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Original
Smart Home Technologies for Cognitive Assessment in Healthcare / Lombardo, L.. - In: IEEE INSTRUMENTATION & MEASUREMENT MAGAZINE. - ISSN 1094-6969. - STAMPA. - 24:6(2021), pp. 37-43. [10.1109/MIM.2021.9513634]

Publisher:
Institute of Electrical and Electronics Engineers Inc.

Published
DOI:10.1109/MIM.2021.9513634

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DOI: 10.1109/MIM.2021.9513634

SMART HOME TECHNOLOGIES FOR COGNITIVE ASSESSMENT IN HEALTHCARE

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With the term “smart home” usual it is intended either a house, or more in general a residential environment, where a set of integrated sensors, devices and technologies provides the occupants with innovative functionalities and utilities which improve both the living comfort and the resource management of the building.

As an example, it is nowadays common to find in several houses smart systems for controlling the heating systems. Such systems, thanks to specific sensors and actuators deployed in the house, are able to automatically set the most suitable environmental conditions, such as temperature and humidity, according to the weather, the number of occupants, and their activities.

Similar systems are available for controlling lights and several domestic appliances with the main advantage of reducing the occupants’ effort in managing such settings, improving their living conditions and optimize the energy consumption.

Recently, however, such technologies have also been employed in the field of healthcare. As a matter of fact, the increasing availability of low-cost sensing and high performance processing devices is paving the way for the employment of smart home technologies in monitoring and assistance applications for either elder people, or for any person who is experiencing reduced capabilities or some kind of impairment. As an example, telemedicine infrastructures and cognitive/well-being monitoring systems are becoming quite diffused in several countries.

With the aim to provide a basic overview on this topic, this article will discuss the technologies, usually employed in the smart homes, which can be successfully applied in the healthcare field.

Smart home technologies

Smart homes base their functionalities on the capability of monitoring environment parameters and detect a set of specific activities the occupants are performing during their daily life [1, 2]. In order to accomplish such a task, smart homes firstly need several types of sensors which collect data, process them and carry out specific actions accordingly what is

