An IoT Approach for an AAL Wi-Fi-Based Monitoring System

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An IoT Approach for an AAL Wi-Fi-Based Monitoring System

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***Abstract*— Among sensible goals of active and assisted living paradigm is the unobtrusive monitoring of daily living activities. Based on such monitoring, anomalies and trends can be discovered, which possibly allows for early assessment of health issues and for prevention policies. However, when dealing with the home environment, and especially with older adults, obtrusiveness, usability, and cost concerns are of the utmost relevance. Smart objects can be designed to this purpose and deployed into the home: they usually feature low data rates and are customarily implemented by relying on conventional wireless sensor network approaches (ZigBee, Z-Wave, etc). This, however, results in "ad hoc" home networking, which is somehow obtrusive, complicated, and possibly expensive. In this paper, we discuss the implementation of behavioral sensors based on the familiar and ubiquitous Wi-Fi technology, suitable for a "plug-and-play" deployment. Sensors are connected to a cloud platform, embodying a genuine Internet of Things approach. With respect to conventional approaches, much better scalability, flexibility, and inexpensiveness can be attained. The main expected drawback comes from the higher power consumption, inherently needed to sustain much higher data rates. This paper focuses on such an issue, illustrating design techniques aimed at optimizing power consumption and battery lifetime. Performance results are shown, which definitely fall within a practical range and are fully comparable with more conventional approaches.**

***Index Terms*— Active assisted living, continuous monitoring, Internet of Things (IoT), smart homes, Wi-Fi.**

I. Introduction

THE progressive increment of the average population age [1] is having a deep social and economic impact. Most notably, the progressive imbalance between younger and older class-ages affects social and health-care policies, questioning sustainability of long-established welfare models.

Reducing the need of social and health-care services currently associated with aging is a primary goal, in order to preserve quality of life of aging population in an affordable way.

Information and communication technologies (ICT) may contribute to the construction of active aging scenarios [2], and are at the core of many worldwide research initiatives and programs. Among them, the "active and assisted Living joint program" (AAL-JP) [3] is exploring opportunities fostered by ICT to improve conditions of life for the older adults.

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The implementation of age-friendly home environments is a relevant goal: concepts such as smart homes [4]–[6], ambient intelligence [7], telemedicine [8], [9], and telemonitoring [10]–[12] converge in such a perspective. Key enabling technologies include sensing, reasoning, communicating, and interacting components. In order to be effective, deployment of ICT solutions within the home environment should not be perceived as intrusive, should not require bothersome changes in lifestyles and habits and needs to be accessible and trustworthy to (possibly unskilled) older adults. This introduces peculiar and stringent design constraints and makes it mandatory to have the end user himself participating in the design process, according to people-centric design paradigms [13].

In this paper, we describe how the above concepts have driven the evolution of the CARDEA system, developed at the University of Parma, Parma, Italy. CARDEA is an assistive oriented "smart home" system, suitable for safety, security, automation, and monitoring purposes [14]. Within the context of several national and European projects, the system has been thoroughly tested in real homes, with actual older users interacting with it for long periods. Based on such experiences, we focus here on the need of solutions being reliable, inexpensive, easy to deploy and maintain, interoperable and highly customizable (for personalization and managing of needs evolving over time).

A promising AAL objective consists of the exploitation of data coming from the home environment (through nonintrusive sensors) for the inference of "behavioral" data patterns, possibly meaningful in evaluating risk conditions or needs related to health and wellbeing. For instance, behavioral monitoring is expected to be relevant in early assessment of dementia and in related safety provision [15]. Most important, behavioral analysis does not rely on end-user skill or commitment and allows for nonintrusive, time-continuous monitoring.

A detailed discussion of data analytics techniques (needed to infer meaningful information from sensor data) goes beyond the scope of this paper and will be given elsewhere [16]; here, we shall discuss the implementation of a sensing network suitable for effectively supporting behavioral monitoring, with reference to specific constraints such as cost, reliability, and end-user acceptance.

More specifically, in Section II we shall introduce a home sensing network architecture fully compliant with the Internet of Things (IoT) [17]paradigm, with Section III discussing practical implementation of Wi-Fi-enabled devices suitable for behavioral assessment and Section IV evaluating their performance, with emphasis of power consumption. Concluding remarks are drawn in Section V.

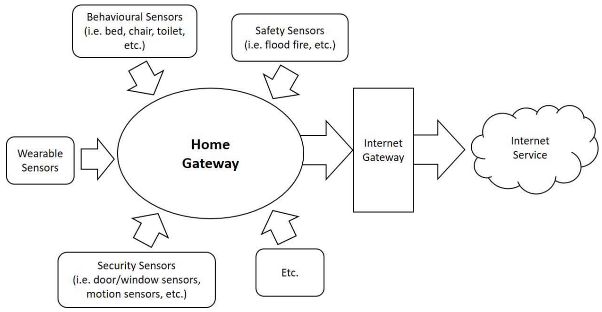

Fig. 1. Generic home sensors system for AAL applications.

