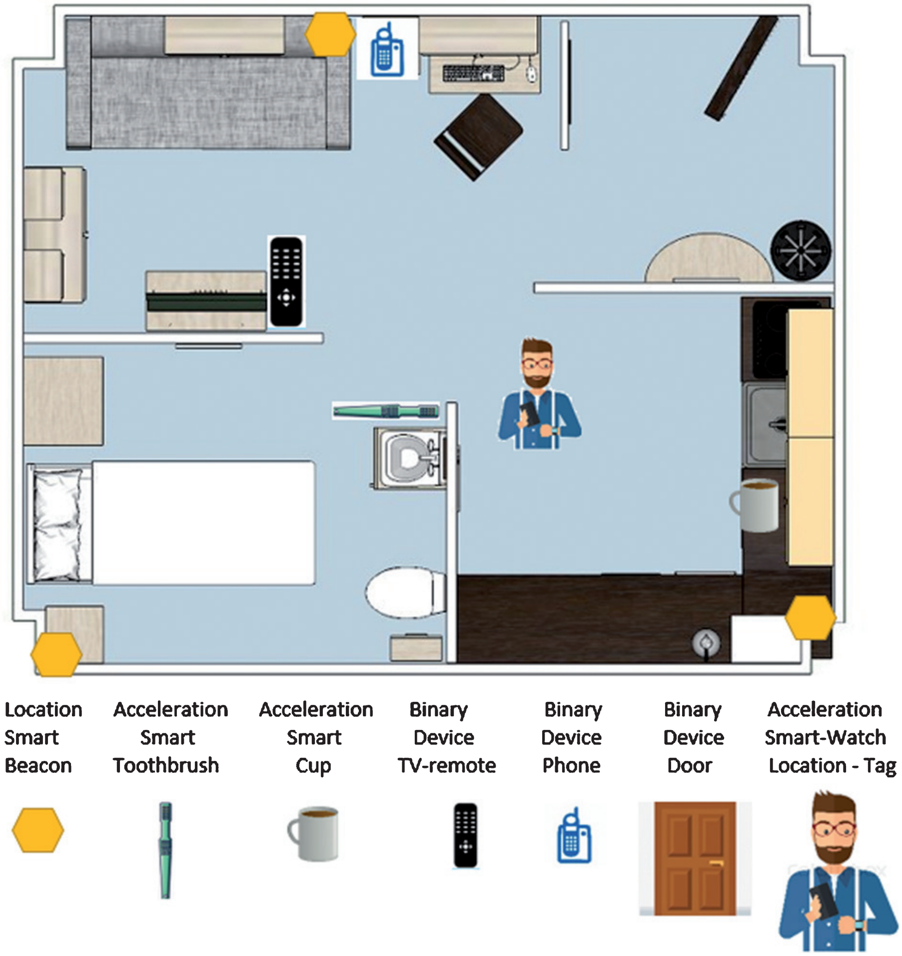

Fig. 3. Smart devices involved in the case study.

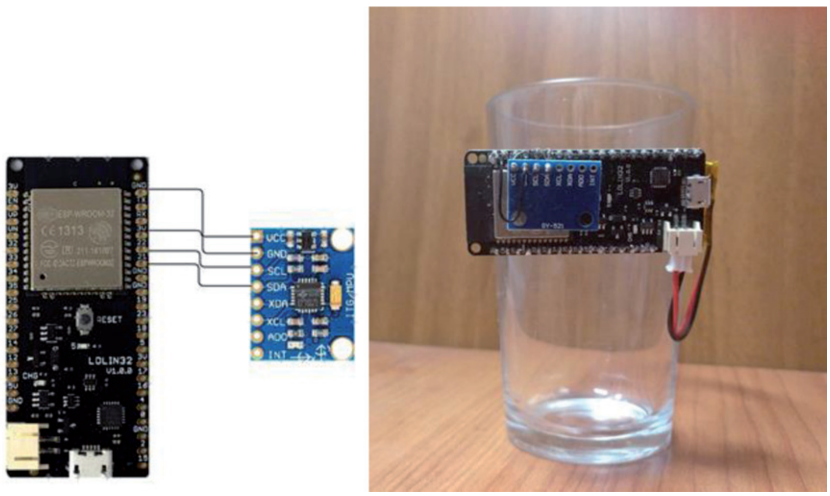

Fig. 4. ESP8266 board (left) that was attached to a cup (right) to collect acceleration sensor data.

