INVITED PAPER

Wireless Architectures for Heterogeneous Sensing in Smart Home Applications: Concepts and Real Implementation

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ABSTRACT | Application of wireless technologies in the smart home is dealt with by pointing out advantages and limitations of available approaches for the solution of heterogeneous and coexisting problems related to the distributed monitoring of the home and the inhabitants. Some hot challenges facing the exploitation of noninvasive wireless devices for user behavior monitoring are then addressed and the application fields of smart power management and elderly people monitoring are chosen as representative cases where the estimation of user activities improves the potential of location-aware services in the smart home. The problem of user localization is considered with great care to minimize the invasiveness of the monitoring system. Wireless architectures are reviewed and discussed as flexible and transparent tools toward the paradigm of a totally automatic/autonomic environment. With respect to available state-of-the-art solutions, our proposed architecture is based also on existing wireless devices and exploits, in an opportunistic way, the characteristics of wireless signals to estimate the presence, the movements, and the behaviors of inhabitants, reducing the system complexity and costs. Selected and representative examples from real implementations are presented to give some insight on state-of-the-art solutions also envisaging possible future trends.

KEYWORDS | Assistive environment; behavior monitoring; passive localization and tracking; power metering; smart home

I. INTRODUCTION

The home technology is moving rapidly from the programmable thermostat to an era where all home systems are integrated into a centralized control one, accessible from multiple entry points like touch pads, computer screens, telephones, and other wireless mobile devices, such as smartphones and tablets. The result is a highly personalized environment, a house that reacts to individual needs and wants, and even anticipates changes. This perspective is a clear consequence of the dramatic impact that pervasive technologies have had on society.

In such a framework, a widely diffused viewpoint on the smart home and its implementation, more specifically the home automation, is related to the idea of comfort that can be explained as follows: "Morning brings a graduated alarm that plays some of your favorite music. The volume builds slowly and the bedroom curtains gently part until you react and tell the alarm. Meanwhile, the bathroom floors are already warming in anticipation of your arrival, and the coffee-maker starts brewing up" [1]. This idea, together with the problem complexity, the competition

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between vendors, the multiple incompatible standards, and the high expenses, has limited the penetration of home automation to home. Only a niche of users is disposed today to (or can) spend money for those expensive and luxury facilities. Other needs are considered more essential with respect to the strictly comfort-based functionalities. As a consequence, much of the potential that would technically be available is still confined to research projects, test beds, or industrial experiments, as clearly shown by the rich state of the art produced in the last years [2]–[6]. Consequently, the researchers are now focusing on testing and deploying technologies in real environments and for long-term periods by reducing the system complexity and implementing solutions providing more evident and tangible advantages to the everyday life of the end users.

Among smart home functionalities, the following ones are here considered as specific case studies of the proposed wireless system. These smart home applications received high emphasis because of their direct impact on money saving for both private users and public services.

- *Smart power management for energy cost reduction*. With the growth of the smart grid research area, concerned with the intelligent control of electricity usage, the smart home plays a key role in the interaction between the grid and the consumers [3]. Power management systems are undergoing an increasing deployment in private homes all over the world because of the government decisions for fulfilling the optimization of resources and from the end-users' perspective of reducing the costs of in-home power consumptions. Many solutions have been proposed for integrating smart meter devices capable of simultaneously communicating with both the energy distributors and the household [7], [8]. Toward this end, two main guidelines have been established. The one direction is to collect energy information through the standard utility meter that gives aggregate information about the consumption of the home [9]. The other direction is that of monitoring individual appliances of interest by means of in-home distributed smart meters and communicating the recorded data to a central data processing unit [10]. This latter solution has been sometimes considered costly and complex to implement because of the need of infrastructure [8]. However, many drawbacks related to wiring, costs, and complexity are going to be overcome thanks to the diffusion of wireless architectures [6], [11]–[18].
- *Assistive services for elderly people monitoring and security*. Healthcare systems have attracted enormous attention worldwide [19], [20], and many national associations have reported the urgent need for in-home assistance due to the high cost of institutional living [21]. In this framework, the social security and healthcare systems are taking advantage of the outcoming assistive technologies [4] that can be integrated in smart home scenarios. Several projects have been developed [22]–[27] giving emphasis and priority to the functionalities provided to the end users. Smart homes have been equipped with various sensors to improve the detection of anomalies or behavioral changes [28]–[31]. Starting from the sensors acquisitions, data fusion techniques are mandatory to extract useful evolutions inside the large set of information. Despite all these efforts, some drawbacks like privacy and reliability are still limiting the wide diffusion and commercialization of such systems. A solution is that of focusing on the unobtrusiveness as a key issue to improve user satisfaction and acceptance. This mainstream idea has been pursued, testing more and more pervasive, noninvasive, and low-cost technologies [6], [32], capable of inferring the user behavior, while avoiding the installation of cameras or microphones. Toward this end, wireless technologies are very promising tools enabling flexible adding/removing of components and facilitating the scalability and the integrability of small devices within other existing wireless backbones [33]–[35].

It is worth noticing that previous topics present common challenges from both technological and methodological points of view. The actual state of the art presents many lessons learned from experiences in project activities, and the difficulties that are limiting the proliferation of next generation smart homes have been pointed out [36]. From the technological perspective, the main challenges are related to the nonscalable integration of heterogeneous technologies that often cannot communicate together, require hard wiring, are *ad hoc* designed, and cannot be evolved, updated, or easily replaced [4]. The lack of a common and flexible infrastructure hosting heterogeneous functionalities according to the user needs often comes out, and it represents a key challenge to be considered in the development of smart home concepts.

Because of these problems, taking advantages of wireless networks as a means for remote monitoring and commanding is considered to be inevitable. Different wireless technologies have been reviewed [6], [37] and applied to smart metering [11], [13], [15], [18], [38] and assistive services [4], [19], [39]–[41], pointing out advantages and limitations of current solutions. As a key requirement, the wireless backbone components must be inexpensive enough, easy to deploy and maintain, thus making them widely acceptable to end users. Moreover, it has to be noticed that the most diffused wireless architecture is represented by the wireless sensor network (WSN) technology [42]–[44]. WSNs are composed of numerous spatially distributed and low-power sensors. They have become increasingly important because of their ability to monitor and manage situational information in various intelligent services. The adoption of WSNs in many and heterogeneous applicative fields [45]–[48] has been stimulated by their well-known features like scalability, low cost, low power, integrability, reconfigurability, and multisensing. These advantages have been transferred to a smart home to fulfill the vision of ambient intelligence through an interconnected, transparent, responsive, and intelligent wireless backbone layer. The real challenge that we face in this work is to exploit the technological advantages of WSNs in managing real-time and context-aware applications without directly capturing privacy-sensitive informations. As opposed to standard multisensor platforms available at the state of the art, we propose to guarantee user acceptability, reducing as much as possible the number and the typologies of invasive sensors to be deployed, also inferring information on the environment and the users from indirect measures coming from wireless signals. It has to be noticed that the design of such an integrated monitoring system solves the problems of complexity and cost common in many services related to smart home monitoring and that can be implemented only if user location information is available.