II. IoT-Based Home-Monitoring Network

Over the years, many kinds of home-monitoring systems have been reported in [18]–[20], featuring different AAL-oriented objectives. Such systems exploit a number of different sensors to track features of daily living activities. Sensors may have manifold purposes, including home automation and control (e.g., interacting with the home lighting or heating systems), safety and security, support and compensation for mobility and sensory impairments, behavioral monitoring.

Home systems might be connected to the Internet, in order to allow for remote monitoring, maintenance, and communication tasks. Therefore, the system "intelligence" can be distributed among the sensing device themselves ("smart" objects), one (or more) home processing units and, possibly, external, cloud-based services.

In Fig. 1, a generic architecture is shown, referring to different classes of home sensors, a home gateway, which stores, aggregates, and processes sensor data, and an Internet gateway providing access to cloud-based services.

Deploying the sensor network into a user's home is a demanding design task, due to the nonintrusiveness, usability, and acceptability concerns mentioned in the introduction above: initially, home sensor systems-based their connectivity over wired technologies, exploiting either proprietary protocols [21]–[23] (e.g., X10, KNX, and LON), or open standards such as Ethernet [24].

However, wired networking has some definite drawbacks, with respect to the specific aim: in fact, wiring the home network calls for a structured wiring approach, which is still unlikely to be already available in most homes (and notably in less technology prone, older adults' homes). *Ad hoc* wiring, on this specific purpose, results in an expensive and intrusive approach. Moreover, the flexibility of the solution strictly depends on the wiring design: a key requirement for any assistive system is the capability of dynamically evolving, in order to adapt to the user's needs as they evolve over time.

Wireless communication therefore came into play, providing much higher flexibility and installation ease, at the expense of some delicate design issues, dealing with propagation of radio signals within a built environment. Also, some maintenance tasks are introduced (checking and replacing/recharging batteries, for battery-operated devices).

In this case too, a number of different technologies have been exploited: among the most diffused, bluetooth is mostly exploited for short-range communication (e.g., body-area networks) whereas Z-wave [25] and ZigBee [26]–[28] protocols (among many others) have emerged as most practical options for the implementation of a home sensor network.

Such approach has been demonstrated to be reliable and technically sound, and its deployment at user's home is considerably more flexible and less intrusive and expensive, with respect to wired networks [29]. Still, the deployment of a dedicated network is needed in this case, ensuring reliable coverage of the entire home environment through sensible placement of network nodes: although not being a major technical limit, this possibly jeopardizes user's acceptability and usability. This holds especially true when the home features a large or irregular surface, or extends over different storeys, this possibly requiring large numbers of network repeaters.

To overcome this problem, a mainstreaming solution can be thought of, exploiting more widespread technologies for networking sensors. The best candidate in this sense is WLAN/Wi-Fi protocol [30]. Wi-Fi infrastructures are, in fact, becoming more and more diffused in every home, with a growing number of devices requiring Internet connection (e.g., smartphones and smart TV). Wi-Fi networking is therefore more likely to be already present in the user's home; should not this be the case, deploying a Wi-Fi network is nevertheless much easier than a dedicated wireless network sensor, requiring no (or fewer) range-extenders and availing itself of a much larger market choice.

The main expected drawback is related to the power consumption [31]: in fact, while ZigBee is a low data rate, power-saving oriented protocol, Wi-Fi is mainly thought to support high-speed data transfers and wide area coverage. This difference inherently yields higher power consumption: in order to make such approach suitable also for low data-rate, continuous monitoring purposes, design efforts are needed to carefully administrate the energy budget of battery operated and wearable devices.

The Wi-Fi Alliance has recently announced a new version (802.11ah, "HaLow," [32]) of the Wi-Fi standard, suitable for low power, low data-rate devices. Nevertheless, this is still far from being widespread diffused, and its features (most notably the 900-MHz frequency range) may possibly result yet in the need of deploying "dedicated" devices (i.e., different from those already available in the home). This would not came handy, for instance, if a limited number of sensors are needed, possibly for a limited amount of time (e.g., to face a temporary illness or disability).

Some studies on porting traditional home automation systems over standard WLAN can be found in [33]–[36]. Wi-Fi-enabled home sensors have also recently entered the consumer market; for instance, motion sensors, video cameras, power meters, temperature sensors/thermostats are readily available.

Here, we discuss the extension of such an approach toward specific devices aimed at assistive, continuous monitoring purpose, with reference to behavioral monitoring concepts, and elderly people target population in mind.

A. CARDEA System

The home system named CARDEA has an open platform architecture and some custom-designed devices specifically conceived for behavioral purposes can be exploited [37].

ZigBee sensors communicate with a coordinator node, which is connected to a home gateway server, which in turn is connected to the Internet, usually through a modem/router. The server may also perform some data processing, and implement locally some basic safety and security functions. A number of routers may complete the infrastructure in order to be able to extend the network's range over the whole home.

