Smartphone-Centric Ambient Assisted Living Platform for Patients Suffering from Co-Morbidities Monitoring

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ABSTRACT

Recently, patients suffering from a set of physical and mental limitations, called co-morbidities, are often treated at home. In this environment, modern communication systems represent a great support to implement Ambient Assisted Living platforms aimed at monitoring patients at home because they enable the seamless integration of heterogeneous sensing units, medical devices, and ubiquitous access to data. This article describes a specific smartphone-centric architecture where smartphones are employed not only as hubs of the health information but also as sensing, processing, and transmitting devices. Smartphones have both short-range (Bluetooth and WiFi employed for local information exchange) and long-range (GPRS, 3G/4G, and WiFi employed as Internet access) communication capabilities; information processing capabilities offered by modern platforms often equipped with different CPUs and with flexible and efficient software; and sensing capabilities implemented through sensors embedded into smartphones such as GPS receivers, accelerometers, microphones, and radio interfaces or through external sensors added to smartphones by cables or connected through local radio interfaces. The specific case of co-morbidities considered in this article implies the necessity to acquire a heterogeneous set of data from patients and from their environment. For this reason this article highlights the information processing capabilities of the introduced smartphone-centric platform. Audio, localization, and movement information processing have been evidenced as well as the specific implementations of these capabilities and their performance.

INTRODUCTION

Due to demographic change and increasing healthcare costs, often patients suffering from a given pathology are treated at home. This approach allows continuous monitoring and treatments, enables improvements of the health status, makes patients and their families play an active role in the care process, and reduces healthcare costs related to hospitalization management. However, the transition of treatments formerly conducted in the hospital to home environments is not possible without obstacles, also from communications, networking, and signal processing viewpoints. It is important to focus on the following major challenges:

- Treatment is not constantly supervised and personalized. At home there are no medical experts who monitor the situation of a patient and immediately adapt the prescribed treatment accordingly in case of need.
- Different treatments applied in co-morbid patients (i.e. patients suffering from a set of physical and mental limitations) may contrast with each other. For effective treatment, it has to be considered that co-morbidity is not merely an accumulation of different illnesses. Rather, a patient's condition is determined by the mutual interaction of different diseases. A supervision action carried on within a hospital, but missing at home, can mitigate the problem.
- Best practice may not be carried out or standardized home-treatment. Most medical protocols and guidelines are intended for clinical treatments and are not easily mapped to home treatment. Moreover, often not enough reliable data are available to get statistical validation to develop home-based treatment guidelines.

Information and communications technologies, currently employed in the medical context to increase safety and efficiency and to enable remote patient monitoring, may help tackle these challenges (see [1–9], among many others). Modern communication systems represent a great support in health-related applications and enable the design and implementation of Ambient Assisted Living (AAL) platforms aimed at monitoring patients at home. For example, many smartphone apps evaluating health status have been developed, and the U.S. Food and Drug Administration (FDA) approved the use of smartphones for the collection of medical data in online-databases concerning vital data monitoring services.

Unfortunately, these solutions often lack of

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interoperability with other devices because they do not implement existing data exchange standards (e.g. HL7) or, as most medical devices for remote monitoring, they are designed as isolated products. This situation hinders their application for co-morbid patients treated at home.

The integration and interoperability of AAL platforms for data exchange could help the development of remote monitoring services for co-morbid patients and of tailored medical surveillance systems.

In this context the acquisition and management of health-related data is a topical task to implement the decentralized treatment of co-morbid patients where multiple medical specialties are involved. Remote assistance requires, on one hand, personalized devices applied to assure continuous information exchange, and on the other hand, ubiquitous access to make feasible an integrated treatment of all involved healthcare providers. This implies the need for a communication architecture able to manage the aforementioned issues by implementing a seamless integration of heterogeneous sensing unit, and medical devices, and by providing ubiquitous access to data. The remainder of this article is organized as follows. The following section introduces the general characteristics of a Communication Architecture for Co-Morbidities Management and describes how the acquired information may be employed by patients, physicians, and medical device manufacturers. We then present a specific implementation of the mentioned architecture based on the employment of smartphones, which are used simultaneously as sensors to acquire signals related to the health of patients, as processors to elaborate such signals and extract information, and as hubs to collect data from external medical devices and sensors. The processing techniques employed to obtain information about the health of patients but suitable to be implemented on board the smartphone are presented after that. In particular, audio, network interface, and accelerometer information processing is discussed. Conclusions are drawn in the final section.