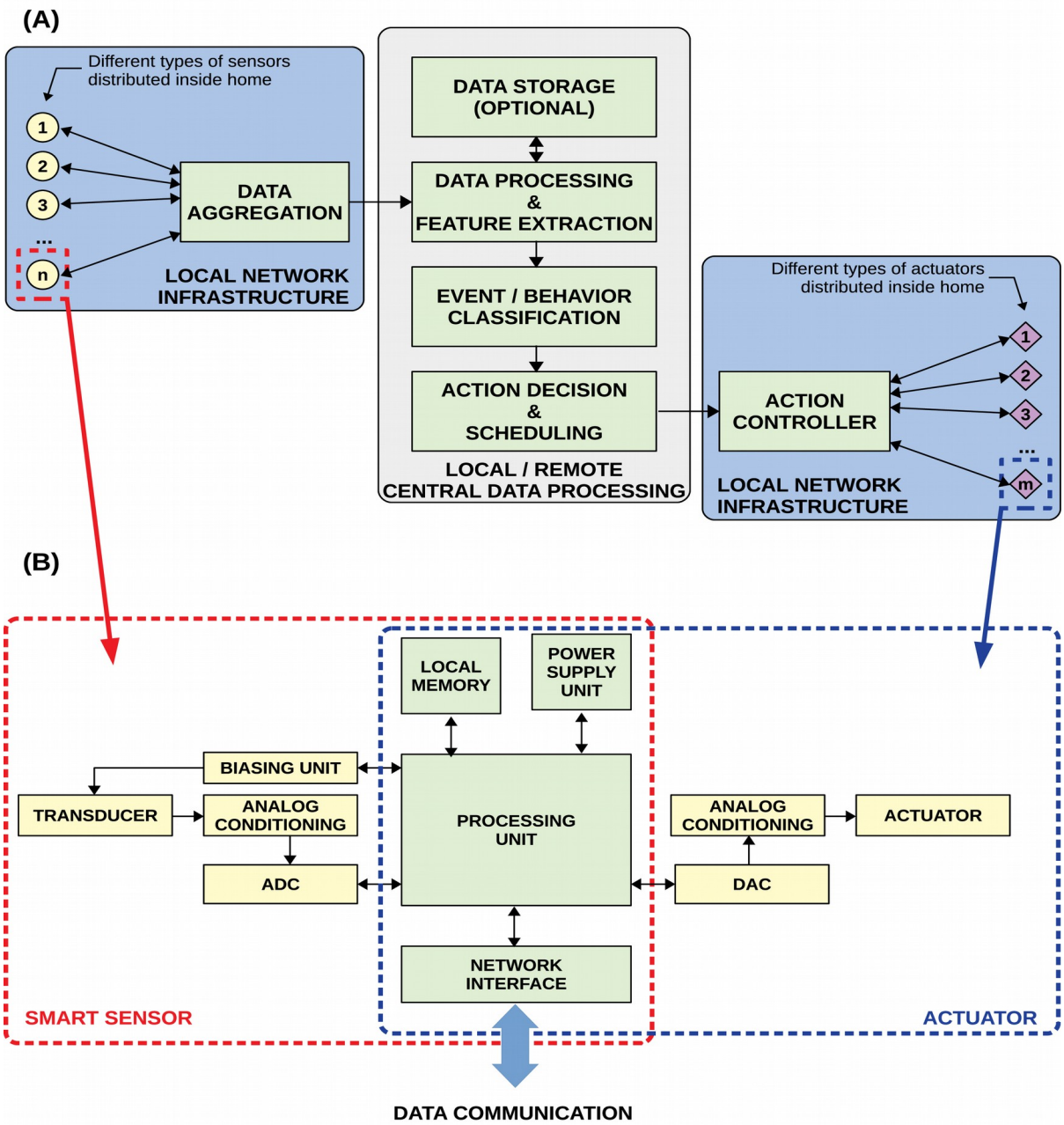

Figure 1: (A) block diagram of a typical smart home setup showing the main components and the data flow; (B) details on the typical implementation of a smart sensors (red box) and a actuator (blue box).

happening inside home. Fig. 1(A) shows the main components embedded in a smart home and how they collect and process data. Smart home technologies can be, therefore, considered as a sort of distributed measurement system which, apart the intrinsic advantages of such

systems [3], embed some sort of “intelligence” and “decision capability” developed with the final aim of improving the living experience of the home occupants.

To this aim a set of “smart sensors” need to be deployed in the home environment. These sensors are able to perform specific measurements, acquiring the required data and, often, performing a preliminary data processing. Each sensor embeds, therefore, a complete measurement chain mainly composed the physical transducer, some analog conditioning circuit, an Analog-to-Digital Converter (ADC) and a processing unit such as a micro-controller or a low-power processor.

Optionally, a biasing circuit is provided as well in order to properly bias the transducer. Quality and reliability of the acquired data are mainly related to the performance of the measurement chain and, therefore, special care should be undertaken in the design of these blocks in order to guarantee the required levels of data accuracy over the operative life of the system possibly including a calibration support. Fig. 1(B) shows the block diagram of a typical sensor which may be employed in smart home applications. Since acquired data need to be transferred, the processing unit is usually also responsible for the communication protocol of the sensor. Moreover, the smart sensor should embed a power supply unit (such as a battery or an energy harvester) and a communication interface suitable for the network infrastructure deployed in the system and optionally a local memory for storing acquired data and settings.