To this purpose, in the CARDEA system, some specific sensors, providing information relevant to behavioral monitoring and not available on the general market, have been exploited. For instance, pressure pads are exploited to monitor bed (or chair) occupancy, fridge sensors are used to get indirect information about feeding habits, proximity sensors are used to monitor toilet usage frequency, etc. Also, a wearable node, MuSA [38], has been developed, which integrates an inertial measurements unit (IMU) [39]. MuSA is capable of providing information about the user's motion, relevant both in a quantitative and qualitative sense. It was originally conceived as a fall detector [40]: other features have been added onboard over time such as the energy expenditure (EE) evaluation [41], and low-level human activity recognition features [42].

CARDEA was exploited in different national and European projects [43], [44]. In the framework of a recent project, called HELICOPTER (*HEalthy LIfe support through COmPrehensive Tracking of individual and Environmental Behaviors* [45]), CARDEA has been deployed in about 30 pilot sites (located in Sweden and the Netherlands). Pilots were run at +65 users' homes for about six months, producing over 2-GB sensor data to feed the behavioral analysis engine. Deployment of ZigBee networks was then extensively tested and, given the large variability in home architectures, the placement of networking gear was not a trivial task. In order to reliably cope with propagation of low-power ZigBee signals, a relatively dense mesh of routing nodes was needed, while all rooms in homes at hand was suitably covered by a single Wi-Fi router. Moreover, since ZigBee routers need to be kept alive all the time, they are not suitable for battery operation: power supplies should therefore needed, connected to home ac outlets. Although, from the technical point of view, such problems were easily managed by a skilled person, they resulted in some users (and their relatives/caregiver) somehow intrusive. This, among other considerations, led us to consider a Wi-Fi network architecture instead, described in the following.

B. CARDEA Wi-Fi Extension

The WLAN/Wi-Fi protocol is described by the IEEE 802.11 standard, which regulates various over-the-air transmission technologies. Within the general IEEE 802.11 domain, the Wi-Fi implementation aims at enforcing actual interoperability and is regulated by Wi-Fi Alliance [30], a no-profit organization born to fill the lack of an official certification of the IEEE 802.11 devices. A typical Wi-Fi network structure is composed by a central device (an Internet modem/router) to which are connected other devices (either end devices or range-extenders), in a star network topology.

Within the CARDEA/Wi-Fi infrastructure, end devices can be home and wearable sensors, providing monitoring features introduced above. All data flowing from or to end devices must go straightforwardly through the modem/router, to be eventually stored and processed in the Internet cloud. That is, a home gateway (apart from the Wi-Fi router) is no longer strictly necessary. Furthermore, the wider coverage of Wi-Fi router makes it easier to ensure stable sensor connection all over the home, limiting the need of range-extenders to exceptional cases.

This vision drives CARDEA toward the Internet of Things (IoT) paradigm: each sensor becomes an Internet node capable of sensing and transmitting data over the Internet, independently of each other.

Compared with a dedicated wireless sensor network, main advantages include as following.

1) Better scalability, with the same architecture being suitable for small systems (down to a single sensor) as well as larger ones (e.g., an elderly sheltered house).
2) Deployment phase simplified if a Wi-Fi network is already in place, sensor installation is not different from connecting any other device (e.g., a TV decoder) and can be carried out by untrained persons.
3) Costs decrease, due to both the adaption of mainstream market technologies and to the absence of dedicated network gear (coordinator and routing nodes, home hub).

Disadvantages, instead, include as following.

1) As already mentioned, power consumption and therefore battery lifetime concerns are mostly critical, and calls for accurate design strategies for energy saving, introduced in Section III.
2) Data delivery time, based on Internet protocols, is not strictly deterministic. This makes the system less suitable for life-critical applications. Such applications, however, are beyond the scope of the current work, which is aimed instead at long term, continuous monitoring. Within such context, uncertainty in delivery time is not relevant at all. Sensor data are tagged with a suitable timestamp, so that the (offline) data analytics engine, irrespectively of such uncertainty, can precisely track the event sequences and timing.
3) The system is more sensitive to external connectivity issues (e.g., temporary failures of Internet services provision). This can be effectively tackled by introducing some buffering capabilities. As explained in the following section, all sensors feature onboard processing and storage capabilities, so that, in case of network failure, data retention can be implemented onboard.

Once delivered to the cloud, sensor data are stored and subsequently processed, in order to extract meaningful information. The cloud solution yields many advantages with respect to a more conventional server-based architecture. Among them, reconfigurable and expandable architecture, data security, performance scalability are worth mentioning.

CARDEA Wi-Fi sensors can be connected straightforwardly to different cloud environment (for instance, the IBM bluemix platform [46]), by suitably coding the access method into the device firmware. The cloud environment also hosts a full set of analytics functions, supporting CARDEA features, and converting raw sensor data into accessible information. Both raw data and synthesized analytics outcomes are then accessible through the cloud methods.

III. Wi-Fi Sensors

A. Design and Implementation

For conciseness' sake, we shall refer, in the following to two different scenarios: on the one hand, we may consider sensors which interact with the user in a "sparse" fashion, i.e., generating a limited number of "binary" events over time. For instance, bed occupancy, door open, toilet usage, and similar sensors pertain to this class; on the other hand, we may consider devices providing more complex information patterns, related to data streams, possibly active over long time intervals or in a continuous fashion. Most notable example in this class is a wearable motion sensor.

