IoT-based Architectures for Sensing and Local Data Processing in Ambient Intelligence: Research and Industrial Trends

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***Abstract*—This paper presents an overview of new-generation technologies based on Internet of Things (IoT) and Ambient Intelligence (AmI), which create smart environments that respond intelligently to the presence of people, by collecting data from sensors, aggregating measurements, and extracting knowledge to support daily activities, perform proactive actions, and improve the quality of life. Recent advances in miniaturized instrumentation, general-purpose computing architectures, advanced communication networks, and non-intrusive measurement procedures are enabling the introduction of IoT and AmI technologies in a wider range of applications. To efficiently process the large quantities of data collected in recent AmI applications, many architectures use remote cloud computing, either for data storage or for faster computation. However, local data processing architectures are often preferred over cloud computing in the cases of privacy-compliant or time-critical applications. To highlight recent advances of AmI environments for these applications, in this paper we focus on the technologies, challenges, and research trends in new-generation IoT-based architectures requiring local data processing techniques, with specific attention to smart homes, intelligent vehicles, and healthcare.**

***Index Terms*—IoT, AmI, Sensors, Local processing**

I. Introduction

Ambient Intelligence (AmI) represents the ensemble of technologies that enable the creation of smart environments that respond intelligently to the presence of people, with the purpose of supporting their daily tasks, anticipating their needs, and improving the quality of life. Examples of AmI scenarios include innovative environments such as smart homes [1], intelligent vehicles [2], smart healthcare [3], smart grid, and smart cities [4], designed and realized to transparently facilitate the people in performing tasks, or promptly help them in responding to unexpected events (e.g., people in need of medical attention).

The realization of AmI technologies is currently an interdisciplinary field encompassing aspects of hardware measurement devices, sensors networks, machine learning, and human-computer interfaces. The recent introduction of advances in all of these fields, such as miniaturized instrumentation, advanced communication networks, small and general-purpose computing architectures, and non-intrusive measurement procedures, fostered the research and development of numerous and innovative AmI environments [5].

Within AmI, the Internet of Things (IoT) paradigm is emerging as an enabling technology to facilitate the interconnection and exchange of information among heterogeneous devices in smart environments, by realizing a communication network between measurement sensors, embedded devices, and human-computer interfaces. The use of IoT in AmI environments is currently growing, with several research trends oriented towards the design and deployment of more efficient networking infrastructures, able to take advantage of more accurate sensors and more powerful computing devices. Such innovations are in turn enabling the collection and storage of large quantities of data, sometimes referred to as big data [6], that recent machine learning algorithms, such as Deep Learning (DL) [7], can process to extract accurate information about the way in which people interact with the environment.

Due to the large computational and data storage requirements of using DL and big data techniques, systems based on IoT and AmI technologies often outsource computation and data collection using remote cloud computing services [6]. However, recent privacy-sensitive applications (e.g., smart healthcare) or time-critical computations (e.g., vehicle safety systems) often require the use of local data processing techniques.

This paper overviews the advances in smart environments requiring local data processing techniques, by describing recent IoT-based architectures connecting novel measurement sensors and local computing devices in AmI scenarios. The paper is structured as follows. Section II introduces the relevant definitions about AmI, IoT, and related technologies such as cloud and fog/edge computing. Section III introduces significant IoT-based architectures in AmI-enabled environments such as smart homes, intelligent vehicles, and healthcare. Section IV describes current challenges and research trends. Finally, Section V concludes the work.

II. AmI, IoT, and Related Technologies

AmI technologies include the sensors, procedures, and systems used to sense the environment and the people in them, with the features of being unobtrusive, embedded, interconnected, adaptive, and intelligent. Devices in AmI-enabled scenarios exchange the sensed data and aggregate the collected information to extract personalized and context-aware knowledge about the users' preferences, habits, and how to support them [5].

To provide a communication infrastructure between the different objects in AmI, the IoT paradigm is being increasingly studied due to its characteristics of "*allowing people and things to be connected anytime, anyplace, with anything and anyone, ideally using any path, network, and service*". By using IoT, different sensors, actuators, and computing devices can exchange commands and data using architectures and protocols that take into account different locations, transmission media, computing capabilities, and power requirements [6]. The role of IoT in AmI-enabled smart environments is emerging as an intermediate layer between the hardware devices and the applications that provide intelligent support to people. IoT deals with establishing the connection between different networked "things", such as measurement sensors, actuators, and displays, collecting the sensed data, and processing the information locally by aggregating the measurements to reduce noise and data uncertainty [8].