The network infrastructure (Fig. 1A) covers the home environment providing the support which allows the sensors to communicate together and to transmit the acquired data to a central processing unit. Such a network can be of any type, according to the application and the type of sensors employed. However, such an infrastructure is typical implemented with a wireless sensor network because of the advantages a wireless link is able to provide: easiness of sensor deployment and maintenance, and possibility of quickly adding or removing sensors (scalability) without the necessity to install wires and cables in the home environment are few of them. The wireless approach has also the benefit of reducing the visual impact of the infrastructure. Several wireless protocols [4] are available with different performance and specifications. As an example we can recall: Bluetooth Low-Energy (BLE) [5], Ant [6], Zigbee [7] and Wi-Fi. Such protocols are quite widespread in smart home applications and their specifications in terms of data-rate and range well-fit the requirements of home environmental monitoring. It is worth to mention also the LoRa protocol [8]. This protocol, dedicated to long range communications (up to few tents kilometers), it is quickly gaining popularity because it provides longer range communications maintaining low power

consumption and a data-rate suitable for most of the applications in Internet-of-Things (IOT) and measurement fields [9, 10]. Furthermore, several novel dedicated protocols are developed for applications requiring specific processing [11].

Regardless of the selected protocol, the employment of wireless links involves some issues. As a matter of fact, a power supply for the sensors should be provided for their operation. This can be provided either by a battery or by an energy harvesting system. The employment of a battery can limit the system operative life and increase its maintenance costs due to the necessity of replacing / recharging periodically the sensor batteries. The employment of the energy harvesting approach, instead, makes the sensors virtually autonomous from any external power source. However, it increases the cost of the sensors themselves due to the additional electronics required and, at the same time, it limits the type of sensors which can be employed. In fact, typically the energy harvesting approach is able to provide a quite small amount of power (up to few milliwatts), and this could be insufficient for the proper operation of several kinds of sensors. Of course other alternative approaches are also available: wireless sensors powered by electric grid, power-line sensors, radio frequency powered sensors (such as the RFID (Radio Frequency Identification tags) and self-powered sensors [12] are some of them.

Therefore, the selection of the most suitable network is a critical point in the design of a smart home system and should be carefully carried out trying to find the optimal trade-off between hardware and maintenance costs, performance and deployment easiness.

Apart the selected approach, sensors and network should guarantee suitable reliability, responsiveness and data security for the specific application.

After measurements have been acquired by the sensors, they are aggregated in some specific way and one or more data receivers/collectors should be available in the monitored environment.

Such devices gather the sensor data and send them to a central data processing unit which will process them in order to detect what event or activity is actually happening in the home. In order to properly carrying out such a task, it is required that the data acquired by different sensors, often placed in different areas of the home, are time-aligned, within few seconds. Indeed, aggregation is typically carried out considering a data time-stamp, or in general a time reference for each collected data provided by the sensor within the data itself. A synchronization protocol [13] is therefore necessary for the sensor network in order to provide usable data.

The central data processing unit can be located in the home itself (local processing) or can be located either on a remote server or on a dedicated cloud infrastructure. In the latter case, of course, an Internet connection should be available in the home.

Usually, a statistical approach based on expert systems and machine learning algorithms [14, 15] is used in order to process the data and "understanding" what is happening in the home. This processing typically requires high computing capabilities and it is carried out by extracting specific features from the acquired aggregated data and, by employing a suitable type of classifier, deciding which among the expected events or behaviors is the one occurring with higher probability. Sometimes, data, scheduled actions and, optionally, some sort of user feedback, can be logged in a suitable storage, and they can be used to continuously tune the decision algorithms with the aim of improving the quality and the reliability of the classifier and the action scheduling.

According to the detected situation, the central processing unit schedules suitable actions and sends to the local actuator controller some specific commands in order to carry out the scheduled actions. The actuators, which typically use the same network infrastructure of the smart sensors, operate on specific devices in order to carry out the required action. As an example, they can switch on and off lights, domestic appliances, or they can change the setting of the conditioning system. As it is shown in Fig. 1(B), actuators, similarly to smart sensor, embed several blocks, like network interface, power supply unit and processing unit, a Digital-to-Analog Converter (DAC) and an analog conditioning circuit for driving the actuator. In some cases, sensor and actuator are physically implemented in the same device and, therefore, they can share part of the hardware resources reducing the cost.