Some prototypal sensors have been designed and implemented to test the feasibility of the approach and select the best low-power design strategy: they consist of a common platform, based on the CC3200 [47] system-on-chip (SoC) by Texas Instruments, which integrates ARM Cortex-M4 microcontroller unit (MCU) architecture and a network processor compliant with the IEEE 802.11b/g/n network protocol radio. For prototyping purposes, a development board (LaunchPadXL board [48]) has been used, and complemented by different sensible elements, depending on the specific aimed function. In particular, the following devices were implemented for demonstration purposes.

1) Bed-Occupancy Sensor: It is based on a pressure-sensitive pad [49], suitable for under-mattress placement. Such a device behaves as a variable resistor, lowering its resistance when pressed. It is therefore connected as a pull-down element in a voltage divider, the output of which is connected to a digital input of the main board. The cable features a detachable connector, to avoid tearing off the cable (for instance while making the bed). An additional digital input therefore comes from the cable connector, to signal a fault condition (disconnected pad). Furthermore, the battery voltage is transmitted, to allow for remote maintenance tasks. An identical setup, except for a smaller-size pad, is exploited for a chair occupancy sensor. The device features a 3-V power supply, obtained by using standard AA-LR06 batteries.

2) MuSA Wi-Fi Wearable Sensor: It is based on operating concepts of its ZigBee-based MuSA [41] predecessor. In this case, a MPU9250 [50] integrated inertial measurement unit (IMU, featuring 3-D accelerometer, gyroscope, and magnetometer), has been connected to the same platform. From the ergonomic point of view, a more compact board redesign is planned. For testing purposes, in order to account for actual use scenarios, a lower capacity battery (Li-Ion 4.2 V, 500 mAh) has been used.

To interface the sensible elements with the prototypal platform, a board has been designed and implemented, carrying all components needed to provide the power supply and control signals. Thanks to the platform-based approach, further sensors can readily be implemented by coupling the platform to different sensing elements.

A key issue in device usability is the network configuration procedure: the Wi-Fi protected setup technology has been selected and implemented. The user is asked to push a button on the device, and a single LED signaling pattern has been implemented to provide feedback. So doing, the installation procedure does not require to connect to a computer or to manage long passphrases. Each device features its own unique identification number, so that association to the cloud environment can be managed by the service provider; this results in a truly "plug-and-play" approach in the home system deployment.

B. Low-Power Design Strategy

As stated before, power consumption is among main concerns in implementing Wi-Fi sensors. The Wi-Fi protocol is indeed aimed toward higher data rates than those actually needed for the monitoring functions we are interested in, so design efforts may trade "overabundant" data rate for power. This can be effectively accomplished by throttling down the communication rate, introducing idle intervals. In this section, we introduce design techniques we followed to implement Wi-Fi monitoring devices, featuring power performance of practical interest, fully comparable with ZigBee counterparts providing similar functionalities.

In the following, optimization strategies suitable for both classes of sensors previously introduced will be considered.

A key point for efficient power management is the ability to save energy while the device is not in use. The CC3200 provides different "power modes".

1) Active: the device works at its full capabilities.
2) Sleep: minimal energy saving; only the peripherals are turned off. MCU and RAM are fully operational.
3) Deep Sleep: the clock frequency is lowered with respect to the sleep mode. User can disable the RAM retention.
4) Low-power deep sleep (LPDS): the MCU stops its main clock while the radio module is awaken, so that the device is still connected to the network.
5) Hibernate: is the lowest energy consumption mode. Both MCU and radio modules are turned off. The system can be reactivated by an external interrupt or by an internal, low-frequency timer. During hibernation, the node is hence disconnected from the network, and a reconnection is needed at wake-up.

Different power modes were exploited, looking for a tradeoff between energy-saving performance, sensor responsiveness, and sampling requirements.

In general, we may outline the operating cycle of a given wireless sensor as shown in Fig. 2, with the device alternating work and sleep phases.

1) During the work phase, the device acquires data from the physical embedded sensor (using internal bus or ports), stores them in buffer, performs some onboard data processing (if needed) and eventually delivers them to the Wi-Fi network.
2) During the sleep phase, the device is in a low-power mode, the embedded sensor is not sampled and neither processing nor transmission occurs.

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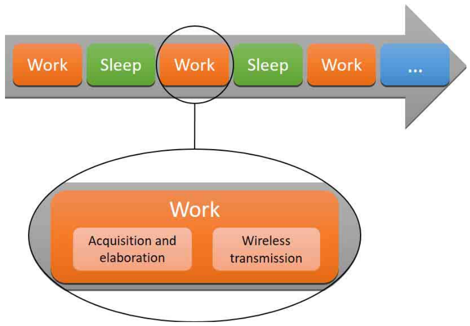

Fig. 2. Typical sensors operating cycle: work phases (data acquisition and processing) are interleaved with idle periods.