Fig. 5. Smart accurate beacon composed of Raspberry pi 3 with UWB technology.

Location is washbasin: PTMB1 and PTMB2.
Location is kitchen: PTFB1 and PTCB2.
Location is living room: PTCB3 and PTFB2.
Location is hall: PTVFB1 and PTMB2.

Where *and* operator is represented with the norm *minimum*.

4.2.2. Movement of the inhabitant

The movement of the inhabitant is generated and computed by the acceleration of the smartwatch worn by the inhabitant. The acceleration signal is represented by m/s^2 in each axis (X, Y and Z) and the following fuzzy sets are defined.

$$UpX(x) : TS(0, 0.25, 0.75, 1)$$

$$UpZ(z) : TS(0, 0, 0.25, 0.5)$$

Furthermore, the magnitude (Mag) of acceleration that considers all three axes is computed by means of the following expression: $\mathrm{Mag} = (\mathrm{sqrt}\,(x * x + y * y + z * z))$.

The following fuzzy sets are defined over the magnitude acceleration.

Low (Mag): TS (0, 0, 0.2, 0.4).

High (Mag): TS (0, 0, 0.5, 0.1).

Two fuzzy temporal windows are defined, considering the current time t_0 with a trapezoidal membership function, being the universe represented in seconds (s).

From5s10 s $(\Delta t) : TS(3.5, 5, 10, 11)$.

From3s5 s $(\Delta t) : TS(2, 3, 4, 5)$.

A Quantifier, Qg, is defined representing "most of the time", which is defined by the following trapezoidal membership function. It is noteworthy that Qg will be used in other smart devices with acceleration.

$$Qg(x) : (0, 0, 0.5, 0.75).$$

According to the fuzzy sets defined previously, the following complex protoforms in the smart wearable device (PSW) are computed:

PSW1: Most of the time Mag Is Low From 5 s to 10 s → Qg Low(Mag) From5s10 s(t_0).

PSW2: Most of the time Mag Is High From 3 s to 5 s → Qg High (Mag) From3s5 s(t_0).

PSW3: Most of the time X Is UpZ From 3 s to 5 s → Qg UpX (X) From3s5 s(t_0).

PSW4: Most of the time Z Is UpZ From 3 s to 5 s → Qg UpZ (Z) From3s5 s(t_0).

For simplicity, the following equivalences are defined:

Movement is low: PSW1.
Movement is high: PSW2.
Movement is up hand: PSW3 AND PSW4.

Where *and* operator is represented with the norm *minimum*.

4.2.3. Acceleration of smart devices

The movement of each device is also generated and computed using the acceleration of each smart device in each axis as well as the magnitude acceleration.

Protoforms in these fog nodes are defined according to the nature of each object in the following sub-sections.

Inclination of Smart Cup: In this smart device, the relevance of the acceleration is its Y-axisused to compute the inclination of the cup. For this reason, the following fuzzy set is defined.

LeanedY (y): TS (0, 0, 0.5, 0.75).

A fuzzy temporal window is defined, considering the current time t_0 with a trapezoidal membership function, being the universe expressed in seconds (s).

From1s3 s $(\Delta t) : TS(0, 1, 3, 4)$.

According to the fuzzy sets defined previously, the following complex protoform in the smart cup (PSC) is computed:

PSC1: Most of Y Is LeanedY From 1 s to 3s→ Qg LeanedY (y) From1s3 s(t_0).

For simplicity, the following equivalence is defined:

Cup is tilted: PSC1.