It should be noted, that the operation of expert systems and classifiers commonly requires some "training data" in order to operate properly. Furthermore, they are always subject to possible errors and misunderstanding, especially if something changes inside the environment: new people enter home, furniture or sensors moved from the original position, or just a significant change in behavior or habit of the occupants. This possible source of errors can be negligible in most applications, such as air conditioning or home appliance automation, but they can become extremely important in applications which can interfere with the well-being and the health of people [16], such as telemedicine applications [17].

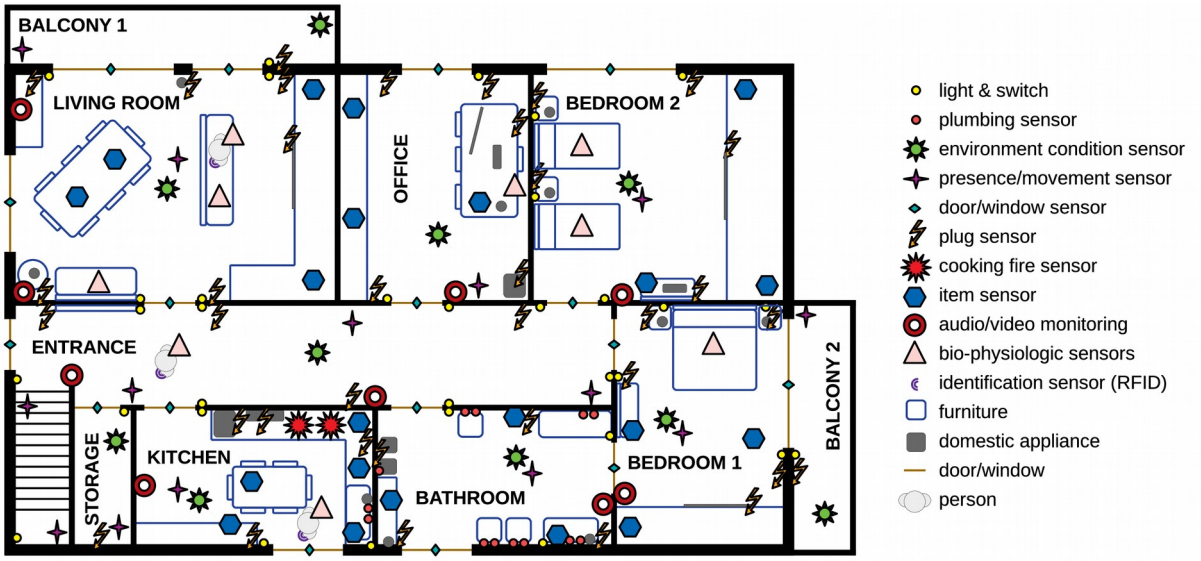

Figure 2: example of sensor deployment in a smart home.

Sensing devices commonly employed in smart home and healthcare applications

Understanding what is happening inside a home and what behaviors are keeping its occupants is not an easy task. This is particularly true when more than one person is living inside the home. In such a situation, the system not only has to correctly interpret the data acquired by the sensors deployed in the home and to determine the current behavior. It has also to recognize who is actually performing the actions. In order to properly accomplish this task, it is fundamental to acquire the most suitable parameters from the environment and from the home occupants.

Therefore, sensors are one of most important devices employed in such applications. Three basic types of sensors can be deployed in smart homes: environmental sensors, wearable sensors and infrastructure sensors. Fig. 2 shows an example of smart home implementation including the placement of different kind of sensors in the environment.

The most common sensor types are surely the environmental ones. Such sensors are directly deployed in the environment or attached to objects present in the home. They are able to gather several kinds of information starting from environmental conditions to people presence and movements. Wearable sensors are, instead, worn by the occupants themselves. They can be either embedded in clothes or in smart devices such as smart phones and smart watches and are able to provide additional information regarding the specific person is wearing them including: movements, posture, and bio-physical parameters.

Lastly, infrastructure sensors are sensors which take advantage from intrinsic home infrastructures, such as conditioning air systems, electric power grid, domestic appliances and

plumbing system to gather generic information about the usage of specific home items. These three types of sensors are able to collect different kind of information and data which, aggregated together, are extremely useful for the feature extraction and behavior classification.