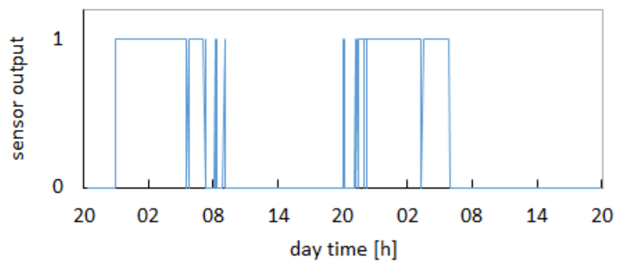

Fig. 3. Example of bed-occupancy data, monitored during two days, logged on IBM-bluemix platform (occupied bed yields 1).

Actual time balance between such phases and processing needs depend on the specific sensor purpose.

C. Bed-Occupancy Wi-Fi Sensor Performance

The first class of devices regards sparse, simple data patterns, requiring no specific preprocessing onboard. The work phase is therefore limited to sensor data acquisition and cloud forwarding. In Fig. 3, a sample bed-occupation plot is shown, illustrating the whole dataflow from actual sensor to the cloud environment (occupied bed yields 1, absence 0). It is related to a real-life test: the bed-occupancy sensor was deployed at a user's home, and connected to the existing Wi-Fi network. The home asymmetric digital subscriber line was then exploited to connect to the cloud (i.e., sensor deployment required no additional hardware device or software setting). Monitoring of sleep quality (based on information such as the amount of time spent in bed, number of awakenings, average times, etc.,) can easily be implemented from such data.

Once validated device functionality, actual power consumption was tested, by measuring current drawn by the device during its operating cycle. Since currents in sleep and active modes differ by orders of magnitude, they were actually measured by using different setups.

In order to measure the active-mode current (which peaks to some hundreds of milliampere), while the device was cycling through subsequent active phases (wake-up, network connection, etc.) a

LeCroy HDO6034 oscilloscope was used, connected to a LeCroy AP015 current probe, featuring a 30-A dc current range and ±1% dc accuracy.

In sleep mode, the current is in the order of microamperes instead. To obtain an accurate assessment, we forced the sleep state by modifying the device firmware, this allowing to measure a stable, constant current. An Agilent 34401A high-sensitivity digital multimeter was used in this case, featuring a 10-mA dc current range and 10-nA resolution.

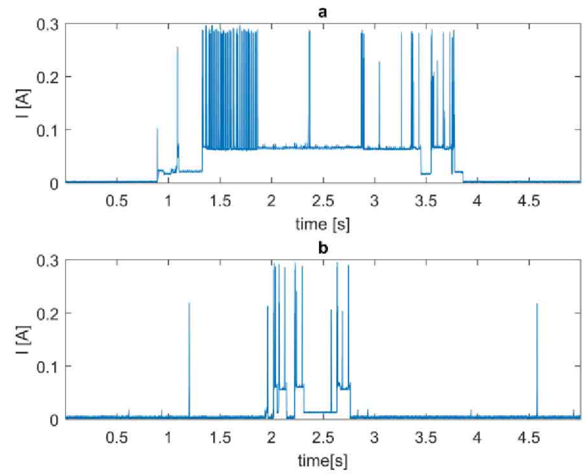

Fig. 4. Current measured during bed sensor ON phase, measured exploiting (a) HIBERNATE and (b) LPDS power modes.

TABLE I
POWER CONSUMPTION COMPARISON

Mode	P_{ON} [mW]	t_{ON} [s]	P_{OFF} [µW]
HIBERNATE	212.1	2.9671	17.16
LPDS	109.9	0.8102	990.0

In order to select the optimal standby mode, we first compared the consumption profile during "work" and "sleep" phases, with reference to the HIBERNATE and LPDS power modes. Measured currents in both cases are shown in Fig. 4. When the HIBERNATE power mode is selected, the device disconnects from the network during standby phases. Then, as the press-pad detects an event (i.e., when status changes from occupied to nonoccupied or vice-versa), the core receives an interrupt and reverts to the ACTIVE mode, to acquire and transmit data. The whole cycle implies waking up and reconnecting to both the access point and the cloud service broker, this resulting in a rather long and energy-hungry phase [Fig. 4(a)]. In the active phases an intense average current is drawn. Most energy is required in initial phases, and is related to the network reconnecting task. Conversely, when sleeping, a remarkably low standby current is drawn, since most of the core is switched OFF.

When LPDS mode is selected, instead, the sensor keep always connected to the network, this resulting in a shorter active phase as shown in Fig. 4(b), at the expense of a much higher standby power.

In Table I, P_{ON} is the average power required by the active phase, t_{ON} is the duration of the active phase itself, and P_{OFF} is the power consumption during standby phase.