In this paper, current trends in exploiting wireless architectures and sensors in smart home applications related both to energy management and assistive services are presented. The key points for the diffusion of wireless smart home systems are underlined, by pointing out advantages and drawbacks of available technologies, which focus on the methodological trends for the behavior monitoring. The development of a very simple and noninvasive wireless backbone capable of exploiting direct and indirect measures to infer environmental characteristics and user behaviors in the two aforementioned application fields is here proposed and described.

II. CURRENT TRENDS

Most manufacturers of home automation systems are moving toward the *app* paradigm with programs that allow one to control appliances, review surveillance records, adjust temperature and humidity settings, lock doors and windows, and many other functionalities available from remote locations [49]. Such an approach provides significant improvements to the "interaction" of the users with the home capabilities, but often relies on the presence of a complex and expensive wired architecture that interconnects a huge set of devices and systems to be actively controlled by users. On the other hand, it is worth observing that the actual trend of smart homes [50]–[52] is not only the capability to measure, control, and interconnect an unlimited number of sensors and actuators according to input commands, but also how to understand the habits and the behavior of inhabitants in order to properly react to their needs, state of mind, or desires [53]–[55]. These latter need the development of solutions with suitable and noninvasive hardware as well as smart methodologies capable of figuring out the real situations, take decisions, and provide proper feedbacks through the available home systems [2].

In such a framework, traditional hardware solutions for home monitoring and control are usually based on hard wiring of components deployed in the electrical system of the smart home. Whenever devices are added or removed, the existing configuration must be revised to ensure correct update and avoid conflicts in the overall system [4]. Since the number and typologies of data acquisition equipments and devices able to assess the states of residents and environments are continuously improving, a flexible and easily upgradeable architecture is mandatory. Besides wired systems, wireless devices represent an alternative and valuable solution for future homes, where monitoring devices have to be easily installed in such a way that the inhabitants can update the components and functionalities following the technological progress and according to their changing needs. Thanks to the hardware miniaturization, a direct result of the actual digital revolution, the dramatic reduction in size of electronics allows people to carry lightweight wireless devices in their pockets or around their neck. Heterogeneous sensor information is effective for revealing different types of situations; accelerometers worn by users have been used to recognize body motions [56], [57]; and movement and presence sensors as well as radio-frequency identification (RFID) tags have been installed on doors, windows, and appliances to detect user proximity and interaction with objects [58]. All these solutions are effective in their field of scope, however, they are still part of an almost invasive and complex ecosystem that is often difficult to be calibrated, maintained, and updated. A more simple and transparent hardware, attentive and adaptable to the user lifestyle, is still an open issue [2] that we propose to solve with our integrated and low-cost wireless architecture for noninvasive monitoring. WSN is an example of a technological solution adopted by researchers to go toward the idea of ubiquitous computing and smart environment. The next steps we focus on in this work are to reduce the hardware invasiveness and fuse advanced algorithms and methods to provide distributed intelligence.

While the initial objective of the home intelligence was to automatically control devices and systems according to specific rules previously implemented [59], today, the purpose of the algorithms is to enable an interactive home environment capable of adapting its operations to accommodate the users. The main requirement to enable interactions is to gather information not only on the environment, but also related to the users presence and location-based activities. Because of this reason, we propose a simple and noninvasive location-detection algorithm that is at the basis of almost every decision-making procedure. The methodologies for the activity recognition vary as greatly as the types of adopted technologies and corresponding sensed data [60]. Currently used methods are mostly based on machine-learning models, such as Bayes classifiers [54], [61], Markov models [62], [63], artificial neural networks [64], [65], and support vector machines (SVMs) [66], [67], thanks to their ability to create context models from measured data and adapt according to the changing behavior and needs, and their computational efficiency enabling integration in low-power wireless devices with constrained resources. The obtained results demonstrate that such approaches are promising for behavior classification and prediction. However, once applied to real test cases, single methods would not suffice to bring forward the best systemic solution, while the combination of different techniques could lead to more sophisticated hybrid intelligent systems [10]. It has to be also noticed that evolutionary optimization strategies [68] have been profitably exploited in many applicative fields thanks to their ability to solve complex problems with a high number of unknowns. Such a feature has been exploited and integrated in hybrid algorithms for decision making to find optimal user preferences adapting to new knowledge without deleting the existing one [69], [70]. However, to the best of the authors' knowledge, robust and reliable solutions capable of understanding the everyday needs of the users and taking proper (from the user's point of view) measures are still not available. Each solution is effective for a limited set of conditions mainly due to the specific initialization given by the experts and to the kind of adopted sensors. Up to now, the decision-making phase is still considered a support tool where the user has to interact to give additional information [71].

During that time, researchers began to recognize the importance of applying and improving methodologies for behavior monitoring and decision making also in the fields of assistance services [72], [73] and power management [64]. In this regard, the implementation of distributed intelligence on top of wireless platforms like WSNs has emerged as a promising solution and is attracting more and more attention [74]. This combination represents a valuable mean to support the development of decision-making strategies toward the paradigm of a totally automatic home tailored to the needs of users, and further motivates the development of our innovative wireless solution for noninvasive behavior monitoring in smart homes.

A. Estimation of Room Occupation for Energy Saving

Many algorithms and methods combined with wireless networks and devices have been investigated to realize smart home functionalities for energy service provision and energy conservation and management [3], [10], [75]. These systems enable monitoring and remotely control appliances within the home and configure rules for decision making devoted to consumption scheduling, load forecasting, and peak shaving [76]. Such intelligent systems contribute to a better use of the resources from both the consumer side and the perspective of governments and utilities. Within energy management applications, WSNs are playing a key role as a flexible communication infrastructure for appliance scheduling management [11], [14]. Automatic demand scheduling has been implemented using particle swarm optimization [75], neural-network-based prediction [77], or game theory approaches [78]. Although capable of providing energy savings, individual preferences of the consumers are often not considered and, more recently, advanced solutions have involved consumer participation exploiting wireless links [11] as an efficient and transparent exchange information system [13]. This represents a step forward toward the perception of consumer needs through an intelligent infrastructure capable to progressively reduce the consumer interaction and perform nonintrusive automatic actions. As a matter of fact, few people want to spend time understanding and coordinating how appliances respond to variable pricing and adapt them to their needs [5]. This is the motivation to improve decision-support tools by incorporating location management frameworks to learn and predict the user occupation starting from activities and habit estimation [10], [75], [79]. Indeed, lifestyle of users has a direct impact on the energy performance of house facilities. Hence, advanced control strategies have to rely on in-home distributed sensing and adapt to user behavior trying to keep optimal balancing between energy consumptions and comfort requirements.