Communication Architecture for Co-Morbidities Management

A communication architecture for co-morbidities management is aimed at allowing diverse medical devices such as sensors and actuators to interact within treatment scenarios tailored to the needs of co-morbid patients and also at improving the coordination of caregivers. The architecture should include location-independent interconnection, decision support, and partly automated functional adaptation according to the distinct needs of a patient. In practice, the communication architecture for co-morbidities management will be composed of different devices acting as one healthcare system to provide personalized care to patients at home, therefore improving social integration and quality of life. This solution will, at the same time, lead to lower costs. Medical decision-support and machine learning algorithms can be employed to orchestrate various components.

	Requirements						
	a)	b)	c)	d)	e)	f)	g)
Solutions							
[1]	Yes	Yes	No	Yes	No	No	No
[2]	Yes	Yes	No	Yes	No	No	No
[3]	Yes	Yes	Yes	Yes	No	No	No
[4]	Yes	Yes	No	No	No	No	No
[6]	Yes	Yes	No	No	No	No	No
[7]	Yes	No	No	No	No	No	No
[8]	Yes	Yes	No	Yes	No	No	No
[9]	Yes	Yes	No	Yes	No	No	Yes
[12]	Yes	Yes	No	Yes	No	No	Yes
This article	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**

Table 1. Comparison of some of the solutions in the literature.

A communication architecture to monitor health may be very useful in case of co-morbid patients who often are elderly and alone. In this view an efficient communication architecture for co-morbidities management should include the following requirements:

a) The presence of multi-sensors that monitor different health parameters that are essential both to check single pathologies and to have a general vision of the co-morbid patient health.
b) The capability to transmit the sensed parameter values remotely.
c) The possibility to set, modify, and control the action and the configuration of each single sensor remotely.
d) The possibility of medical and non-medical caregivers interacting with the patient remotely.

In addition, the architecture should include the following requirements linked to information processing capabilities:

e) To know if the patient is alone or not, possibly getting additional information about the environment where he/she is living, such as the number and identity of people at home, and the level of noise in the environment.
f) To identify the position of the patient both outdoors and indoors with a high degree of precision, such as a specific room within a house.
g) To recognize the type of physical activity the patient is performing, for example, walking, running, or sitting.

Table 1 shows a comparison of some of the solutions available in the literature. The architecture proposed in this article is the only one meeting all requirements, including the information processing-based requirements, i.e. e), f), and g).

This solution employs the smartphone simultaneously as a sensor to acquire signals related to the health of patients, as a processor to elaborate such signals and extract information of interest, and as a hub to collect other data from external medical devices.