Based on such figures, the total energy required to manage a single event can be obtained

$$E_{\mathrm{ON}} = P_{\mathrm{ON}} \times t_{\mathrm{ON}}.$$

Let n be the number of daily events; the total energy spent to manage such events therefore reads

$$E_{\mathrm{active,tot}} = n \times E_{\mathrm{ON}}.$$

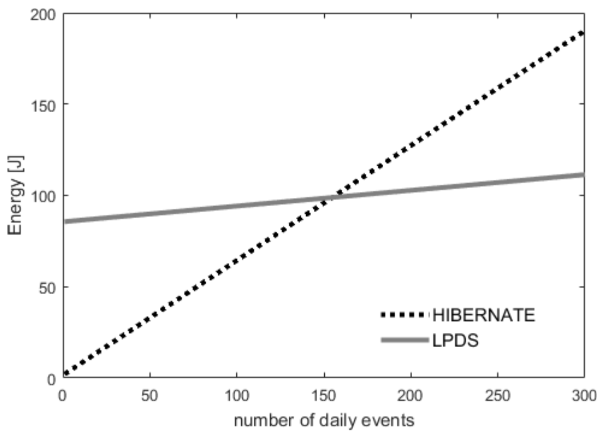

Fig. 5. Comparison between total daily energy consumption in HIBERNATE and LPDS modes.

The complementary standby time, in seconds, is

$$t_{\text{standby,tot}} = 24 * 3600 - n \times t_{\text{ON}}.$$

The standby daily energy is therefore

$$E_{\text{standby,tot}} = t_{\text{standby,tot}} \times P_{\text{OFF}}.$$

Finally, the total daily energies can be estimated

$$E_{tot,\text{HIB}}(n) = E_{\text{active,tot,HIB}} + E_{\text{standby,tot,HIB}}$$
$$E_{\text{tot,LPDS}}(n) = E_{\text{active,tot,LPDS}} + E_{\text{standby,tot,LPDS}}$$

for the HIBERNATE and LPDS power modes, respectively.

In Fig. 5, such quantities are shown, depending on the number of daily events. The balance between active and standby energies is quite different in the two cases, so that the HIBERNATE mode clearly outperforms LPDS at low daily events number. The break-even point, in the setup at hand, occurs at about 155 daily events: beyond such number, LPDS allows better energy performance. In evaluating such figure, it is to be considered that, besides actual events, the device is usually activated anyway at given intervals to allow for keep-alive messages and for periodic checking of battery status (or other parameters of interest). If we assume, for instance, a 15 min keep-alive interval, 96 daily events are needed for this.

Hence, the HIBERNATE mode is suitable for very sparse activation patterns, such as bed occupancy, toilet usage, main door open. Room presence (passive InfraRed) sensors, or other devices monitoring frequent daily activities, are instead more likely to be effectively managed through LPDS power mode.

If a low event number (and thus HIBERNATE mode) is accounted for, the power consumption mostly depends on the keep-alive interval. By assuming a 15-min interval, and a battery capacity of 2500 mAh (typical of AA-LR6 batteries) the estimated battery lifetime for the bed sensor (about 9000 h) exceeds a year, which is a more than suitable result for practical deployment in elderly users' homes. Comparable results hold for other devices featuring similar activation patterns, with minor differences depending on the actual current drawn by the embedded, physical sensor (which is usually responsible only for a small fraction of the energy budget).

It is worth mentioning, however, that, besides the average frequency of events, also their distribution in time matters. Awakening from a sleep interval may require different amounts of time, depending on the sleep mode (and, to some extent, on the actual network traffic and responsiveness). Wake-up is triggered by a sensor event: if a single thread process flow is assumed, further events occurring during the awakening phase (while waiting for the trigger event to be served) are ignored. We therefore characterized this behavior, in order to provide reference figures suitable for appropriate selection of power-saving strategies. To this purpose, we tested actual detection rates for sensor data coming at different frequency: since the actual reading time of physical sensor is negligible with respect to that needed for network management, we replaced the sensing element with a properly configured microcontroller board, featuring an Atmel ATmega328P-AU MCU, operating at 8-MHz clock frequency. The board was exploited to generate a regular stream of digital stimuli at variable, controlled frequency. For every time interval test, a stream of 100 events was sent through the sensor platform, looking for missing elements in the cloud storage caused by sensor wake-up blindness.

The actual detection rate was computed as the ratio between the number of events reaching the cloud storage and the total number of events sent to the sensor platform.

Results are shown in Fig. 6 for the LPDS and HIBERNATE modes, respectively. When LPDS is selected, the device needs not to reconnect when awakening, and measures show a wake-up blindness time in the order of 0.5 s, which is more than appropriate for most condition of interest. If HIBERNATE mode is selected instead, the wake-up blindness time increases significantly. Such a measurement, of course, may depend on some unpredictable conditions also, such as the traffic congestion of the Wi-Fi network, or concurrent events: nevertheless, based on several test we carried out in different conditions, a conservative, worst case estimate of the wake-up blindness interval may range around 20 s. In practice, this means that two subsequent events cannot be reliably detected if closer (in time) than such interval. Of course, a multithread processing scheme would avoid this issue: nevertheless, given the inherently sequential behavior of sensor data, this seems to be an overkilling approach, which would make the sensor management more demanding and possibly less robust. To deal with this in a more practical fashion, we just introduce a double-check procedure, according to which the sensor status is updated at the end of the awakening procedure: this means that, even if some rapid variation of sensor data during the blindness interval may be missed, the sensor status is correctly set when eventually awakened. Given the behavioral dynamics we are interested in, such a short blind interval is irrelevant in many cases of practical interest, this allowing to exploit HIBERNATE sleep mode features as well.