With the increasing deployment of IoT-based technologies, AmI applications often require cloud computing services to store and process large quantities of data. Cloud computing, in fact, "*enables ubiquitous, convenient, on-demand network access to a shared pool of configurable computing resources*" [9]. However, the access to cloud resources has the drawbacks of requiring a constant connection to the internet, being affected by network delays, and lacking a complete control over the data. To compensate for these problems, AmI applications that handle privacy-sensitive data, require highly-usable low-latency responses or need time-critical operations often perform data processing locally. To this purpose, the fog computing paradigm has been recently proposed to combine the advantages of local and cloud computing, by extending computing capabilities to the local network, closer to the sensors and the end-users, therefore processing most data locally, before accessing the cloud [8]. In some cases, fog computing is referred to as "edge", when the computing capabilities are integrated into the sensing devices themselves [10].

III. IoT-based Architectures for AmI

This Section reviews the most significant applications of IoT-based architectures for sensing and local processing data in AmI, with a focus on smart homes, intelligent vehicles, and healthcare. To give an overview of the sensing techniques, Table I summarizes the main sensors used by IoT in the different AmI applications.

Table I
Main sensors used in IoT-based architectures for AmI.

Sensor	Application: Smart home	Application: Intelligent vehicles	Application: Healthcare
Camera	[11]	[12, 13, 14]	[15, 16]
Temperature	[17, 18]	-	[19, 20]
Sound	[11]	[12]	[3]
Wi-Fi	[21]	[22]	[23]
Humidity	[17, 18]	-	[20]
Motion	[11]	[12, 24]	-
Accelerometer	-	-	[19, 25]
Gyroscope	-	-	[19, 25]
Power meter	[18, 26]	-	-
GPS	-	[12]	[19]
RFID	-	[27]	[23]
ECG	-	[24]	[19]
Radar	-	[12]	-
Magnetometer	-	-	[25]
Light	[18]	-	-
EEG	-	[28]	-
Gas	[17]	-	-

A. Sensors and IoT in Smart Homes

Smart homes are domestic environments that use AmI technologies to transparently support one or more occupants in performing their daily activities. In smart homes, sensors are distributed throughout the rooms to measure environmental conditions and the human presence. The information collected by the sensors is processed by IoT-enabled computing devices to control actuators and provide context-aware information to the users [1]. Action recognition techniques have also been studied in the context of AmI and smart homes to provide context-aware information based on users' activities, realize advanced human-computer interfaces, and detect possible dangerous situations.

In smart homes, IoT communication networks based on Wi-Fi, Bluetooth Low Energy (BLE), or ZigBee collect and process data from several sensors such as electrical meters, surveillance cameras, microphones, light sensors, temperature sensors, and gas sensors [1]. While complex inference systems, for example based on big data and DL, are often performed off-site with the help of cloud-based computing systems [29], sensing operations and data aggregations are usually performed locally.

The most common IoT-based applications in smart homes include power management, indoor environmental monitoring (e.g., air quality, illumination, temperature), and action recognition. To optimize power management in smart homes, the work presented in [26] describes the use of smart meters based on microcontrollers to sense and aggregate the power consumption of electrical devices over time. The method uses the collected data to recognize the appliances drawing power and build statistics leading to optimal use of the home devices. Similarly, the technique proposed in [30] uses IoT-enabled devices to aggregate such statistics of power utilization with users' position and habits to obtain an optimal power utilization pattern. Such pattern is fed to a control system performing an automatic activation or deactivation of smart sockets.

To monitor the home environment and improve the quality of life in indoor scenarios, the technique proposed in [18] uses a set of wireless sensors to detect environmental parameters such as temperature, light intensity, and humidity, as well as sensors to monitor the power consumption and the water temperature. The system aggregates the measurements collected by the sensors and processes them to determine the optimal balance between a solar-based water heater and an electrical-based heater. To improve the air quality in polluted environments, by giving indications and performing actions about ambient conditions, the work presented in [17] uses gas sensors to detect different possible air pollutants, processes such information locally, and combines it with data originating from temperature and humidity sensors to optimize the use of air filtering systems.

To perform both action recognition and indoor location management in smart homes, recent techniques consider the use of general-purpose Wi-Fi-based sensors, which can precisely locate individuals in a confined space and enable context-aware actions (e.g., turn on lights when someone is present). Wi-Fi-enabled sensors are also proving effective in detecting the relative position of the parts of the body, allowing to accurately recognize people's activities using a non-intrusive, low-cost, and pervasive infrastructure [21].

B. Sensors and IoT in Intelligent Vehicles

Intelligent vehicles include the means of transportation, private or public, that use IoT and AmI technologies to support the activities of drivers, passengers, or nearby pedestrians.