Movement of Smart Toothbrush: In this smart device, the relevance of the acceleration is in its magnitude, to compute the movement. For this reason, the following fuzzy set is defined.

High (Mag): TS (0, 0, 1, 2).

A fuzzy temporal window is defined, considering the current time t_0 with a trapezoidal membership function, being the universe expressed in seconds (s).

$From1s2\,s\ (\Delta t) : TS(0, 1, 2, 3)$.

According to the fuzzy sets defined previously, the following protoform in the smart toothbrush (PST) is computed:

PST1: The great part of Mag Is High From 1 s to 2s$\rightarrow$ *Qg High(Mag) From1s2 s*(t_0).

For simplicity, the following equivalence is defined: *Toothbrush is moving: PST1.*

4.2.4. Active smart binary devices

The activation of each smart binary device is generated by a binary value $b \in \{0, 1\}$. In this case study, there are three smart binary devices: the phone (PH), the TV remote (TV) and the exit door (ED).

When the PH is off-hook, the device generates a value of 1, otherwise a value of 0. When the TV is on the device generates a value of 1, otherwise a 0. When the door is open, the device generates a value of 1, when closed a value of 0 is generated.

The following classic set is defined over each smart binary value. It is worth noting that this crisp set is represented by the identity function:

$ActivePH\ (b) = b$.

$ActiveTV\ (b) = b$.

$OpenD\ (b) = b$.

The simplicity of the values generated by these devices allows for simple discrimination of interactions within the environment.

To process the activation of these devices in a temporal way, a fuzzy temporal window is defined, considering the current time t_0 with a trapezoidal membership function, being the universe in seconds (s).

Now (Δt)*: TS (0, 0, 1, 2).*

Due to the crisp nature of these devices and the straight relation of the binary value and the object activation, they lack the quantifiable form. Therefore, according to the sets defined previously, the following complex protoforms in each smart binary devices are computed:

PPH: Phone is active now $\rightarrow$ *ActivePH (b) Now* (t_0).

PTV: TV is active now $\rightarrow$ *ActiveTV (b) Now* (t_0).

PD: Door is open now $\rightarrow$ *OpenD (b) Now* (t_0).

4.3. Fusing protoforms in cloud for activity recognition

In the fuzzy fog approach, each smart device publishes the fuzzy computed degree and linguistic description of protoforms to a subscriber in the cloud. This information is received by any interested publisher. In this work, the central node fuses the protoforms from smart devices for AR in real time using fuzzy operations, generating complex protoforms.

The complex protoforms are related to activities presented in this case study. The degree to which the protoform is related to the activity is calculated in real time. They have been defined utilizing expert knowledge as follow:

PSleeping: location IS bedroom AND movement IS low.

PTooth brushing: location IS washbasin AND movement IS up AND toothbrush IS moving.

PDrinking: location IS kitchen AND movement IS up had AND cup IS tilted

PWatching TV: location IS living room AND movement IS low AND TV IS active now

PCalling phone: location is living room AND movement IS up had AND phone IS active now

PExitHome: location is hall AND door IS active now.

Where *and* operator is represented with the norm *minimum*.

4.4. Results

Within the scenario, each smart device computed its protoforms following the proposed fog computing approach. Only the degree and description of the computed protoforms in each smart device were published in real-time, reducing the amount of information sent through the network and providing more linguistic information of sensors and objects.

In order to illustrate the computations of the protoforms in each device, examples of computed protoforms from the fog nodes are described.

Regarding the location of the inhabitant, the raw distance expressed in meters (Y-axis) over time (X-axis) by the three smart accurate beacons is represented in Fig. 6, considering the position of the tag that is worn by the inhabitant.