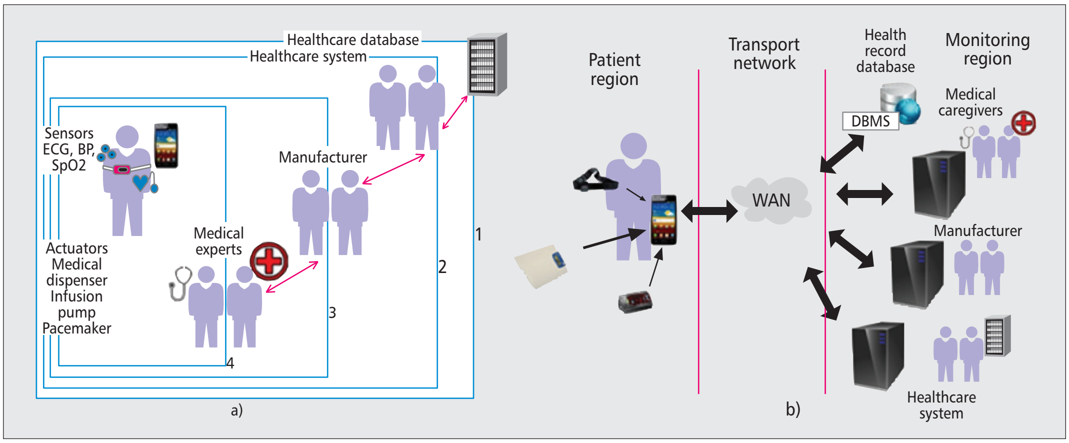

Figure 1. a) Integrated healthcare system; b) the smartphone-centric aal platform for co-morbidities monitoring.

The transfer of information may be structured into four groups. The presentation of relevant information should be adapted to the needs of the particular medical specialists and experts receiving information. Data communication groups can be represented by the loops in Fig. 1a. From the outer to the inner loop:

Device — Healthcare Database. Data detected by devices are forwarded to a remote database where they are memorized. Data available in the database might also be accessed from devices.

Device — Healthcare System. Information is utilized to control device functions. Time-relevant information such as remote warnings can be addressed to patients as well as to on-site healthcare personnel.

Device — Manufacturer. Data can be delivered in abstract and anonymous form to the device manufacturer. This information can be used for the development and refinement of next generation devices.

Device — Medical Experts. Medical experts access information via web-access services. They can affect the treatment system, change the therapy, and give medical advice displayed on user interfaces.

Moreover, medical experts, manufacturers, health system personnel, and the healthcare database may want to communicate each other (red arrows in Fig. 1a).

Smartphone-Centric Solution for e-Health Applications

A specific implementation of the general architecture presented in the previous section is represented by the smartphone-centric solution detailed in [9].

This solution employs the smartphone simultaneously as a sensor to acquire signals related to the health of patients, as a processor to elaborate such signals and extract information of interest, and as a hub to collect other data from external medical devices. In [9] this working modality is called the "hub+sensor+processor" paradigm. The smartphone transmits and receives such data by using several communication interfaces (e.g. WiFi, 3G/4G, GPRS). This smartphone-centric solution and its "hub+sensor+processor" action may be exploited to obtain a communication architecture for co-morbidities management with the features recommended in the previous section. The smartphone-centric choice allows reducing the number of required components and implementing ubiquitous, automatic, and precise monitoring. The block scheme composing the smartphone-centric architecture is shown in Fig. 1b.

In general, the architecture can be divided into three regions: patient, transport network, and monitoring. The patient region is usually a Personal Area Network (PAN) and may be composed both by wearable sensors that define a Body Area Network (BAN) as well as by non-wearable sensors. In the case shown in Fig. 1b, there are two non-wearable sensors: a pulse oximeter to measure the saturation of peripheral oxygen, and a scale to measure body weight. The smartphone is used by following the aforementioned "hub+sensor+processor" paradigm: it receives data from external sensors and manages data detected by embedded sensors, processes information as detailed in the next section, and conveys information through a Wide Area Network (WAN) to the final destination. In addition, smartphones can also send data to such external sensors, thus giving to the medical caregivers the possibility to set, modify, and control the action and the configuration of each single sensor remotely.

This approach exploits the great expansion of cellular communication networks and solves many problems concerning connectivity coverage. The authors in [6] outline three other critical factors for tele-monitoring platforms: usability, quality of transmitted data, and interference with other devices. The described smartphone-centric platform does not completely solve all such issues but represents a suitable solution.

The WAN is the transport network. It is a telecommunications network accessed through either a mobile phone network typically used for data by smartphones or through WiFi interfaces. The final destination, in the described platform, is the monitoring region and may be:

- A database server where the parameters of all monitored patients are stored and made available to medical staff, manufacturers and healthcare systems.
- Healthcare system personnel.
- Manufacturers.
- Medical experts, as discussed in the previous section.

Beyond the access to the database, the smartphone-centric architecture also assures seamless communication between the staff within the monitoring region.