B. Behavior Monitoring for Assisted Living

The smart home system can process sensor data, make timely decisions, and take appropriate actions for assisting the daily living of elders or sick people. Health-assistive smart homes are receiving increasing attention [80] and the need for activity recognition systems is great [81]. There are several projects [22], [82] assessing the broad range of enabling technologies (e.g., WSNs) with increasing capabilities of generating heterogeneous sensor data related to inhabitants and domestic events. Many of these standard assistive homes react to emergencies and alerts from the inhabitants, like falls or strokes. Dedicated sensors like infrared motion detectors, magnetic door, or floor pressure have been tested to recognize specific movement patterns or physiological parameters as well as to give real-time feedback in case of alarm detection [80]. However, unlike other spaces like offices or public areas, the private home is a place where currently available technologies for behavior monitoring may be inappropriate, impractical, or undesirable. As an example, dedicated sensors, often wearable, are not feasible because patients affected by mental diseases could remove or damage them. More recently, context-aware and knowledge-driven approaches for activity recognition are coming out [83] to address complex activity scenarios where uncertainty is given by noisy sensor data or multiple occupancy. The amount of large-scale data set collection and training can be reduced thanks to the capability to extract information from the personal-level details of the daily routines of inhabitants. The exploitation of such methodological advantages together with a flexible wireless architecture represents a good solution to match both user acceptance and system performance.

III. WIRELESS ARCHITECTURES FOR LOCATION-AWARE SERVICES

Different wireless technologies have been incorporated at home due to interoperability, flexibility, cost effectiveness, and the consequent improvements in many smart home applications [6], [84]. The proliferation of well-known wireless standards like ZigBee, Z-Wave, WiFi, Bluetooth, Insteon, and EnOcean can be considered an advantage from a technological point of view, but a commercial drawback at the same time [15]. Many investors consider today's situation to be still unstable and they wait to understand which emerging standard will consolidate. As a result, the characteristics of many solutions are still under investigation, even though many real test beds have been deployed with good outcomes. The large diffusion of WSN-based smart home systems [12], [85], [86] confirms the feasibility of such a technology designed to merge the physical and computational infrastructures and that allows smooth integration of new functionalities and services. One of the most diffused wireless specification is the IEEE 802.15.4 [87], designed for low-power wireless personal area networks with low data rate up to 250 kb/s. IEEE 802.15.4 can be used as a basis for higher layer protocols like the well-known ZigBee developed by the ZigBee Alliance [88] that incorporates predefined routing and networking functionalities for easy network management. Thanks to its characteristics, ZigBee fits the smart home market and many compliant devices are already available. Many efforts have been devoted to provide ready-to-use devices requiring very simple configurations to enable the creation of distributed wireless networks among the home rooms. It has been claimed that, although in some cases ZigBee underperforms with respect to other communication standard technologies [89], the arising key advantages like network self-organization, low cost, and low power make this communication platform a good solution for many in-home services. In the field of people monitoring in smart home scenarios, also body area networks (BANs) represent a valuable solution thanks to the capability of collecting vital data from wearable sensors. IEEE 802.15.6 is a candidate standard to provide interoperability, low consumptions, and specification for applications. However, even if the BAN architecture provides high-precision data for user/patients monitoring, particularly in assistive environments, our proposed system goes toward a noninvasive and passive solution, avoiding as much as possible the use of wearable sensors.

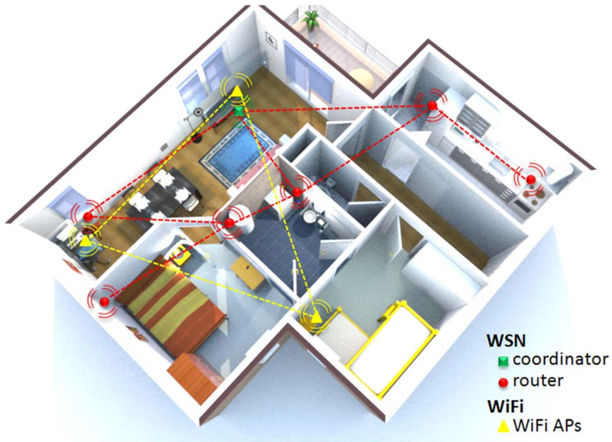

Fig. 1. ***Wireless architecture in smart home test site.***

By assuming the adoption of ZigBee wireless devices and using the corresponding terminology, our basic architecture of the WSN deployed for smart home applications relies on a set of *routers* plugged in power outlets (to ensure the near absence of battery maintenance), supporting mesh network typology, and associated to a network *coordinator* that manages the network and collects the data (Fig. 1). The coordinator is interconnected to a control unit like home gateway, smart TV, laptop, etc., for enabling data forwarding, processing, and visualization. Starting from such a backbone, heterogeneous functionalities should be easily integrated adding to the network a set of specific *end devices* deployed throughout the home and establishing wireless links with the nearest *routers*. End devices can be wearable sensors, environmental sensors, motion detectors, and so on, according to the sensing devices hosted by the wireless hardware platform. As graphically shown in Fig. 1, our wireless architecture is composed of a WSN and a set of WiFi access points (APs). The WSN nodes are represented by the coordinator and by the set of routers (power meters). Specific end points have been avoided in order to reduce system invasiveness, complexity, calibration, and user intervention. To properly address these latter issues and limit the use of end devices, instead of adopting dedicated sensors, the concept of indirect monitoring through measurements of wireless signal strengths available on every wireless home device is here proposed.

The electromagnetic (EM) field generated by a radio transceiver integrated in WSN nodes, WiFi-enabled home gateway, smart TVs, home personal computers, or smartphones and tablets has its own sensing capabilities as any other dedicated sensor. The EM field that propagates throughout the environment collects information about physical and electrical characteristics of objects in the form of radio-frequency (RF) perturbations. Accordingly, the problem of human presence and movements estimation can be recast as the following inverse problem [68]: "Starting from measurements of electromagnetic field, reconstructing information on the characteristics of the propagation scenario that led to the measured data." The transceivers of the low-cost and low-power devices at hand provide a raw information on the RF signal quality, which is called the received signal strength indicator (RSSI). Such an index is proportional to the magnitude of the received EM field and it "contains" a valuable information for the estimation of the human behavior. As a matter of fact, human positions are inferred by measuring the absorption, reflection, scattering of the EM field caused by the human bodies. It has to be noticed that, as opposed to most of standard sensors, EM sensors permeate the home environment since the primary role of the RF signal is to provide wireless connectivity throughout the home (and often not limited to the perimeter of the house). It is worth noticing that people have already accepted the presence of the home wireless network to enable Internet connection and mobile services, thus implicitly accepting the presence of EM sensing. Accordingly, the measurement of RSSI by WSN nodes or other available devices turns out to be a transparent procedure that does not require dedicated sensors and gives a preliminary estimation of user activities.