In last decades, the advancement of new electronic technologies has led to a rapid improvement in the performance of both sensors and processing devices and, at the same time, a decrease in their size, their power consumption and their cost. Moreover, the introduction of the so called Micro Electro-Mechanical Systems (MEMS) and sensor fusion paradigm has revolutionized the sensor industry allowing the manufacturing of different types of transducers and the related electronics in a single chip by employing lithography technologies traditionally used for standard digital and analog chips. In particular, MEMS technology allows one to manufacture both complete mechanical devices featuring dimensions in the order of few micrometers and traditional electronic circuit in a standard silicon chip. Instead, the paradigm of sensor fusion expresses the idea of gathering data from different sources, processing them together with the final aim of improve data quality and accuracy. As a result of such technological advancements, a large selection of integrated and "intelligent" smart sensors has become available. Such devices embed in a single element both the transducer and the measurement chain providing directly a digital measurement of the acquired parameters and some sort of data pre-processing.

A type of sensors which can surely provide useful information are microphones and video cameras. Such devices are available in very small size, and they are able to provide good quality recordings at a quite low price. Nevertheless, their employment in smart home applications encounters significant limitations. Firstly, audio and video processing, such as image recognition algorithms, requires very high computational capabilities and high data-rate for the data transmission. Moreover, such devices, in order to provide useful data, should acquire continuously the home occupants during all their activities and this, clearly, is a critical privacy issue. For these reasons, such devices are rarely employed. Other alternatives, such as 3D microwaves scanners [18], have been developed with promising results. However, they are quite expensive and still in a prototypical stage.

More traditional sensors are able to provide information on the environmental conditions. As an example, several ultra-low-power wireless sensor networks have been developed for monitoring the climatic conditions in closed environments [19]. Parameters, such as environmental temperature, humidity, lighting, pollution and dangerous gases, can provide

useful data both to assess the occupants' comfort and safety, and to automatically control conditioning systems and illumination.

Other environmental sensors typically employed in smart home applications are designed to detect the presence of people in specific areas of the home. Different technologies are available but, probably, Passive Infra-Red (PIR) detectors are the most frequently used for detecting both the presence and the movement of people inside the rooms because of their good sensibility and low-cost.

Behavioral identification can be improved also by data coming from home openings, such as doors and windows. Either mechanical or magnetic switches are commonly employed in smart home to detect the opening and closure of doors and windows. Acquired data can, of course, being also employed for optimizing energy consumption. As an example, smart homes often feature intelligent systems able to automatically disable the heating system in that rooms where some window has been opened.

Nowadays, another typology of sensors is spreading out quickly. Several domestic appliances embed complex digital systems featuring sensors. Such systems are employed firstly for enhancing functionalities, performance and security of the device. As an example, several hobs and ovens have fire and temperature sensors. Many of such smart appliance also provide internet or wireless connectivity (Bluetooth) which allows the users to remotely control them. Smart homes can take advantage of these integrated sensors to retrieve additional information of the occupants' behavior. As an example, it is possible determine if a person is cooking by monitoring hob sensors.

Other sensors can be, instead, embedded in the infrastructures of the building. As an example switch sensors and plug sensors can be attached to the electric grid in order to detect when and where the occupants are switching on/off lights or attaching loads to some plug. It is also common the employment of smart lamps which include a WiFi interface for controlling them and detect their status. Other sensors can be connected to the plumbing system so that it is possible to determine if the person is using water. All this information can greatly improve the reliability of the behavior classifiers providing both activity-related and positional data. Moreover, proximity or tactile sensors can be easily attached on several items and tools. This way, it is possible to understand if anyone is using or moving a specified object inside the home.