Also the accuracy of the sensor has been tested: a set of 200 actions (100 sitting down and 100 raising up) with a 30-s time interval (much longer than the estimated wake-up blindness). Neither false positives nor false negatives occurred, thus yielding a 100% accuracy.

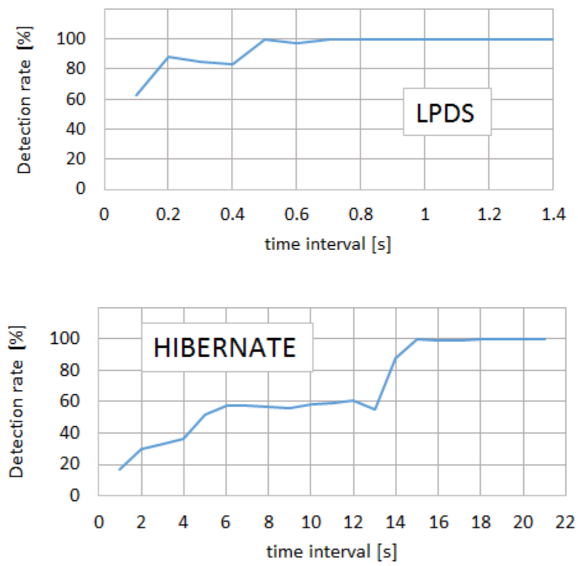

Fig. 6. Detection rate, when LPDS and HIBERNATE sleeping modes are selected.

D. Wearable (Motion) Wi-Fi Sensor

Very different considerations hold in this case as follows.

1) Information coming from such sensor is more complex and articulated: instead of a binary variable, the physical sensor output consists of a tuple of analog values (3 for a 3-D accelerometer, up to 9 if a gyroscope and a compass are accounted for).
2) Semantic interpretation is less straightforward: acceleration data are in general not significant in themselves, but need interpretation to infer meaningful information (e.g., fall detection).
3) Evaluating human motion features may require sampling rates as high as, for instance, 50 samples per second.
4) Battery capacity is usually much more limited, due to ergonomic constraints (size and weight).

To begin with, we may think of adopting the same approach exploited in the previous example, plainly transmitting every sensor sample to the cloud, for subsequent processing and interpretation. Measures were carried out with the setups introduced above: we assumed a sampling frequency of 50 Hz, and a full nine degrees-of-freedom datum (i.e., 3-D output from accelerometer, gyroscope, and compass) was sent as soon as sampled. No sleep phase is accounted for in this case, and the average current is measured at 65.16 mA. If we assume a battery capacity in the order of 500 mAh (which is compatible with weight and size constraints) a battery lifetime shorter than 8 h is obtained, which prevent such approach to be actually usable in a real-life context.

As long as the energy budget is dominated by the transmission task, we may take advantage of onboard processing features. For instance, we may greatly reduce transmission overhead by packing data into larger bursts, exploiting internal memory for buffering.

In Fig. 7, the current pattern is shown, when the very same data of the previous example are sent, grouped in 522 B (i.e., 29 9-DOF samples, exploiting the MPU9250 internal buffer), sent every 580 ms (29 samples collected at 50 Hz, thus keeping

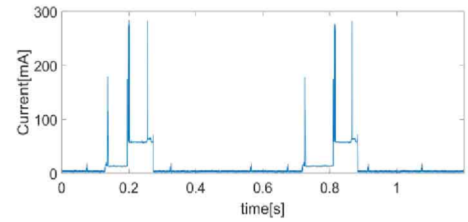

Fig. 7. Current measured on the wearable sensor, with buffered transmission of raw sampled data.

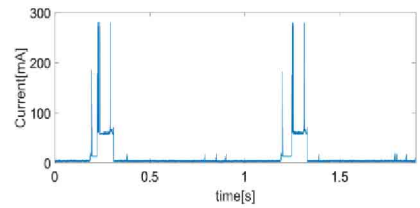

Fig. 8. Current measured on the wearable sensor, with onboard EE calculation (update interval: 1 s).

the sampling frequency and data rate unchanged). The buffer size is chosen, in this case, to match the internal capacity of the IMU device, this minimizing further processing onboard: the MCU RAM is not involved in buffering and this allows for powering down the MCU during sampling intervals.

The transmission rate is no longer compatible with HIBERNATE power mode, so that LPDS mode is exploited to this purpose. So doing, the average current drops down to 10.09 mA, this resulting in an expected battery lifetime (at 500-mAh capacity) of 2.07 days.

Further energy savings can be obtained by transferring (part of) data processing and interpretation from the cloud to the sensor itself, taking advantage of the onboard computational resources. Suitable algorithms can be coded into the device firmware, allowing to infer from raw accelerometer data much more compact and expressive information.