Usually, localization methods refer to a single wireless technology as sensing infrastructure. In order to further exploit all the smart home devices, the RF data sensed by all the home devices are shared among the systems and processed making additional data correlations. Our system, as a future wireless infrastructure of a smart home, allows a high level of interoperability and a seamless communication between heterogeneous devices, hiding the complexity of the technological heterogeneity. Therefore, abstraction layers have been considered in the software architecture of the central coordinator where all the information coming from the different wireless technologies flows into a unified digital ecosystem (Fig. 2). Heterogeneous technologies at the physical layer generate information that are interpreted by abstraction layers and made available to higher

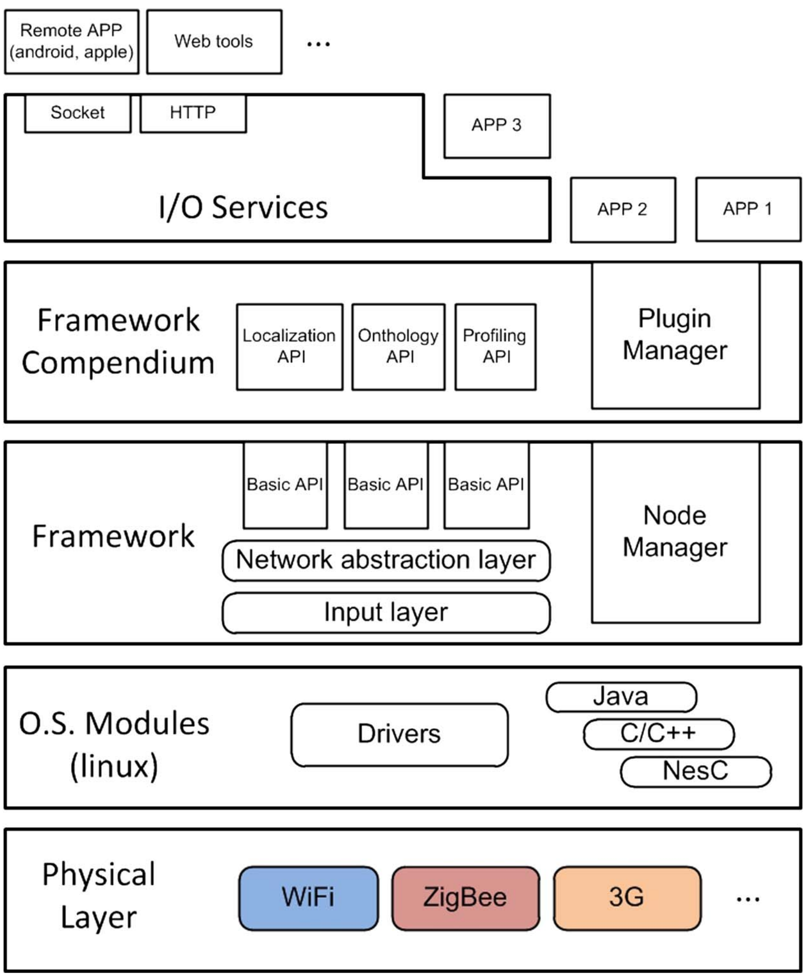

Fig. 2. ***Software stack of the system coordinator for the fusion of data coming from different wireless technologies.***

application tools. Service developers can have access to physical data, which is easily exposed, without worrying about hardware compatibility.

A. Active and Passive Wireless Solutions

This opportunistic way of exploiting EM signals is here adopted both for *passive* (i.e., the target does not need to carry any RF transceiver to be localized) [90]–[95] and *active* (i.e., the target is an active RF node of the wireless network) [96] localization and tracking of targets moving throughout areas monitored with wireless technologies. Consequently, the following classification arises from the role of the user.

- *Cooperative user*. The end user actively interacts with the components of the system. The personal wireless devices such as smartphones, WSN nodes, or other dedicated wearable sensors are used by the cooperative user for a direct communication with the smart home infrastructure. In such a configuration, the user is a mobile node of the network, and it is recognized by the system through the identification of the associated devices. The localization and the behavior interpretation are based on the processing of data actively exchanged with the wireless network devices. Cooperative users refer to an active localization strategy.
- *Noncooperative user*. Unlike cooperative users, no wearable devices are present and no direct communication with the system is established by the user. The user is part of the environment instead of being part of the wireless network infrastructure. Therefore, the behavior monitoring depends on the ability of the system to sense the environmental changes and, in particular, the perturbation caused by the user presence and movements. Passive localization strategies have to be adopted in order to acquire representative parameters influenced by the human body presence.

The integration of our active and passive approaches in the same wireless hardware backbone enables the behavior estimation of both cooperative and noncooperative users, thus enhancing the system performance in several domestic situations. The reference scenario of a smart home where our heterogeneous wireless devices coexist to cooperatively extract information on cooperative and noncooperative users is shown in Fig. 3. As can be seen, the noncooperative target can be monitored by passive strategy, while the cooperative target may be localized also by active architecture (yellow links with the WiFi access points in the map). Both active and passive localization systems are present, but users should not be aware of their existence. The noninvasiveness of our smart home system is guaranteed since inhabitants are not compelled to follow procedures or activate devices. As a consequence, the best way to make our system transparent is to integrate the functionalities in existing devices that the user is already used to interact with. Let us consider that almost everyone has a cellphone today and smartphones with integrated WiFi connectivity are becoming popular. Moreover, the number of houses without at least a personal computer and an Internet connection is rapidly declining. Under these assumptions, our proposed active strategies can leverage the presence of a minimal wireless infrastructure for the localization of devices like smartphones and tablets.

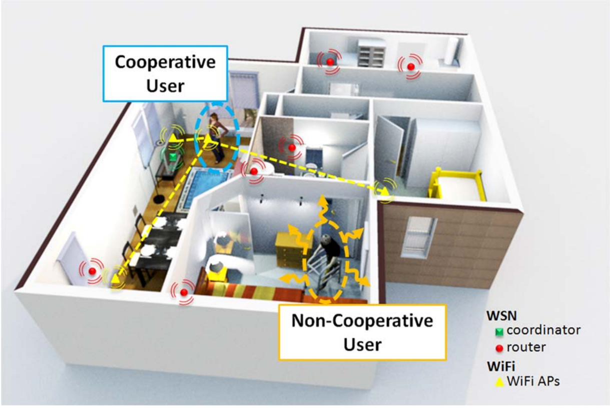

Fig. 3. ***Cooperative and noncooperative users localized through active and passive localization strategies.***

IV. WIRELESS SYSTEM IMPLEMENTATION

Our experience in wireless systems and services has led to the development of both technological and methodological solutions for home applications. More specifically, the main objective is the integration of multiple services on top of a unified wireless architecture with great attention to user acceptance and noninvasiveness. Such an idea has been implemented through exploiting the wireless technologies that the user recognizes as useful means to gain personal advantages. Toward this end, the proposed solution relies on a WSN (in general, a wireless network) infrastructure for distributed power metering and on a set of WiFi-enabled devices widely present in standard homes. The hardware platform of the proposed wireless system is based on the integration of off-the-shelf components in order to guarantee high flexibility and avoid customization. The components of the WSN have been deployed in a real test site as graphically represented in Fig. 1. The details of the WSN nodes (for power metering and passive localization) and of WiFi-enabled devices (for active localization) are reported in Sections IV-A and IV-B, respectively. The implementation of the software stack integrated in the control unit is described in Section IV-A.