A completely different category of sensors is represented by the wearable sensors. Such sensing devices are employed in several applications, including sport and fitness, medical rehabilitation and healthcare. The development of these sensors is extremely difficult because

several critical constraints exists in such applications. Firstly, these sensors should be comfortably wearable, and they should not provide any impairment to subject movements. Subsequently, they have to be very small and lightweight. Moreover, they must have a wireless capability because wires attached to the body for long periods are surely uncomfortable. Severe issues are related to safety and power supply of such devices which usually employ small rechargeable batteries or energy harvesting techniques. Nevertheless, wearable sensors are quickly spreading and several technologies have been specifically developed for the healthcare field [20]. As an example, inertial sensors, force, pressure and strain gauge sensors can be successfully employed to determine the posture and the physical activity of a person. Such sensors can be employed also for acquiring bio-physical activities and parameters. As an example, ballistocardiogram is a non-invasive technique which allows one to detect breath and heart rate [21] by employing special piezoelectric flexible films in contact with the body by monitoring the small movements and deformations due to the breathing and the heart beating. These sensors are, therefore, able to provide very useful data about the health and the physical activity of the subject.

Self-powered sensors [12] are also very important in this kind of applications. They have a very advantageous characteristic: they do not require a power supply or a battery to properly operate. Therefore, they are perfect to be embedded in clothes or any object of common use. Radio-Frequency Identification tags (RFID) belong to this category. In the simplest form, they are passive resonant circuits which enables themselves when they enter in proximity of a suitable tag reading system. Such sensors can be successfully employed for object proximity or for person identification. As an example, each person living in the smart home can easily worn an RFID. Several readers, deployed in different key points of the home, are able to identify each person during his movement around the home. This can be a valid solution for behavior classification because it allows the classifier to properly associate data incoming from the sensors with the specific person.

Cognitive and well-being assessment systems

Taking advantage by the already established technologies employed in smart homes, it is possible developing several applications for the cognitive and well-being assessment of people who, either for old age or for impaired capabilities, require a certain level of assistance [15, 22, 23, 24].

Interest on these systems is constantly increasing in the last years, because of the several advantages they can provide both to the assisted people and to the caregivers. Firstly, such technologies allow mild-impaired people to maintain an independent life without the necessity of being continuously or partially assisted by anyone. Moreover, these systems also permit relatives and healthcare personal to remotely monitor the health condition of the patients and undertake the required actions only when actually required. As consequence, there is a reduction of overall costs for the healthcare system and the improvement of safety and well-being of patients, which can be engaged in their daily activities without requiring an external assistance. Most of cognitive and well-being systems monitor the daily behaviors of the occupants in order to detect possible anomalies. As an example, the fact that a person, who typically awakes at a certain time and take breakfast, suddenly changes his behavior may