In intelligent vehicles, cabled networking was traditionally used for connections due to the fixed positions of the sensors. However, recent technologies are increasingly considering wireless vehicular networks based on the Internet of Vehicles (IoV) due to their reduced weight and increased ease of installation and maintenance [2]. Intelligent vehicles usually perform data processing locally, due to the unreliability of mobile internet communications while the car is moving (e.g., no reception inside a tunnel).

The sensors and communication technologies installed in intelligent vehicles can be categorized into two main types, based on the purpose of the collected information. The first type includes sensors and devices for intra-vehicle communication, which sense and collect data relative to the vehicle. The second type includes sensors for inter-vehicle communication, which collect data regarding the environment surrounding the vehicle, to determine the status of the car with respect to other vehicles, people, or fixed structures (e.g., roads, buildings, or traffic signs) [2].

1) Intra-Vehicle Communication: Intra-vehicle communication includes dedicated sensors for water pressure, engine temperature, and cabin temperature, as well as vision sensors based on cameras and image processing techniques [13, 14]. Recent research trends are also considering monitoring the state of the driver, for example by using methods based on Electroencephalography (EEG) sensors [28].

Based on the used sensors, recent IoT-based applications of intra-vehicle communication include monitoring the driver's health and analyzing road conditions, to increase the safety and comfort of the driver and of the other vehicles and people present on the road. To monitor the driver's health, the work presented in [24] reviews the use of different wearable sensors such as Electrocardiogram (ECG) integrated in smart watches, smart glasses monitoring eye activity, and motion sensors. The information originating from the different sensors is transmitted using a wireless IoT-based network, aggregated, and processed by a local computing device to determine possible signs of drowsiness or distraction in the driver. The method described in [14] proposes an alternative approach, based on a vision-based system, to detect facial expressions and link them to possible driver's stress.

To monitor road conditions, the technique proposed in [13] uses a camera mounted on the vehicle as a sensor. Using different image processing algorithms, it is possible to create several vision sensors by analyzing a single image. In particular, the work describes the analysis of the road in front of the vehicle to detect the position of the car inside the lane as well the position of possible obstacles.

2) Inter-Vehicle Communication: Inter-vehicle communication networks exchange data collected by GPS, proximity sensors, or vision sensors by using IoV-enabled communication devices. In some cases, complex algorithms for non-critical applications can be executed remotely (e.g., navigation systems with real-time traffic analysis). However, time-critical information concerning safety (e.g., other vehicles in the close proximity) is often processed locally to minimize the response time [2].

Examples of applications of inter-vehicle communication include collision detection, lane change warnings, and traffic management. To achieve a precise location of the vehicle for the purposes of collision detection or lane change warnings, intelligent vehicles often use the communication between the vehicle and external fixed structures, since GPS information in some cases is not reliable (e.g., inside tunnels) or not precise enough (e.g., for determining the position of the car with respect to road borders). The work presented in [12] reviews the combination of GPS, inertial motion units, cameras, RADAR, LiDAR, and ultrasonic sensors to sense the position of the vehicle in a reference map. It is also possible to use radio-based sensors and cooperative location techniques based on wireless IoT-enabled networks to sense the position of the vehicle with respect to other vehicles or fixed structures [22].

To improve traffic management, several recent applications of intelligent vehicles deal with analyzing the real-time use of public transportation to increase its efficiency and usefulness. To this purpose, the work described in [31] uses a Bluetooth-based IoT network to detect the smartphones of the users traveling on public buses, while the architecture proposed in [27] describes an IoT-based system to track the location of public vehicles, identified via Radio-Frequency Identification (RFID)

C. Sensors and IoT in Healthcare

Smart healthcare includes the smart environments that use AmI and IoT technologies to provide intelligent support to the health of the people in them. In particular, smart healthcare can be an enabling technology for smart homes, which can include intelligent healthcare mechanisms to support and provide assistive care to occupants in need of medical attention, or be a part of intelligent hospital structures, which use AmI technologies to assist and support the patients during their stay [23].

Healthcare systems usually process data collected by the sensors at a local level, due to the need of guaranteeing a fast and reliable response for emergency monitoring applications and ensuring secure processing of privacy-sensitive data. The measurements are then transmitted via an IoT-enabled network and aggregated to establish a preliminary evaluation of the patient's health or to detect the current activity. In non-emergency situations, it is possible to use cloud-based computing architectures to take advantage of higher processing capabilities. To combine the advantages of local processing and cloud computing, recently the fog computing paradigm is being increasingly investigated for IoT-based healthcare applications, with the purpose of both performing time-critical processing locally and complex computing on the cloud [32].