Membership degrees of the computed protoforms related with the location of the inhabitant are illustrated in Fig. 7. The protoforms of the locations are

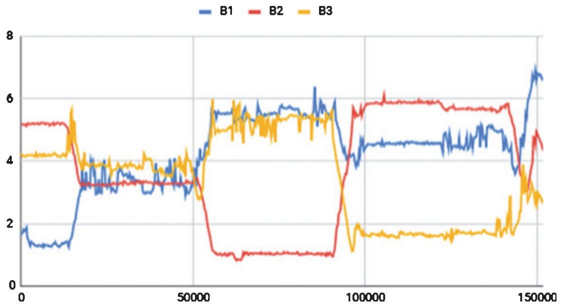

Fig. 6. Raw data expressed in meters (Y-axis) of the smart location beacons over time (X-axis).

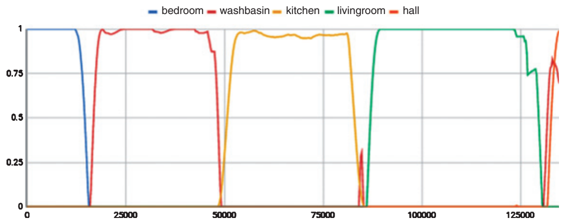

Fig. 7. Membership degrees of the locations protoforms over time.

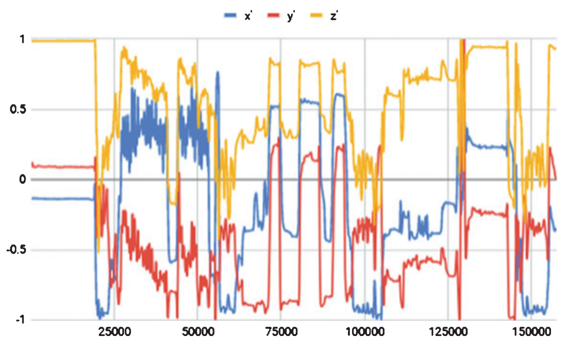

Fig. 8. Raw data expressed on meters (Y-axis) of the wearable devices over time (X-axis).

computed by fitting into the area where each activity is carried out.

Between the kitchen and the living room, the membership degree of the hall location slightly increases. This is due to the fact that the hall is between the kitchen and the living room, as can be seen in Fig. 3.

Regarding the movement of the inhabitant, the acceleration in its three axes (X, Y, Z) and the magnitude over time is illustrated in Figs. 8 and 9, respectively.

Membership degrees of the computed protoforms related with the movement of the inhabitant are illustrated in Fig. 10.

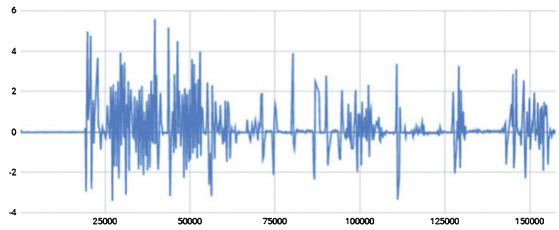

Fig. 9. Magnitude of the acceleration (Y-axis) of the smart wearable devices over time (X-axis).

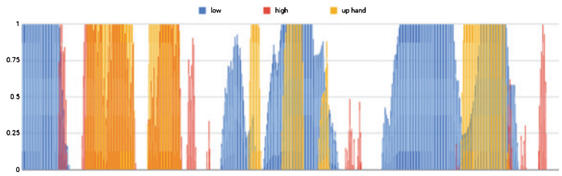

Fig. 10. Membership degrees of movement of the inhabitant over time.

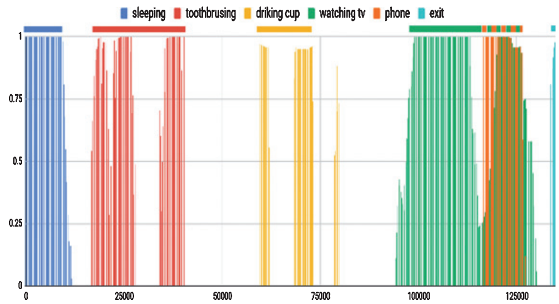

Fig. 11. Membership degrees of activity protoforms (Y-axis) over time (X-axis) from a fuzzy point of view. Ground truth is represented at the top.