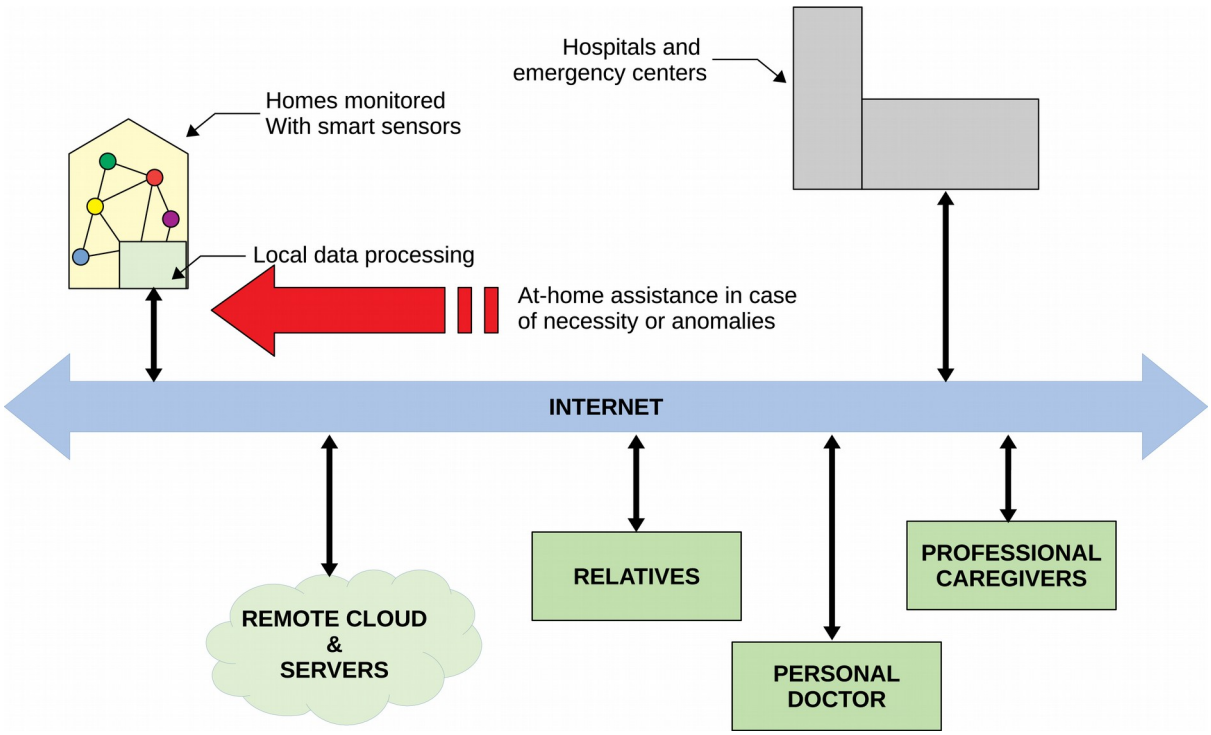

Figure 3: organization scheme for a typical well-being assessment system.

indicate a health problem that needs to be investigated.

Apparently, there are only minimal differences between the technologies employed in smart homes and that ones employed for healthcare. Both of them need sensors deployed in the environment to acquire sufficient information so that a dedicated algorithm can determine the health condition of the occupants and the activities they are carrying out. However, few fundamental differences exist between this two types of applications. Smart home applications have the possibility to work only in a local environment without exchanging data outside the home. Despite the fact that many smart home systems normally employ cloud and

remote servers also for remote control and surveillance, they can be considered self-sufficient. Differently, healthcare systems necessarily require the transmission of the data collected inside the home to external parties, such as relative and professional caregivers. Otherwise, no intervention or investigation can be carried out. Therefore, healthcare applications require an external support infrastructure for their proper operation. Fig. 3 shows the typical structure required by a remote healthcare application.

Data acquired in the home, independently from where they are processed, are transmitted to dedicated servers and cloud infrastructure which, after collecting them, dispatch notifications and physiological data to doctors and caregivers which have to monitor for the health conditions of the patient. Therefore, healthcare applications require the cooperation among hardware and software systems, healthcare institutions and caregivers. Such a cooperation is still not available in several areas.

Moreover, as a matter of fact, the acquired data, which are related with the patient activities, habits and health status, are transmitted to external subjects and this creates several problems related to the privacy and security of the monitored people. Therefore, such systems should be designed in order to guarantee the data security and avoid that any acquired data can be disclosed to unauthorized people.

Conclusions

Healthcare cognitive and well-being assessment is a valid technique for supporting and assisting elder and mild-impaired people without limiting their independence and their daily activities. The advancements in electronics and communications are rapidly creating new low-cost technologies which can be successfully employed for implementing such kind of applications. Nevertheless, different issues still limit the actual diffusion of these applications.

As a matter of fact, privacy and data security issues, together with the natural opposition old people experiment towards innovation and pervasive systems, are surely important limiting problems for the diffusion of such applications. However, they are not the most relevant. In particular, the missing of infrastructures on a national scale for supporting the cooperation of the service providers and the caregivers is a serious limitation. Lastly, it should be considered that these systems can seriously affect both health and life of the patients. Therefore, they should be reliable and effective in their operation, and they should provide accurate and

trustable data. As a result, there are several critical validation steps that should be carried out before such complex systems can be safely applied in the real life applications.

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