A proposal for architecture of kitchen-related activity recognition system with multimodal sensor fusion

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***Abstract*—The recognition of human activity is a relevant topic in the scientific community due to its high applicability to ambient assisted living. One of the main challenges in smart environments is to adapt them to a given daily context, where activities are composed by multiple interactions and developed in multi-occupancy way. In this paper, we propose: i) a deployment for sensing actions in the kitchen including non-invasive and long autonomy sensors, ii) an architecture for distributing data in real-time in edge/fog computing guaranteeing the privacy of the inhabitants, and iii) a fuzzy inference engine for computing activity recognition using a knowledge-driven approach.**

***Index Terms*—smart kitchen, multimodal sensor, activity recognition**

I. Introduction

Monitoring daily-related activities based on lesser invasive sensors is a wide topic of scientific interest [1]. In this work, we focus on the space of a smart kitchen, where humans spend a large part of their daily lives and key task within this environment. Sensing and monitoring the kitchen represents a relevant challenge because in a small space, several tasks and inhabitants can be presented simultaneously.

Moreover, the development of kitchen-related activities are connected to physical and mental well-being of people [2]. For example, a suitable Activity Recognition (AR) for the kitchen allows us to know if they are following the right eating habits, if they are eating at the wrong time of the day due to dementia symptoms, etc. In concrete, monitoring and AR in the kitchen is interesting for elderly people or people with disabilities, due to it provides the supervision of wellness promoting independence at home in a safe way for this collectives.

In recent years, scientific approaches have broadened their horizons in the use of AR using sensor fusion approaches [3]. They have proposed the combination of wearable and environmental sensors to provide a more reliable source of information. New trends include multi-modal devices which integrate video, audio, wearable devices to increase the capabilities of Internet of Things (IoT).

On the other hand, privacy preservation is established as a key requirement for the deployment of real-life smart homes [4]. It is the reason behind the promotion of non-invasive sensors is increasing to keep the privacy issue. For solving that, the use of thermal vision sensors is increasing in smart environments.

In this paper, an architecture is presented where non-invasive multimodal sensors are integrated in a smart kitchen to recognise human activities by means of a fuzzy knowledge approach. The contribution of this work can be summarized as follows:

- A selection of non-invasive, low-cost, high autonomy multimodal sensors are presented for sensing the area of kitchen of real-life homes.
- Fuzzy inference engine for activity recognition based on temporal modeling under a knowledge-driven approach is included.
- The two previous contributions are combined in a proposal for an architecture that locate the real-time processing of data under an edge-fog computing schema and only the high level AR information is sent to cloud to guarantee the privacy of collected data of users.

The remainder of this article is structured as follows: Section II describes related work on the topic of multimodal sensors, activity recognition and sensor fusion. Section III describes the approach, describing in detail each of the modules that compose the proposed architecture. Finally, conclusions

European Union's Horizon 2020 research and innovation programme under the grant agreement No 85718

are drawn in Section IV.

II. Related work

IoT systems which describe human daily activities are changing rapidly on demand [5]. The development of smart environments represent a challenge in several fields of the technology: hardware development of sensors, real time processing, precision and recall in the recognition of activities, flexible architectures, etc.

Over the years and with the advancement of technology, the proposed systems have become increasingly robust through the use of different types of sensors, such as environmental, wearable, multimedia devices. In the initials approaches, binary sensor were proposed for the low cost and maintenance [6]. The main drawback of them is the poor description in user interactions disabling the multiple occupancy recognition within smart environments. More recently, ambient sensor-based approaches have been extended to include Smart Meters [7], which allow identifying user interaction with electrical devices [8] based on energy consumption [9].

Moreover, wearable devices have been shown to be an excellent descriptor of the physical daily activity [10]. The long-term adherence of the wearables increase physical activity among youth [11], adults and seniors [12] promoting a positive change in the health behaviour. In smart environments, the wearable devices face the discrimination of users in multi-occupancy problems [13].

Audio processing using microphones for event tagging is opening a promising field of research within AR [14], including fog computing models to guarantee privacy. Similarly, vision sensors have been integrated in IoT proposal, for example, in egocentric sensing in kitchen [16]. However, the use of visible-spectrum vision sensors arise problems in terms of indoor privacy for users, so the emergence of thermal vision sensors has brought a balanced sensing keeping privacy in AR approaches. The performance of these sensors has been shown in recent work to adequately detect data on posture estimation [15] or fall detection [17].