Finally, the complex protoforms have been computed in the wearable device of the inhabitant, considering its own protoforms as well as protoforms published by other smart devices using light and intuitive operations based on fuzzy methodology. Membership degrees of the complex protoforms, activity protoforms, are shown in Fig. 11. The colored horizontal lines in the figure above indicate when each real activity begins and ends over the time, ground truth. The colored vertical lines represent membership degrees for each activity using the complex activity protoforms.

4.5. Discussion

The proposed fuzzy methodology and the expert knowledge has successfully described activity

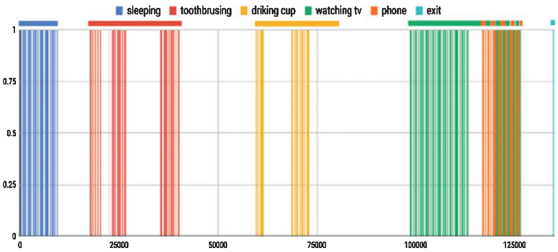

Fig. 12. Membership degrees of activity protoforms (Y-axis) over time (X-axis) from a crisp point of view. Ground truth is represented at the top.

degrees which match up with the sequence of activities of the scenario. It is worth noting that in the end of the scene, two activities: watching TV and using the phone, overlap in time, which is the sequence which was undertaken during the scenario.

In order to compare the results generated by the fuzzy fog proposal, Fig. 12 shows the results with the same methodology from a crisp point of view. To do so, we apply an α-cut with a value of 0.9 to all membership functions involved in the case study.

Regarding the crisp point of view, the activity of drinking (drinking from the cup) is more accurate from a fuzzy perspective. From the crisp perspective, this activity is reduced in time.

Furthermore, in our case study, there is a situation with overlapping activities. Specifically, watching TV and using the phone. The crisp point of view loses the progressive state of changing from one activity to another. So, the fuzzy point of view represents this progression in a more adequate way.

Finally, the main advantage of the fuzzy model is that it represents the progress in starting and finishing each activity with a membership degree in the timeline. The crisp model reduces the space in the timeline where information on the development of the activity is provided, obviously including the degree that is also lost.

5. Conclusions

In the IoT paradigm with a cloud–fog approach, multiple and heterogeneous smart devices cooperate with each other in order to make intelligent decisions or predictions in various contexts, such as, medicine, healthcare or smart cities. The accuracy of such decisions depends upon the reliability of the generated sensor data, which contain uncertainty due to incompleteness, ignorance, vagueness, imprecision and ambiguity.

In this paper, the cloud-fog computing approach has been extended with a fuzzy point of view in order to model the uncertainty involved in this paradigm and process it in a linguistic and interpretable way.

From the fog computing point of view, the sensor data stream in each fog node has used fuzzy temporal windows and linguistic quantifiers to manage uncertain sensor data. Each fog node publishes relevant linguistic information defined by protoforms, which summarize the sensor data stream from each smart device linguistically.

In the fuzzy cloud computing approach, complex protoforms have been computed, providing a new and intuitive linguistic representation of the highest-level information from the protoforms computed and transferred by the fog nodes.

The proposed fuzzy cloud-fog approach has been applied to AR in real time. The benefits of this new fuzzy cloud-fog computing approach are shown to achieve the objective of recognizing the activity in real time. Our proposal has been developed and implemented in the smart lab of the University of Jaén with multiple smart devices (UWB beacons, smart objects and a smart wearable device) to recognize six activities of an inhabitant in a real life scenario to demonstrate the effectiveness of the proposal put forward in this paper.

Finally, the results obtained with the proposed fuzzy approach in the smart lab have been compared with the results generated by a non-fuzzy approach. The benefits of the fuzzy approach are mainly that it offers a progression of each activity closer to the ground truth, providing a membership degree of each activity.

Regarding to the managerial implications, smart devices offer cost efficiency and are becoming smaller and consuming less energy. The installation and setup of these devices is also not very complex. Therefore, it is relatively easy to operate these devices in the proposal of fuzzy cloud-fog computing approach.

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