In order to assess the effectiveness and reliability of the proposed system, a set of experimental tests has been performed and some selected results will be reported in the following for illustrative purposes.

A. In-Home Localization for Energy Management

Home energy management systems and power metering devices are considered next generation energy saving solutions [35]. The European Union and European regulators are proposing initiatives to encourage installation of energy meters in all homes during the next decade. It has been verified that the visualization of power consumptions could reduce the total expenses thanks to user awareness [97]. Following such a trend, a distributed power monitoring system based on WSN technology has been developed and integrated in our proposed wireless architecture. The system prototype installed in the real test site aggregates the consumption data through a set of $P_{\mathrm{WSN}} = 7$ wireless smart plugs installed on the power cable of the main home appliances (Fig. 4). In particular, the following monitored appliances that are almost uniformly distributed in the rooms of the considered smart home have been selected: a fridge, a washing machine, a dishwasher, a television set, a desktop PC, a water heater, and an air conditioner. The adopted power metering plugs are easily interposed between the power network outlets and the power cables. Once installed, active power $[W]$ and consumed energy $[Wh]$ of the monitored appliances can be measured. The smart plugs are the *routers* (Fig. 1) of a IEEE 802.15.4 compliant ZigBee-based mesh network. The transmission power has been set to +3 dBm, and the working frequency is 2.4 GHz. The wireless links among routers enable RF coverage in the whole monitored house. The quality of the links is monitored through the RSSI parameter available on the main control unit where the network *coordinator* is attached through a standard USB port. A commercial

Fig. 4. ***Prototype of a wireless smart meter for energy consumption measurements and EM sensing.***

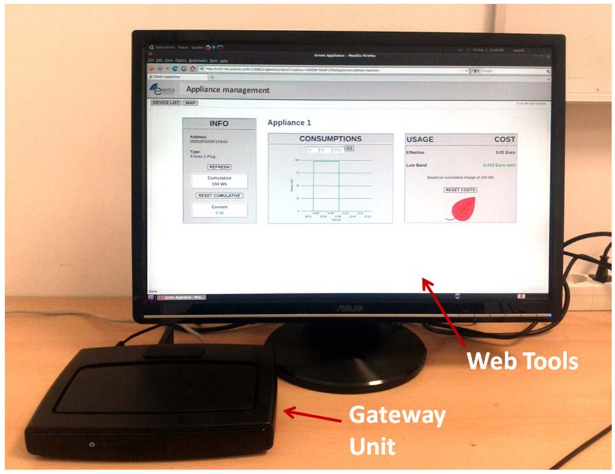

Fig. 5. ***User-friendly GUI hosted by the network coordinator for data visualization and system management.***

home gateway has been used as the control unit since it represents the basic and widely deployed hardware device essential for home Internet connection. A service-oriented architecture based on the Open Services Gateway initiative (OSGi) has been adopted in the gateway to easily install, update, or remove software components (called "bundles") that can dynamically manage services without affecting the basic system functionalities. Fig. 2 shows the software architecture implemented for the management and processing of data acquired at the physical layer by heterogeneous wireless technologies. In particular, our system exploits the WiFi radio module integrated in the adopted home gateway and the external ZigBee coordinator. The drivers for hardware control are managed by the embedded linux operating system that also hosts the higher frameworks where the application programming interfaces (APIs) are implemented. Both basic APIs and advanced APIs are available to the higher application layer for the implementation of the location-aware services. The I/O Services layer integrates the implemented algorithms (e.g., localization methodologies, power consumption representation, etc.) that also interact with the end user through web tools or applications running on mobile terminals. Moreover, the control unit is capable of storing historical data on a local or remote database and makes them accessible through user-friendly web tools (Fig. 5) on the user side and through broadband network for the remote configuration manager. As for the remote management of the system, a specific OSGi bundle for data exchange with a remote manager has been implemented. A bidirectional SOAP/HTTP protocol has been adopted for the encapsulation of simple messages (e.g., detection of strange movements, unexpected power consumptions, etc.) in XML format. This implementation follows the well-known technical guidelines (e.g., technical report 069) provided by the Broadband Forum (BBF) [98] for the remote configuration and management of residential gateways. In particular, the home gateway initiative (HGI) designs the requirements for digital home building blocks, which have been taken in consideration for future extensions of the proposed system. Besides data visualization, methodologies for behavior monitoring are hosted on the home gateway, as well. Real-time RSS data of the WSN links are always available and constantly updated for diagnostic purposes. At the same time, the RSS data are given as input to a customized learning by example (LBE) approach based on a multiclass SVM classifier, whose performance has been validated by the same authors in [91] and [92]. The SVM is an attractive candidate for the solution of the arising classification problem thanks to the advanced generalization capabilities and the computational efficiency in dealing with high-complexity real-world problem. The proposed strategy learns from "examples" (i.e., couples of known input/output data) during the training phase executed offline and only once. The learning process aims at defining the unknown inverse mapping from the measured RSS data to the corresponding domain characteristics. Our proposed approach provides a real-time estimation of user position by giving a probability map of presence for each room of the smart home scenario. The experimental results deal with the detection and the spatial localization of a user standing inside the monitored areas. Fig. 6(a) shows the user sitting on the bed that represents one of the positions of interest for user presence monitoring. With respect to standard detection sensors like infrared sensors, the proposed system is able to detect the target even if still (e.g., sleeping during the night). As can be observed in Fig. 6(b), the probability distribution determines a region with high values that turns out to be spatially close to the actual position of the user. The mean localization error of $\varepsilon = 3.61$ m has been statistically evaluated over a set of 100 position estimations.

One of the most important parameter for user behavior estimation in the field of energy management is the estimation of the room occupancy, which is evaluated based on the variances of the RSS data and on the estimated user positions. If a movement is detected within a room through RSS variance, a room occupancy timer is initialized and stopped only when RSS variances are lower than an adaptive threshold. The proposed strategy has been validated during long-term monitoring of the considered scenario, and the evaluated occupancy reflects the real situation even though it is slightly overestimated because of the high sensitivity of the RSS variance to user movements.