Collecting, distributing and processing data from heterogeneous devices needs sensor fusion approaches [18]. The methods used in this regard are often referred to as Early Fusion (EL) (sensor readings from several devices are combined to obtain a single input vector and subsequently classified) and Late Fusion (LF) (data from different devices are processed separately by performing a first-level classification, and then the set of predictions produced are combined to produce the final classification) [19].

In real-time AR as in our proposal, where the start and end of events are unknown, sliding window-based approaches are required to segment the data stream [20]. In the context of multimodal sensors, the use of deep learning models has shown promising performance [21]. Moreover, fuzzy logic has been shown to provide an adequate representation of sensors [22] and has increased performance in AR [23] under non data-driven approaches (where non labelled data are available). Furthermore, fusion and aggregation by means of fuzzy logic of heterogeneous data from sensors have become the key to edge-fog distributed architectures [24], [25].

If we focus on activity recognition in a specific context, such as the kitchen, we found a light lack of scientific proposals. Most approaches use a general methodology for indoor spaces. In the scientific literature related to Human Activity Recognition (HAR) in kitchen we find several proposals [26]–[28]. Most (or all) mainly develop the AR by means of visible spectrum video, without exploring the integration of multimodal or non invasive sensors.

Based on the works and approaches reviewed in this section, this paper presents an architecture that combines and integrates non invasive and low cost devices of different nature to overcome the shortcomings found in other proposals and enabling the deployment in real-contexts. Also it is coupled with a multi-occupancy approach [29] to solve the problem that most people do not live alone. It includes an improvement in data privacy, as data is processed locally and the information from each device is processed separately following a LF approach. This simplifies the classification task and enables the deployment of the system on devices with reduced computing capabilities.

III. Sensors, components and architecture for a smart kitchen

In this section, we present a well-modulated approach for the recognition of kitchen-related activities through multi-modal sensor fusion. The proposed architecture presents a set of discrete components that interact with each other to generate knowledge from the data.

The selection of non-invasive sensors and data processing models are straightforwardly scalable and deployable in any home, making the system more affordable for people. The architecture is inspired by the edge/fog computing paradigm [30], where data processing models are embedded in IoT boards close to the sensor sending the data. This avoids the transmission of sensitive data such as thermal camera data.

The first group represents the connection of different types of sensors, in our case environmental, wearable and thermal vision sensors. Data from these devices are collected according to their nature (described in subsection III-A, III-B and III-C). Subsequently, those that require pre-processing, as is the case of the thermal camera and audio sensor, pass through an edge node that generates the output that awaits the next node. The fog node finally collects the data with the corresponding format in order to process them. The output generated by this node is the recognised activity, which can then be sent to a cloud node. Persistence of activity data could be performed on both the fog node and the cloud node.

The location of the sensors in the environment is key to be able to describe as accurately as possible the activity that the person is performing. A generic 3D drawing of a complete kitchen has been taken and each sensor has been numbered according to its location in Figure 1.

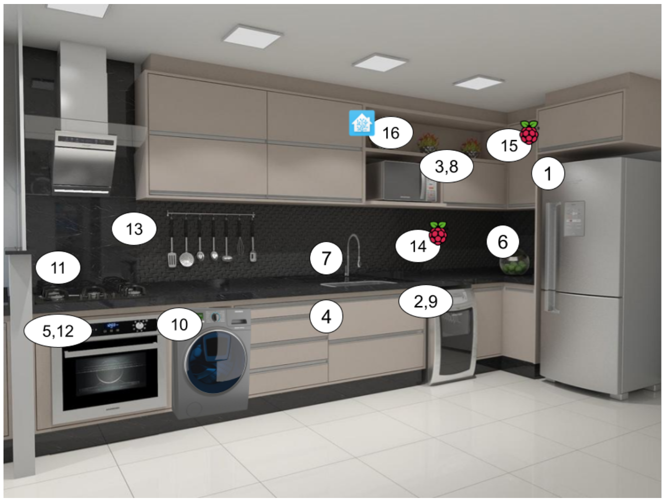

Fig. 1. Location of the sensors in a generic kitchen.

The following subsections present in detail the set of devices, how data is collected from them and their purpose in activity recognition.