Neither accelerometer nor localization external dedicated sensors are used because motion identification and localization are provided by using the smartphone itself. For example, as detailed in the next section, the accelerometer sensor embedded in the smartphone can be exploited to accomplish a precise recognition of the patient's physical activity. Currently adopted applications track distances and times covered during workouts and fitness activities by means of GPS receivers. The use of embedded accelerometers allows the detection of the type of performed physical activity because it can recognize specific movements.

Smartphones communicate with external devices in the patient region by using Bluetooth interfaces. In addition to the instruments shown in Fig. 1b, other useful sensor systems may be considered, such as: chest strips worn by patients, which can provide an approximation of the trans-thoracic impedance and of the heart rate; ElectroCardioGram (ECG); ElectroEncephaloGram (EEG); and glucose and blood pressure sensors. The smartphone-centric platform solves the open technical problem of interoperability, typical in tele-monitoring systems, between devices and the hub, and between the hub and the final destinations. Smartphones are already integrated with telecommunication network interfaces for data and voice transmission and, in many cases, already provide the necessary interfaces to connect to devices. In practice, using smartphones [4, 9, 10] simplifies the connection with sensors and the forwarding of measurements to the interworking network. Moreover, the presence of such a common device may facilitate the patient's acceptance of the monitoring system.

As stated, the viewpoint presented in this article is to give smartphones a new additional role: not only "hub+sensor" but "hub+sensor+processor." The idea of using a "hub+sensor" capability is in the literature (e.g. [4] and [10]). Sensor technologies combined with mobile communications were used to track patients' health measurements. Actually, sensors embedded into smartphones can be efficiently used for health monitoring: accelerometers can register different motions and walking gaits; infrared photo-detectors can measure body temperature; and more recently external sensors can be added to smartphones to measure heat flux, heart rate, and blood glucose levels. The additional "processing" capability may be an important added value for the platform. In summary, the platform offers:

- Both short-range (Bluetooth and WiFi employed for local information exchange) and long-range (GPRS, 3G/4G, and WiFi employed as Internet access) communication capabilities by exploiting the smartphone's network interfaces.
- Sensing capabilities: modern smartphones can acquire data by embedded sensors (always available on smartphones) such as GPS receivers, accelerometers, microphones, and radio interfaces often employed for localization purpose, or by external sensors such as pulse oximeters and scales connected through cables or local radio interfaces.
- Interaction capabilities, by exploiting the smartphone's multimedia features, useful to provide warnings, suggestions, and recommendations to patients when needed.
- Information processing capabilities provided by modern smartphones often equipped with different CPUs, efficient operating systems (such as Android), and flexible software. The following section reports on three important smartphone actions implemented over the proposed platform, audio recognition, localization, and physical activity detection, which are made feasible by the mentioned processing capabilities.

Information about whether a person is alone or not, about the number of people with him/her, about their identity, and about the level of noise, may stem from an audio processing-based approach concerning speakers' count and recognition such as the one presented below.

Information Processing Capabilities

We focus our description on smartphones' information processing capabilities that, from the authors' viewpoint, represent the new key function of the "hub+sensor+processor" paradigm and of the proposed AAL architecture. As stressed earlier, co-morbidity management implies not only multi-sensor acquisition and transfer, but also additional functions to know if the patient is alone or not and who is with him/her; to identify the location of the patient; and to recognize his/her physical activity.

Information about whether a person is alone or not, about the number of people with him/her, about their identity, and about the level of noise, may stem from an audio processing-based approach concerning speakers' count and recognition such as the one presented below.

Localization may derive from information processing based on signals received by smartphones' network interfaces. A possible algorithm is proposed below. In particular, the place recognition scheme proposed in [12] has been taken into account. Information required to carry out such a process is obtained from multiple sources such as the WiFi interface (in the case of indoor places) and the GPS receiver (in the case of outdoor places). The method, suitable for smartphone implementation, is briefly described and its recognition accuracy performance is presented for the specific case of monitoring a patient at home.

A physical activity recognition method based on raw data acquired directly from the measurements carried out by the smartphone accelerometer is reported below.