It is possible to divide the sensors and networking infrastructures of smart healthcare applications in two categories, based on whether they are close to the body or embedded in the environment. The first category includes wearable sensors, which are usually attached to the body or woven in the fabric of the clothes [33]. The second category includes ambient sensors embedded in the environment, connected using similar architectures like the ones used in smart homes. The use of ambient sensors for smart healthcare applications is often included as one of the features of smart homes, which may include assistive technologies to monitor health-related aspects of daily life and respond to emergency situations [3].

1) Wearable Sensors: In the majority of the cases, wearable sensors are connected in IoT-based Body Area Networks (BAN) based on RFID, BLE, or ZigBee. Most wearable sensors are small, light, and unobtrusive and include body temperature sensors, heartbeat sensors based on ECG or photoplethysmography (PPG), brain activity sensors based on EEG, pressure sensors, and breathing rate monitors, for example, capacitance-based [33]. In some cases, wearable accelerometers and motion sensors are used to detect falls [34].

The main IoT-based applications of wearable sensors for smart healthcare consist in continuously monitoring the vital signs of the person, detecting falls or performing activity recognition. To monitor vital signs as well as detect activities, the system described in [19] uses a set of wearable sensors to collect data related to physiological signals such as blood pressure, body temperature, heart rate, breathing pattern, and brain activity. The system also uses location sensors to detect the position and accelerometers and gyroscope sensors to detect motion. The system collects data continuously and processes it to detect emergency situations and to provide context-aware information based on the current activity (e.g., eating, walking, sleeping).

To detect falls, the method proposed in [25] describes an IoT-based energy-efficient wearable sensor based on a 3-D accelerometer, gyroscope, and magnetometer. The data collected by the sensor is transmitted via BLE and processed by a local gateway, which ensure a prompt response and quickly alerts emergency services.

To achieve an accurate activity detection, the technique described in [35] uses a recent DL-based processing algorithm. The work describes optimized neural models able to locally process the data collected from wearable sensors. The method performs preliminary filtering and registration of raw data collected from accelerometers and gyroscopes, with the purpose of enhancing local correlations. Therefore, it is possible to train a deep neural network with a limited number of connections between neurons, ensuring an efficient computation even on low-power architectures. The method is then tested by classifying each action corresponding to the data collected from multiple users.

2) Ambient Sensors: Recently, the use of IPv6 over Low-power Wireless Personal Area Network (6LoWPAN) is emerging as an innovative networking technology to exchange data between ambient sensors in healthcare applications [23]. Examples of sensors include cameras, microphones, pressure sensors, infrared motion sensors, and RFID detectors [3].

Based on the used ambient sensors, the main applications for healthcare consist of activity analysis, fall detection, location detection, and patient identification. To analyze health-related activities, the work described in [16] uses several cameras connected via IoT to capture patients' actions, identify them unobtrusively, and detect their emotions. The system then analyzes the emotions to recognize possible stressful situations. The method proposed in [32] uses an architecture that combines wearable and ambient sensors to monitor health-related behavior as well as environmental parameters causing possible health issues. To analyze health issues related to sleep activity, the work described in [20] presents a combination of wearable sensors and ambient sensors for sleep apnea monitoring. Ambient sensors include temperature and humidity sensors embedded in the room. The system collects data continuously from both wearable and ambient sensors and transmits it to a processing hub via IoT-enabled 6LowPAN or ZigBee networks to monitor the quality of the sleep cycle and detect possible apnea situations.

To detect falls, the method proposed in [15] uses DL techniques to analyze frame sequences captured by surveillance cameras in smart home scenarios. The use of surveillance cameras allows continuous and unobtrusive monitoring of the patient's activities. However, detecting possible falls in video sequences requires more complex data processing techniques with respect to using wearable sensors. For this reason, sometimes optimized neural models are used [36] to allow local processing of data.

The architecture presented in [23] introduces a smart hospital system that includes location sensors based on wireless signals, as well as RFID-based identification systems, to track the position of patients, doctors, and nurses. Smart displays connected via IoT are then used to provide context-aware medical records of the chosen patient to the closest doctor. To provide an efficient and power-aware communication network, the technique proposed in [37] describes a network for smart hospitals based on narrowband IoT. The network is used to exchange information between devices that measure drop rates of intravenous infusion systems.

IV. Challenges and Research Trends

Numerous research trends are recently focusing on IoT technologies and AmI environments, as shown by several research projects [38], initiatives [39], and publications [40] dedicated to the topics. To present an overview of current research directions, this Section introduces recent challenges and trends in the use of IoT-based technologies for sensing and local processing in AmI applications. In particular, it is possible to divide challenges and recent trends based on whether they are related to devices, algorithms, applications, or user acceptance.