A. Ambient sensors

The activation of environmental devices such as binary, presence, power consumption and temperature sensors in key elements of the home generates a wealth of information about people's daily lives, routines and habits [31]. In this work we propose a set of devices that have been previously tested, having been selected for their great autonomy, low cost and ease of installation:

- **Door Open/Close Sensor "Mi/Aqara Door/Window".** They are key for controlling the interaction of people with everyday objects. They are placed in the main household appliances: microwave, refrigerator, dishwasher, washing machine, furniture containing cutlery and, optionally, the door (see Figure 1, item 1-5). The price is around €10.
- **Presence Detection Sensor "Mi/Aqara Motion".** This device allows describing human activity without compromising the privacy and comfort of the user, as it uses passive infrared (PIR) to detect movement. It supports the thermal camera and the wearable sensor, as a single sensor covers the entire room (see Figure 1, item 6). It is priced at around €12.
- **Vibration sensor "Aqara Vibration".** Its function in our proposal is to detect the opening of the tap (see Figure 1, item 7), as it detects changes in movement by having an inertial sensor inside. Its price is around 18€.
- **Smart plugs "Mi Smart Plug".** These sensors report the power consumption of the device that is plugged into it. They are placed on appliances where their activation (not just interaction) can describe an activity such as cooking, laundry, etc.: microwave, washing machine, dishwasher and ceramic hob (if possible) or oven (if possible) (see Figure 1., item 8-12). The price is around €15.
- **Temperature and humidity sensor "Aqara Temperature".** Temperature and humidity control in the kitchen (see Figure 1, item 13) is essential to prevent possible domestic incidents such as fires, preserving the safety of the inhabitant. The price is around €22.

All the devices are integrated in an **Open Source sensor platform (Home Assistant)**, our gateway implemented in a Raspberry PI (see Figure 1, item 16). The integration under this platform has as main advantage the incorporation of commercial devices in a friendly and direct way, facilitating the homogenisation of the data regardless of the protocol in which the sensors send the information. Home Assistant has a module to send sensor data through MQTT in real time, which allows us to transmit this information following the structure "sensor/property/" in the topic, and the value in the message content.

B. Wearable sensor

The impact of wearable devices has grown in recent years, as they are descriptors of physical activity of the inhabitant [32]. Among the wide range of commercial devices, whose capabilities and sensorisation are growing every year, for this proposal we have selected the **Xiaomi Mi Band 3 device**, once again for its autonomy and low cost (around €20). Compared to more modern models (Band 4, 5), this activity wristband does not require an authentication token to collect your data, which makes the procedure easier.

The function of this device is to estimate the location of the inhabitant using the **RSSI (Received Signal Strength Indicator)** value received from Bluetooth Low Energy, as well as to collect the steps and intensity of these to determine whether the person is moving. For this purpose, several Bluetooth beacons are placed in the home, including one in the kitchen (see Figure 1, item 14). In our case, we propose the use of a Raspberry Pi to make the connection with the activity bracelet, obtain the RSSI value, intensity, HR and steps, and use it as a gateway to subsequently transmit this information with the defined structure of "sensor/property/value".

C. Thermal vision sensor

Vision sensors together with audio sensors have been proposed as multimodal devices to recognise patterns of inhabitants. Considering the intrinsic privacy concerns of visible spectrum cameras, thermal vision sensors are used as they have a higher degree of privacy [33]. In this work, we propose the integration of the **FLIR Lepton 3.5 camera with the PureThermal 2 - FLIR Lepton Smart I/O Module** connected on a Raspberry Pi, which configures an IoT thermal vision sensor with data collection, distribution and computation capabilities. It has Plug and Play connectivity, making it easy to deploy and perfectly adapted to the low-cost IoT boards that we use as an edge node for processing the collected images. Its price is around €250.

This device is interesting because of its high image resolution (160 x 120 pixels) despite its small size. Its role in this proposal is crucial, as it is in charge of multi-occupancy detection. It is important that it is positioned high enough so that the image captures most of the room (see Figure 1, item 15). For this purpose, the use of bounding boxes or the detection of human body landmarks is proposed to detect how many people are in the sensed environment. In this context, the use of bounding boxes would be sufficient, as the detection of body landmarks is significantly less advanced in thermal images and can be misleading due to the occlusions that are generated. However, if this scheme is further developed, once the bounding boxes are detected, the body landmarks could be recognised in these boxes [34].