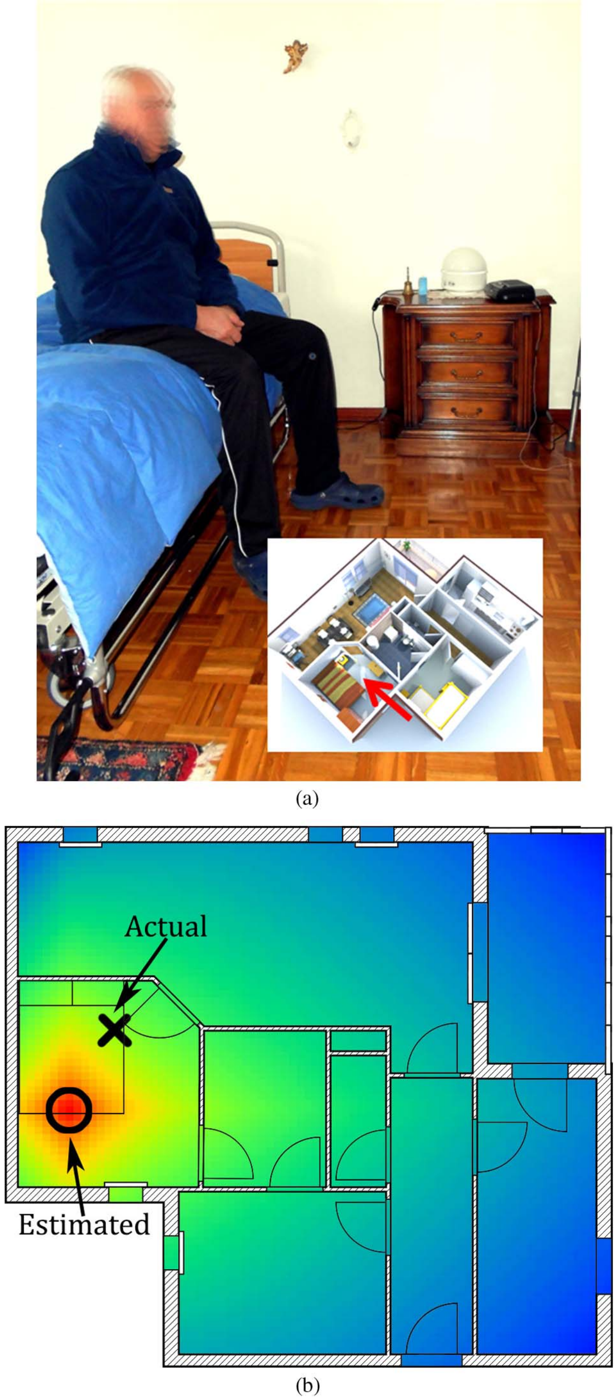

Fig. 6. ***(a) Passive localization of a user standing in a room of the smart home; and (b) estimation of the probability of presence.***

B. Activity Estimation for Elderly People Monitoring

A key objective of assistive services is to enable in-home safe independent living for elderly people and patients. Today, many state-of-the-art solutions are focused on activity recognition to extract information on habitant behaviors and to detect eventual anomalies in health parameters. Our proposed approach combines the use of both active and passive wireless solutions. The active part of the system includes the adoption of standard smartphones (Fig. 7) capable of collecting both movement information through the integrated sensors and the RSS data of the WiFi links established with other WiFi-enabled devices. In particular, a set of $P_{\mathrm{WiFi}} = 3$ standard WiFi

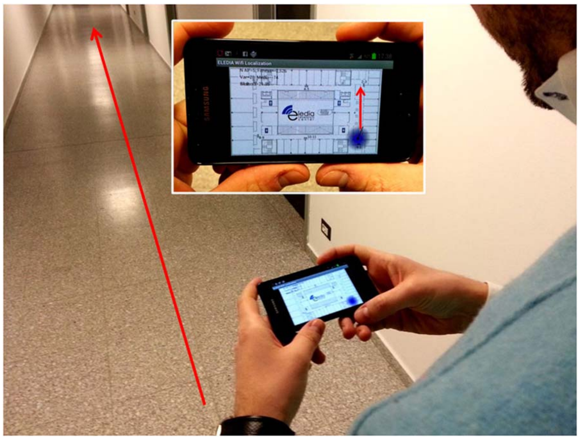

Fig. 7. ***Smartphone application for active localization starting from local sensor data and RSS measurements.***

devices have been considered: one desktop PC, one notebook, and the access gateway that directly manages the WiFi network. All these components run a dedicated software module that makes all the WiFi devices similar to WiFi access points and enables the RSS acquisition and transmission. Their position has to be known and fixed to enable relative positioning of mobile devices. A dedicated *app* for data acquisition and processing has been developed for the Android operating system and installed on the user smartphones. The *app* interacts with the access points and sends RSS data to the control unit where the location server runs for real-time position estimation. The active localization method is formulated as a nonlinear constrained problem to optimally determine the parameters of an indoor channel model and the unknown patient locations that best match the RSS measurements. The arising optimization problem is solved by means of a particle swarm optimization (PSO) procedure for the minimization of a suitable cost function. Toward this end, the difference between the estimated RSS (i.e., the output of the numerical path-loss model that is a function of the channel parameters and the target position) and the measured RSS (i.e., the RSS of the links among the wireless devices) is minimized. The output of the minimization gives the optimal target position. In order to filter out inaccuracies and predict the most likely position and velocity of the moving patients, a postprocessing technique based on Kalman filtering [99] is added. As a result, the implemented strategy is a recursive process that iterates the prediction (i.e., the *time-update* phase) and the correction (i.e., the *measurement-update* phase) of the patient state estimates. The active localization strategy has been experimentally verified in the smart home real test site. The statistical analysis of localization performance over a set of 100 estimations has led to a mean localization error of $\varepsilon = 3.24$ m, even with only three WiFi access points. The same approach has been also validated in a large area and in presence of many WiFi access points. An example of user trajectory estimated by exploiting wireless links among the smartphone and a set of $P_{\mathrm{WiFi}} = 12$ WiFi access points installed in our department (84 m $\times$ 49 m wide) is shown in Fig. 8. As can be noticed, a good match between actual and estimated paths has been obtained with a mean localization error of $\varepsilon = 2.93$ m. The positions of the considered APs are shown on the map.

It has to be taken under consideration that users do not always carry a smartphone during daily activities. To account for these situations, the passive localization method based on WSN data is always active, and results of both active and passive localizations are fused together. Besides the active localization that works only in presence of cooperative targets, the same WSN architecture adopted for distributed power metering is the backbone for the pervasive acquisition of the RSS among the nodes of the network. The real-time processing of the raw RSS indexes enables the estimation of the daily activities of elderly people that can move without restrictions and are unaware of being continuously monitored. Given the continuous sampling of RSS data measured by the WSN nodes and the arising probability maps evaluated by the SVM classifier, the following health markers are estimated in real time.