Audio Information Processing

In this context, audio processing over smartphones is aimed at classifying an audio signal acquired by embedded microphones so providing information about the noisy level of the

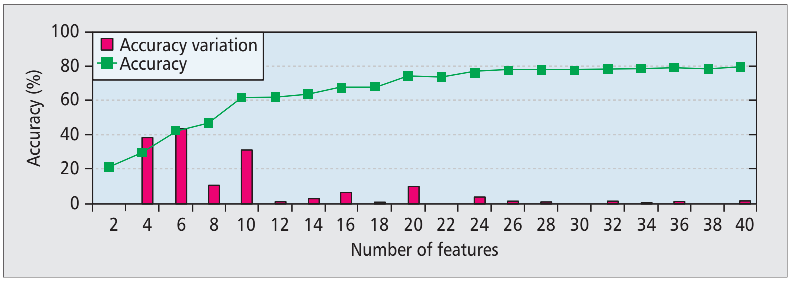

Figure 2. Accuracy of the speaker recognition method.

environment (e.g. excessive volume of audio/video equipment), and about the number and the gender of active speakers in the smartphone's surroundings. Audio processing may also be used to check the identity of a person, and this is the case briefly treated in the following. Actually, having information about the identity of caregivers will also provide information about the number of people with the patient and, implicitly, if he is alone or not, even if this information may also be retrieved through different algorithms in the literature. Several speaker recognition algorithms can be found in the literature, both for closed-set and open-set applications. Closed-set implies the classification of data belonging to a set of speakers known a priori, while in the open-set scenario there is no available knowledge on the set of speakers. In more technical detail, after the raw audio signal is acquired, the smartphone extracts a compact representation of the signal called *features*. Coherently with the state of the art in the field, the Mel Frequency Cepstrum Coefficients (MFCC) and their Delta Delta Coefficients (DDC) have been used in this article. The *features* feed a classifier that provides the result (i.e. the recognized speaker). Speaker recognition is implemented through a process divided into two phases, offline and online. The former aims at training the employed classifier, a Support Vector machine (SVM) in the case of this article, by using the *features* extracted from the speeches of different reference speakers (i.e. people expected to be in the patients surroundings), representing the predefined set. The latter is the recognition, where the *features* are extracted from an unknown speaker and used as input for the previously trained SVM. Finally, the unknown speaker is recognized as one of the speakers of the predefined set or he/she remains unidentified.

Figure 2 shows the accuracy, that is, the percentage of correct speaker recognitions of the described method versus the number of employed *features*. The aim of this test is recognizing a patient and five members of his/her family. In practice, six speakers have been used to train the SVM model. The green line represents the obtained accuracy. When the number of used *features* is above 26, the accuracy remains constant. Figure 2 also includes the accuracy variation histogram, which represents the accuracy gain obtained by increasing the number of *features* with respect to the previously tested value. For example, the employment of four *features* instead of two allows obtaining an accuracy increase close to 40 percent. Practically, the audio information processing capability of the smartphone-centric platform allows individuating the correct speaker within the set composed by the patient and his relatives in the 80 percent of cases.