D. Fuzzy Inference Engine for AR

In this section, we describe a Fuzzy Inference Engine for AR (FIEAR) which: i) extracts knowledge from heterogeneous sensor data streams, ii) fuses information from rules in order to recognize activities. The fuzzy rules are composed by protoforms which have been described as a suitable linguistic approach for sensor processing [36]. In this application, the following protoform has been proposed to define to process the sensor streams, $A_r\ T_j$ where:

- A_k is a fuzzy linguistic term that is defined in the context of the linguistic variable V_r related to a sensor S_r. Several linguistic terms A_k describe the status of the sensors: binary sensor) on / off; RSSI wearable) close, far; thermal sensor) worktop area, laundry area, dining area, etc.
- T_j is a fuzzy temporal window (FTW) [37] described straightforwardly according to the distance from the current time t^* to a given timestamp t_i as $\Delta t_i = t^* - t_i$. The linguistic descriptions of the FTW are related to time interval representations, such as, now (in the last 2 minutes), recently (around 2 and 5 minutes), etc.
- The protoform $A_r\ T_j$ aggregates the values s_i defined in the term A_k of the sensor stream S^r in a temporal period T_j with a degree:

  $$A_k \cup T_j = \bigcup_{\bar{s_i} \in S^r} A_k(s_i) \cap T_j(\Delta t_i) \in [0, 1]$$

  For t-norm and t-conorm we propose the fuzzy weighted average equation [36].

The protoforms are integrated as antecedents of IF-THEN rules to extract knowledge from the sensor streams [24].

First, the location of the user is processed in order to relate the interaction of the inhabitant in several areas of the kitchen. A given module Fuzzy Location Estimator collects data from the RSSI of the wearable of the users and the thermal vision sensor in order to determine which inhabitants are in the kitchen and whose are close to the appliances using the next protoforms:

1) L1 (user, area): RSSI of user is close in the area while at least 2 and 5 minutes
2) L2(user, area): User detected from thermal in area while at least 2 and 5 minutes

The fuzzy location rule *L(user,area): IF L1(user,area) AND L2(user,area) THEN user is in area* fuses the information from thermal sensor device and RSSI from wearable in order to determine a degree of occupancy of the user in a given area .

Second, the interaction of a user with a given appliances is developed when the binary or energy consumption sensor from the appliance is enabled:

1) L3 (appliance): Appliance has been active while at least 2 and 5 minutes

developing the interaction of the user and appliance defined by the fuzzy rule: *I(user,appliance): IF I(user,area(appliance)) AND L3(appliance) THEN user interacts appliance*. We note, the degree of $I(user, appliance)$ and $L(user, area)$ is computed for each time stamp generating an information stream which is straightforwardly processed in a similar way as we describe for sensor streams.

Forth, in a upper level, the temporal processing of rules *I(user,appliance)* or *L(user,area)* can be fused with other protoforms by high level fuzzy rules which determines a middle-long temporal interaction to compute different AR developed in the kitchen. For that, longer fuzzy temporal windows aggregate the information streams with domain context AR in the kitchen, for example:

1) *fridge(user): IF I(user,fridge) while at least 2 and 5 minutes THEN user opens fridge*
2) *dishwasher(user): IF I(user,dishwasher) AND I(user,cutlery cupboard) AND dishwasher is ON while at least 30 and 50 minutes THEN user sets dishwasher*
3) *cook(user): IF fridge(user) AND (I(user,microwave) OR I(user,oven)) while at least 5 and 10 minutes THEN user is cooking*
4) *eating(user): IF L(user,dining area) while at least 10 and 15 minutes AND I(user,cutlery cupboard) in the last 30 minutes THEN user is eating*

Finally, we discuss key pros and cons of the proposed Fuzzy Inference Engine for AR. First, the definition of the rules are developed by expert knowledge. It enables a straightforward and quick definition of AR using the fuzzy protoforms and rules defined as schemes in this work. Some difficulties to identify time intervals for FTWs has been identified in previous works, which require context aware evaluation for each kitchen and inhabitant habits. On multi-ocuppancy, the proposal is defined to support it, due to the location and interaction of several inhabitants is processed by Fuzzy Location Estimator in a independent truth degree; however, the interaction with appliance is based on the proximity location which is a general descriptor of activities, but it can be affected by noise, imprecision or not real use of appliances by the inhabitant.