- *Walking speed*. Each position estimation is associated to a unique timestamp from the processing control unit. Thus, the real-time calculation of the walking speed is enabled. The estimation of such a kinematic variable is also used for the calibration of the acquisition sampling period to efficiently monitor patients even in rapid movements.
- *Standing time*. Elderly people spend a lot of time standing still in the same position, and the estimation of time elapsed between two movements represents an important indication for assisted rehabilitation and therapy control. Starting from the velocity evaluation, the proposed system keeps track of time periods with speed values lower than a predefined threshold and gives a statistical analysis of standing duration as a percentage of the total monitoring time.
- *Trajectories*. People suffering from chronic diseases such as Alzheimer's dementia may loose sense of direction and degenerate in strange and often repetitive movement patterns. The real-time trajectory estimation enables the detection of such anomalies by correlating successive position estimations to extract the characteristics of movement patterns like shape (e.g., linear or circular) and repetitiveness.
- *Room occupancy*. Since multiple rooms are involved in the passive monitoring, information about elders stationarity in subdomains is available. The time elapsed between the entrance (generation of an *in*-event) and the exit (*out*-event) from the same room is labeled as the room occupancy time.

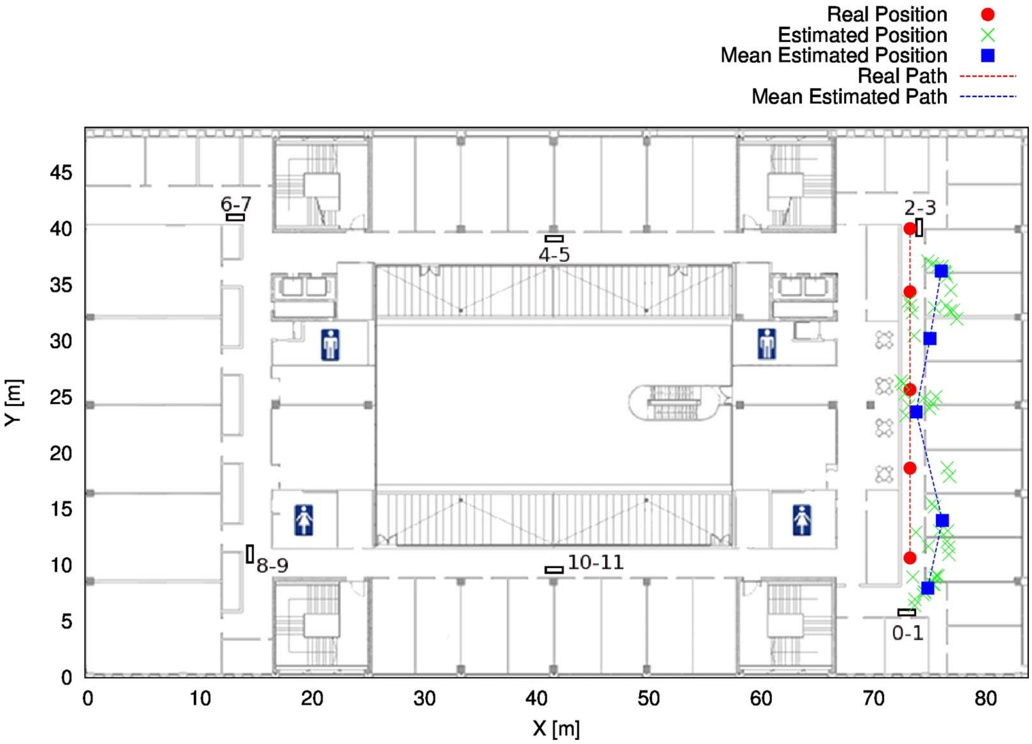

Fig. 8. ***Trajectory estimation of a cooperative user moving with a smartphone throughout the smart environment covered by WiFi connection.***

The detection of such activities deals with nonlinear system dynamics and is further complicated by the fact that RSS data acquired in indoor scenarios are very noisy. These assumptions make the accurate extraction of kinematic variables a complex task. When position information comes from both active and passive strategies, it is merged (a *data fusion* process) to reach more robust estimations. Our proposed strategy has been validated during long-term monitoring. The experimental validation has been performed in a real test site for a period of one week. In order to show the effectiveness of the solution in the estimation of room occupancy and standing time, a selected and controlled experiment lasting 60 min has been considered, during which a noncooperative user spent different percentage of time in three different rooms. The results of the experimental room occupation are reported in Table 1. As can be noticed, the occupancy times turn out be slightly overestimated because of the high sensitivity of the RSS variance to patient movements that partially reflects also when the patient moves in confining rooms.

Table 1 Room Occupancy Time

Rooms	Room Occupancy Time		
	Actual [%]	Estimated [%]	Error [min.]
Entrance	20	23	+1.8
Bedroom	55	60	+3.0
Bathroom	25	32	+4.2

Moreover, in order to get an insight into the advantages of the proposed approach over the localization of walking people and estimation of kinematic indicators like trajectory and walking speed, the localization has been applied to a time-varying scenario where a moving user is considered. The actual trajectories as well as the estimated trajectories are shown in Fig. 9. More in detail, two different estimated paths are reported on the map; the red line refers to the positions identified by the maximum of the probability distributions while the green one is the output of the Kalman filtering procedure. For the sake of readability, the position estimations have been averaged over a sliding time window. As can be observed, although the mean localization error is higher with respect to the test case with a standing patient (i.e., $\varepsilon = 4.47$ m), the obtained trajectories reconstruct, with a good degree of precision, the user behavior who moves from the bedroom to the kitchen. The Kalman filtering procedure demonstrates its suitability in dealing with noisy input data for the estimation of smooth and more realistic trajectories. As for the estimation of the kinematic parameters, the velocity and the acceleration vectors are estimated starting from the positions predicted by the filter. The evolutions of velocity $|\underline{v}|$ [Fig. 10(a)] and acceleration $|\underline{a}|$ [Fig. 10(b)]