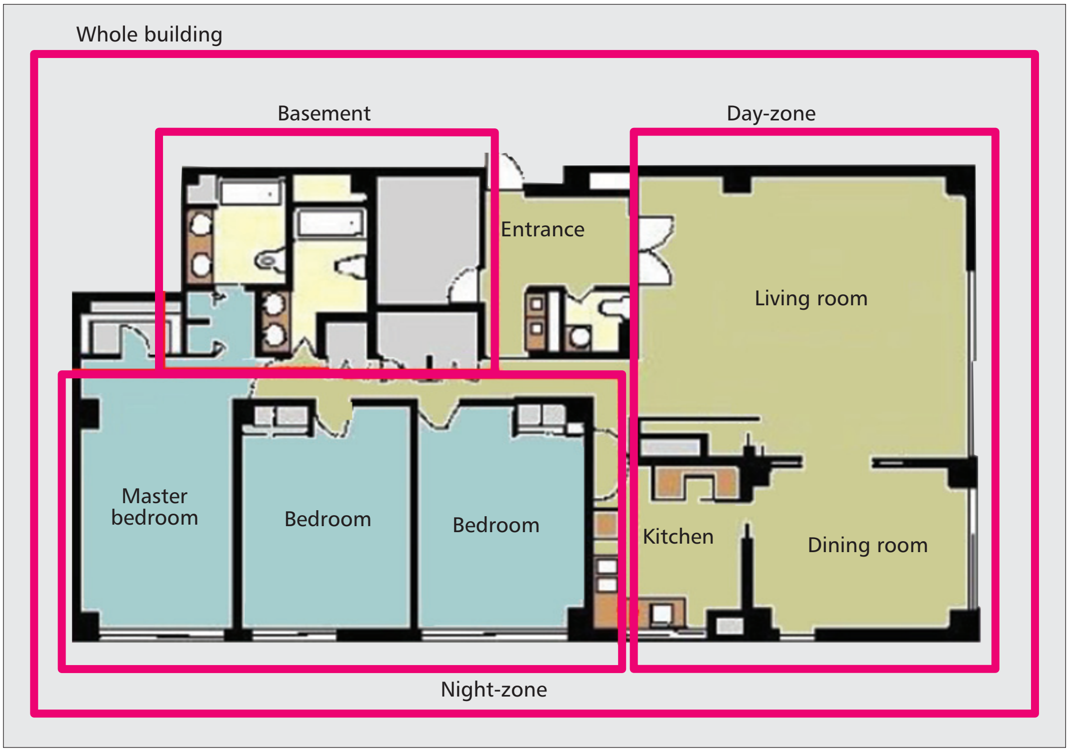

Figure 3. Considered localization places.

Network Interface Information Processing

Processing of signals received by smartphone network interfaces is the basis of Location-Based Services (LBSs), which are information services, accessible through mobile devices, such as Smartphones, that provide people and object localization. LBSs can be used in many applicative scenarios, such as health, object search, entertainment, work, and personal life. A well known localization process concerns the family of place recognition (PR) algorithms. The key idea of such algorithms is to recognize user localization not by identifying geographical coordinates but simply understanding in which place a user is staying (e.g. at home or at the gym). In this article we consider the Location Recognition Algorithm for Automatic Check-In algorithm (LRACI) [12] in the context of the AAL smartphone-centric platform. LRACI is employed to determine, in a completely transparent, automatic, and non-invasive way, in which room a patient is. The only request to the patient is having the smartphone with him/her. The performance of LRACI applied to a case in which there are four different places where the patient can be is reported in the following. The scenario is shown in Fig. 3. Localization output can be:

1. Day-zone (living and dining room, and kitchen) where a WiFi access point (AP) is installed.
2. Night-zone (bedroom).
3. Basement.
4. The whole building.
5. No location.

Whole building obviously contains places 1, 2, and 3, and is employed to recognize if the patient is at home but not within any of the first three places. No location represents the case in which the patient is not localized at home.

Also, this algorithm is based on offline and online phases. During the offline (or training) phase the patient's smartphone collects measurements related to GPS/HPS signals and/or to detected WiFi APs for each considered place. These measurements are then used in order to build the reference finger print (RFP) characterizing a place. RFPs are either stored remotely or directly on-board the smartphone. In the online (or recognition) phase, the smartphone collects the same measurements (GPS/HPS and/or WiFi AP signals) online and computes a finger print (FP) that is compared with the stored RFPs. The patient is localized in the place whose RFP is the closest to the acquired FP.

The obtained performance is reported in Fig. 4. It is the confusion matrix of the PR algorithm and shows the percentage of rooms correctly recognized during the tests. In the offline phase, the RFPs of the five considered locations have been built by collecting GPS/HPS and WiFi AP signals in 50 different points.