A. Devices

The creation of smart environments where AmI technologies are deployed requires the availability of IoT-capable high-power computing devices with small size and low-cost, especially in private sectors such as smart homes. The higher computing power allows running complex algorithms (e.g., deep neural models) at a local level, without relying on cloud-based solutions [32, 35]. The lower cost of devices, either computing devices or sensors, enables the installation of a greater number of nodes to achieve more pervasive monitoring of the environment. At the same time, sensors with limited battery requirements or autonomous functioning (e.g., solar power) enable longer periods of monitoring time and the installation of sensors in places difficult to reach [41].

Recently, the research is progressing towards the use of miniaturized sensors, to create more comfortable wearable devices [33] that draw less power, thus reducing battery requirements and allow an autonomous operation [25]. The use of surveillance cameras to create vision sensors is also increasing in recent years, due to the possibility of performing unobtrusive continuous monitoring even at long distances [14] and using different analyses on the same data (e.g., action recognition, biometric identification) [11, 13, 15, 16].

B. Algorithms

Recent AmI applications require advanced algorithms able to process data collected by the sensors and extract high-level knowledge regarding actions, people, and situations, with the purpose of providing context-aware information and responding intelligently to the current activities [5]. Recently, the use of microphones (e.g., Google Home, Amazon Echo) and surveillance cameras is increasing to perform ubiquitous and unobtrusive monitoring in smart environments [13, 15, 16]. To process data captured from such devices and extract high-level knowledge, recent methods are increasingly using algorithms and machine learning models based on DL, which can make use of the large quantities of data captured in AmI applications, allow to process raw data, and can adapt to different operational environments [7, 35].

However, the adoption of DL in IoT-based architectures for AmI is currently limited due to high computational requirements and the need for large quantities of labeled training data. To adapt DL models to the computing and network limitations in IoT, recent research trends are considering methods to compress neural structures [42] or shift part of the computation to edge nodes [10]. To reduce the need for labeled data, recent methods are proposing the use of unsupervised DL techniques, that do not require labels, or Deep Reinforcement Learning, in which labels are assigned based on users' feedback [7].

C. Applications

The number of application scenarios for IoT and AmI technologies is constantly increasing, both concerning the introduction of new smart environments and the introduction of new functionalities in existing AmI-enabled environments. In the first case, recent research trends are proposing intelligent infrastructures to create smart buildings, smart grids, or even smart cities [4]. In the second case, new-generation devices and advanced algorithms are enabling the introduction of new functionalities in healthcare, smart hospitals, smart homes, and intelligent vehicles, by increasing the number of actions and emotions recognized [11, 16], monitoring a wider range of health conditions [3, 19, 28], and detecting a greater number of dangerous situations [12, 13].

D. User acceptance

Numerous architectures, methods, and algorithms have been recently proposed to include IoT and AmI technologies and create smart environments in an increasing number of situations. However, the intake of such technologies is limited by factors such as low user acceptance or limited technical expertise, especially regarding smart homes applications. To increase the adoption in smart home scenarios, IoT and AmI technologies are progressing towards a more user-friendly interface with a limited learning curve [43]. For example, recent human-computer interfaces based on microphone sensors and natural language processing are allowing people to interact using vocal commands similar to the ones uttered to other individuals [1], while unobtrusive biometric identification methods using surveillance cameras are enabling to provide context-aware information relative to the individual without requiring the user to perform any specific action [44].

V. Conclusions

This paper presented an overview of IoT-based architectures for sensing and locally processing of data for AmI, focusing on the main applications such as smart homes, intelligent vehicles, and healthcare. In these applications, research trends are considering IoT infrastructures connecting smaller dedicated sensors with limited battery requirements, able to perform ubiquitous and transparent monitoring with reduced human intervention. Recent methods are also analyzing the possibility of creating vision sensors based on general-purpose cameras, with the advantages of performing non-obtrusive monitoring with a low-cost infrastructure.

Local computing architectures are often used in AmI to process data for privacy-sensitive or time-critical operations such as healthcare and intelligent vehicles. In other cases, cloud-based solutions are often used to take advantage of higher computing capabilities. Recently, the fog/edge computing paradigm is emerging as an intermediate layer between local processing and cloud computing, by enabling a part of data processing to be performed locally, before using remote cloud computing solutions.

To increase the technology uptake by the general population, recent methods and systems are also focusing on increasing the user-acceptance of IoT and AmI technologies, by using more user-friendly interfaces and unobtrusive monitoring systems.

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