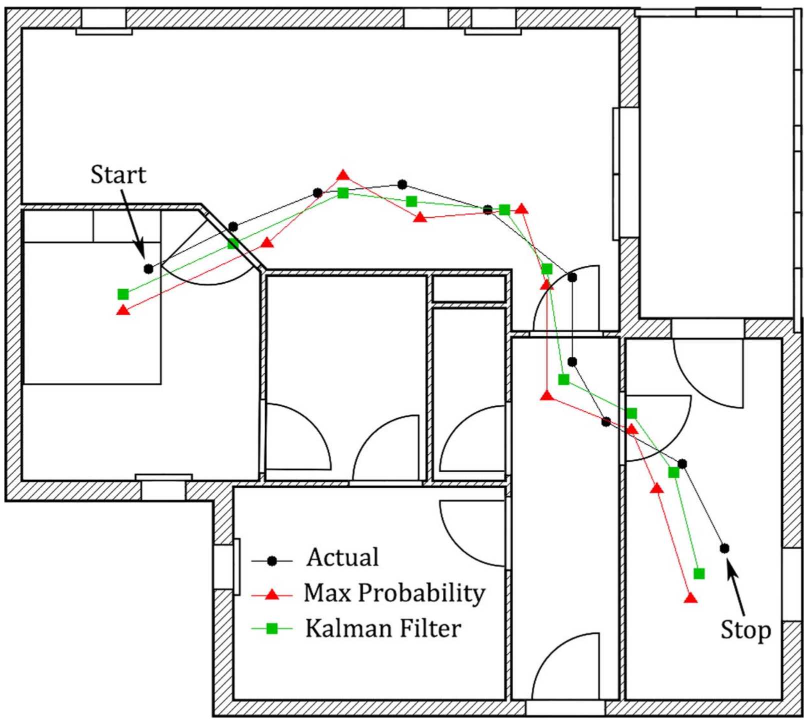

Fig. 9. ***Actual and estimated trajectories of the walking user moving throughout the monitored domain.***

during the movement are compared with a reference scenario in the presence of a standing user. As expected, increased velocities and accelerations are evaluated in the case of a walking target. In particular, after an initial time interval being still, the user keeps moving toward the kitchen. The values of the estimated parameters point out that the passive localization strategy is able to extract valuable information about the activities. Whatever the walking speed at hand, a quite careful indication on the velocity has been obtained.

V. LESSONS LEARNED FROM THE SYSTEM AND USER EXPERIENCE

Our experience in the development of the proposed wireless architecture has been shaped by the idea that today researchers have to exploit and promote as much as possible the already available technologies and information in order to reduce the costs, take advantage of integration, and enhance the value of existing domestic systems. With this in mind, we learned to evaluate the performance of existing smart home monitoring systems from multiple perspectives. Instead of evaluating only the accuracy or the robustness of available state-of-the-art solutions, we considered also their impact on both the existing homes and on user habits. During the installation phase and the measurement campaigns that we performed in real test sites, we found different user typologies, characterized by their experience with new technologies. Many people show distrust of new smart home solutions because they are too different, complex, and expensive, even if they comprehend the advantages in terms of safety, security, energy saving, and better life quality. Moreover, considering the actual negative situation of the construction market (we refer to the ongoing national situation in Italy), we have found that more and more people prefer to renovate old buildings instead of fabricating them from scratch, thus fostering the use of noninvasive solutions. Following these trends, our system goes toward the exploitation of known devices (like smartphones, notebooks, etc.) and technologies (such as WiFi), besides a simple WSN for home consumption monitoring, trying to reduce the installation complexity, the sensor calibration, configuration, maintenance, etc. (i.e., avoiding the use of dedicated sensors and exploiting implicit characteristics of wireless signals). These properties of the proposed system have been refined step by step, making experimental tests, during which we learned that, first, users require simplicity and stability. To satisfy these requirements, we progressively reduced the system complexity, the number of sensors, the number of parameters, and the number of user interactions, moving the complexity from the hardware platforms to the higher software layers. The localization methodologies have been designed to process few and raw information of wireless signals in real time through the integration of multiple localization strategies, both active and passive. They have been fused together in the same software to satisfy as much user typologies and

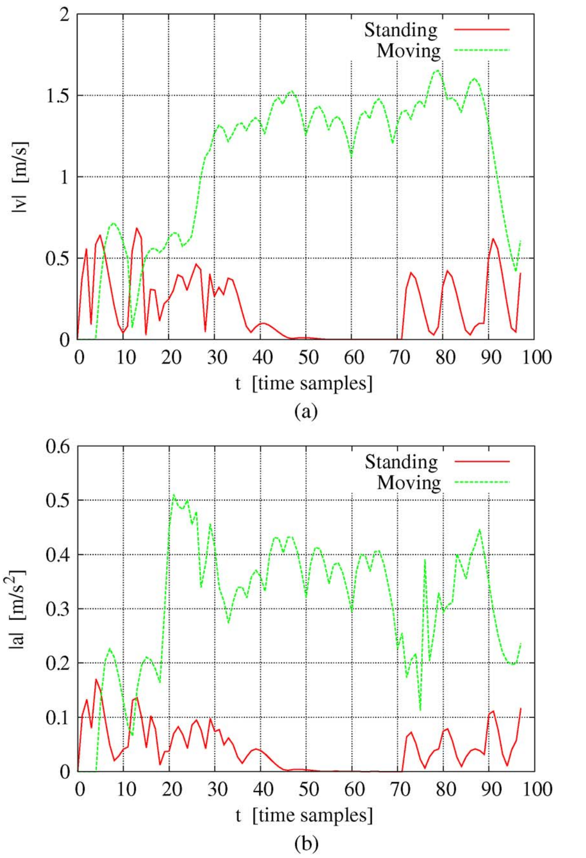

Fig. 10. ***Comparison of estimated velocities and accelerations when the (a) standing or (b) moving user is considered.***

habits as possible. Finally, we can summarize that according to the collected user experiences, the selected wireless technologies can be easily accepted by the smart home users, and that the proposed architecture represents an alternative and innovative backbone for heterogeneous location-aware services, starting from those we described related to energy management and elderly monitoring.

VI. CONCLUSION

In this paper, current trends in the exploitation of wireless architectures for smart home applications have been discussed. The wireless technologies usually adopted in smart homes have been considered and WSNs have been analyzed as a suitable architectural tool to implement in-home monitoring. Among smart home functionalities, distributed smart metering and elderly assistance have been considered as two representative examples that can drive the adoption of smart home wireless systems. As a matter of fact, both energy saving and the reduction of health-related costs are of particular interest in a world where the energy resources are running low and the population is rapidly aging.

The advantages coming from the use of wireless architectures have been analyzed focusing on the estimation of user behavior. Dedicated methodologies for the evaluation of the daily activities have been studied and integrated in the proposed wireless architecture for user monitoring and localization. Noninvasive wireless solutions that exploit the electromagnetic sensing and the widely diffused mobile devices such as smartphones have been adopted. The opportunistic exploitation of already available information provided by electromagnetic field perturbation has been proposed to guarantee two important key points of the future smart home: user acceptance and low system complexity. Some representative results of the ongoing activities at the ELEDIA Research Center at the Department of Information Engineering and Computer Science (DISI), University of Trento, Trento, Italy, have been reported to provide examples of the potentials of an opportunistic exploitation of wireless technologies that are already a part of our actual daily life. ■

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