E. Architecture

In this section, we describe the global architecture of the proposal of a kitchen-related activity recognition system with multimodal sensor fusion. An edge/fog computing scheme is proposed and only the recognised activity is sent to the cloud preserving the user privacy.

For distributing the heterogeneous data of sensors in real-time using a standard protocol, we integrate MQTT which allows us to transmit information from sensor stream following the schema of "sensor/property/" in the topic, and the value and timestamp in the message content [38].

In the edge computing, we process the data of the thermal vision sensor into the Raspberry Pi where is connected. So, the raw data are evaluated on the air in real time in the Raspberry Pi where is computed the prediction of user locations in the edge node. The recognized location (bounding box) is sent to the fog node with the rest of the information coming from the sensors.

In the fog layer, the Fuzzy Inference Engine for AR is connected. Here the data which feed the Fuzzy Inference in real-time are received by subscription from MQTT protocol. First, the Fuzzy Location Estimator collects and processes the data from wearable and thermal sensor providing a description in real-time of the user location in MQTT. Second, the fuzzy rules of the Inference Engine are connected to sensor streams and fuzzy location to generate new information which is distributed also in real-time under publishing protocol of MQTT [24].

At the end, the protoforms which define the user activities are connected to cloud layer in order to provide only high level information (without raw sensor data). The connection from local to cloud services is enabled by REST-services and JSON format [38].

In Figure 2, we describe the architecture of components described in this work.

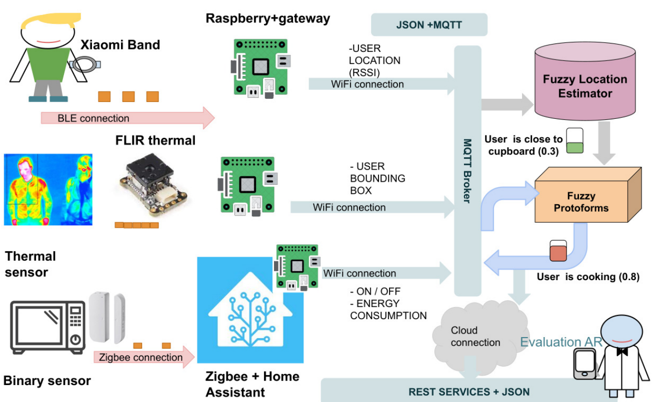

Fig. 2. Architecture of components described in the proposal for architecture of kitchen-related activity recognition system with multimodal sensor fusion

IV. Conclusions and ongoing works

In this work, an architecture for a kitchen-related activity recognition system has been proposed, which is a topic of interest due to its close relationship with people health status and eating habits. A system of different components has been carefully designed to be straightforwardly integrated and deployed keeping privacy guarantee using non-invasive sensors. The proposal is inspired by an edge/fog architecture to avoid the transmission of sensitive data, performing all data processing and machine learning techniques to process thermal data or fuse information at the fog node, so that only high level recognised activity is transmitted to the cloud if desired. In addition, a selection of sensors is presented that have a number of common characteristics (low cost, high autonomy and easy integration) and cover most of the elements in the kitchen with which the inhabitant interacts. The multimodal sensor selection comprises environmental sensors (binary, power consumption, motion and temperature), wearable inertial sensor (steps, RSSI location and intensity) and a thermal sensor to address multi-occupancy in the environment. Finally, a fuzzy inference engine that uses of multimodal sensor fusion for activity recognition by means of fuzzy temporal rules integrated under a knowledge driven approach is presented.

The aim of this study is to present a long-term approach for scientific and technical community, so next steps follow the deployment in real-life context and collecting data to evaluate the capabilities in real-time conditions. In addition, the multi-occupancy issue is handled by the proposal, which has some limitations to be addressed in future works. Moreover, different sensor fusion and transfer techniques will be applied to evaluate the kitchen related activities of inhabitants in heterogeneous contexts, being crucial the evaluation of different behaviour and patterns. The challenge we intend to address is to achieve a robust system that adapts to any context in a specific environment, in this case, the kitchen.

Acknowledgment

This publication received funding from the European Union's Horizon 2020 research and innovation programme - Pharaon Project 'Pilots for Healthy and Active Ageing' under Grant agreement no. 857188. This contribution has been supported by the Spanish Institute of Health ISCIII by means of the project DTS21-00047.

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