A simple example consists of fall detection: several methods can be exploited to correlate specific acceleration patterns to actual falls [51]. If, compatibly with computational constraints, the fall detection is carried out onboard, the whole acceleration data stream needs no longer to be transmitted over the network, replaced by the binary fall alert.

Such a synthesis process thus allows for trading radio-link power with MCU processing power, possibly resulting in a favorable balance.

A further example may consist of the onboard evaluation of EE [52]. EE is a common parameter, used to provide a quantitative evaluation of the physical activity throughout the day. EE provides a continuous assessment of the intensity of physical activity, sampled at a much coarser rate than the acceleration components themselves. EE computation is carried out onboard [41]: for instance, we may update the (4-B) EE value once per second, which provides already a very detailed photograph of the physical activity pattern. The data rate, with respect to previous examples, is drastically reduced: from 900 to 4 B/s, to the benefit of the power needed by radio module. However, this is partially counterbalanced by the increase in the MCU power consumption. Nevertheless, in the configuration at hand, a marked improvement can be

TABLE II
EFFECTS OF BUFFERING (4 B/s DATA RATE, 500-mAh BATTERY CAPACITY)

Buffer size (bytes)	Period [s]	Mean Current [mA]	Battery Lifetime [days]	Yield
4	1	6.57	3.17	1.00
12	3	3.46	6.02	0.63
120	30	2.00	10.42	0.11

attained: from the overall current pattern shown in Fig. 8, an average current of 6.57 mA is measured, which yields a battery lifetime of 3.17 days.

By combining such approach with some buffering, a further performance increase can be obtained: in Table II, results of sensor current measurement are reported for different buffer sizes, keeping the same 4 B/s output data rate, on the average.

It is shown that, at least in this range, buffering benefit overbalance the increased processing effort. A "yield" parameter is also introduced, correlating the battery lifetime increase and the buffer size. Such a figure is computed as

$$Y = \frac{\text{lifetime}/\text{lifetime}_{\text{ref}}}{\text{buffer size}/\text{buffer size}_{\text{ref}}}.$$

By assuming the 4 B—1-s case (i.e., no buffering) as the reference, it is seen that the yield decrease with buffer size, i.e., keeping increasing the buffer size is progressively less effective, due to the inherent computational overhead. Since MCU RAM is limited, this may help in selecting an appropriate buffer sizing.

Similar to the EE, other concise, yet meaningful, indicators can be computed onboard, by looking at posture, gait balance, etc. or by implementing simple activity recognition tasks (sitting down or standing up, making stairs, counting steps, etc.). The actual power performance inherently depends on the aimed function and specifications: this makes almost impossible to carry out an extensive and exhaustive characterization. Here we content ourselves by demonstrating that, in a few cases of practical interest, performance figures have been obtained which fall within a fully usable range: the wearable device, in fact, is meant to be recharged overnight, this making figures above more than adequate.

IV. CONCLUSION

In this paper, a new architecture for a continuous home and personal monitoring system has been presented. The system relies on Wi-Fi networking and implements a genuine IoT vision, in which each sensor in the network directly logs its data to a cloud service. The system is aimed at supporting independent life of elderly people: within such perspective, the adoption of Wi-Fi technologies may result in great simplification in system deployment and installation, with respect to more conventional wireless sensor network technologies (e.g., ZigBee). Being a less intrusive and more familiar approach, Wi-Fi should foster much better accessibility and acceptability. Also, by taking advantage of mainstream technologies and of inherent design features, a cost decrease and better scalability can be achieved.

The major expected drawback came from power consumption concerns: the Wi-Fi protocol targets high bandwidth, fast communication, this possibly resulting in overkilling solution, when considering the lower data rates inherent to the aimed application domain.

In this paper, design strategies have been discussed, aiming at implementing battery operated, Wi-Fi compliant sensors, suitable for practical and effective operation. Different use cases were considered, ranging from time-sparse event detectors (a bed-occupancy sensor was used as a testbench) to continuous motion monitoring (aiming at wearable sensors).

The TI-CC3200 SoC has been selected as the core of the system. Power saving was allowed by exploiting sleep power modes, selecting appropriate configuration with respect to the use case at hand, and by introducing well-balanced buffering techniques.

All sensors were connected directly to a commercial cloud service (IBM Bluemix) with no need of home gateways (except for the Wi-Fi access point, of course). This again allows for flexibility and ease of personalization, especially when dealing with monitoring needs which may possibly change over time.

Functional and power performance test were carried out: in particular, power performance was assessed, more than suitable for practical exploitation and fully comparable with devices featuring similar functions and based on, e.g., ZigBee wireless sensor networks.

The envisaged system will now be thoroughly tested on field applications: within the framework of the "Activage" project (EU-Horizon 2020 LSP-IoT) and of the "NOAH" project (EU-AAL-JP, Call 2015), a total of about 160 pilot homes will be equipped with the CARDEA-WiFi infrastructure introduced here. This will allow for testing, besides technical features illustrated so far, also the user perception, in terms of usability, accessibility and reliability. Engineering, ergonomic, and service aspects will be refined in such contexts, availing ourselves of user involvement in a "people centric" design approach.

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