The percentage values reported in Fig. 4 have been computed by averaging the results obtained by 50 recognition phases. The performance is very satisfying. If the patient is in the day-zone, he/she is localized there in 94.5 percent of cases and confused with the night-zone in 5.5 percent of cases (first line in Fig. 4). The presence in the night-zone is correctly identified in 81.1 percent of cases and mistaken with the day-zone in 10.8 percent of cases and no location 8.1 percent of cases. The basement is recognized in 91.3 percent of cases and sometimes confused with no location (8.7 percent of cases). The presence within the whole building is correctly identified in 98 percent of cases and mistaken with no location in 2 percent of cases. No presence at home is recognized in 83.9 percent of cases and mistaken with the presence in the day-zone in 14.7 percent of cases and the night-zone in 2.3 percent of cases. The average accuracy is 89.8 percent. The accuracy is higher in the day-zone also thanks to the presence of an AP in the location. In general, when a location contains an AP, its radio signal dominates the others, characterizes the RFP of the location, and enables an efficient recognition. The absence of a dedicated AP causes a degradation of the location recognition accuracy. LRACI performance is not so satisfying when two adjacent locations must be discriminated. This is the case of the night-zone: about 11 percent recognitions are not correct because the night-zone is confused with the adjacent day-zone. This problem happens when WiFi signals are shared. The accuracy obtained for whole building is high because, in this specific case also, GPS/HPS positioning information can be efficiently used.

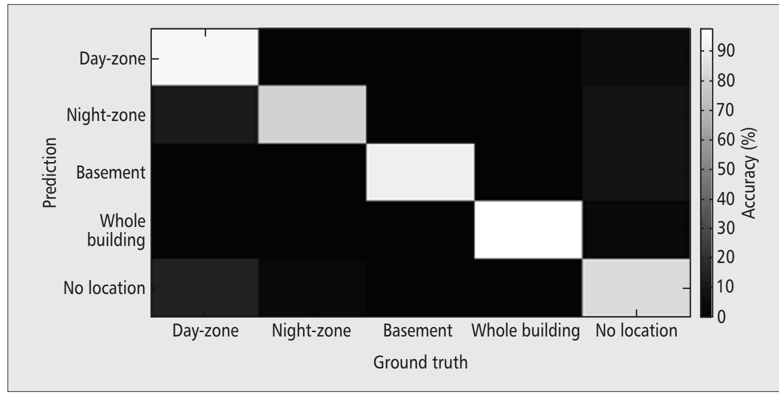

Figure 4. Accuracy of the place recognition represented by the confusion matrix.

Accelerometer Information Processing

The last information processing capability considered in this article concerns the physical activity recognition of the co-morbid patients. It is based on the action of sensing, processing, and classification of the signal provided by the smartphone-embedded accelerometer. The algorithm is designed to recognize eight different classes of physical activities: idle, sitting, standing, walking, going up and down the stairs (contracted in upstairs and downstairs), running, and cycling. These classes are particularly useful in case of cardio circulatory pathologies.

Again, two phases, offline/training and online, are the basis of the processing procedure. The acquisition of training signals is performed by keeping the smartphone in different positions. The algorithm periodically collects the raw signal from the smartphone accelerometer and organizes it into frames. A feature vector is computed for every frame and is used by a classifier, in this case

Features set		Kilometers	
Activities	**Percentage (%)**	**Activities**	**Percentage (%)**
Cycling	84.9	Cycling	60.3
Downstairs	69.5	Downstairs	0
Idle	79.2	Idle	0
Running	99.2	Running	96.1
Sitting	98.4	Sitting	85.5
Standing	91.2	Standing	47.3
Upstairs	63.1	Upstairs	70.7
Walking	51.1	Walking	54.7
Average	**79.5**	**Average**	**51.8**

Table 2. Accuracy of the activity recognition algorithm.

a decision tree (DT), to classify the frame into one of the movement classes previously listed.

In order to determine the best classification accuracy of the movements, numerous features were evaluated and compared: mean, zero crossing rate, energy, standard deviation, cross-correlation, sum of absolute values, sum of variances, and number of peaks of the signal obtained from the accelerometer. The *feature* vector chosen for the tests shown in this article is made of nine features (i.e. mean, standard deviation, and number of peaks of the accelerometer measurements along the three axes) as in [9]. This approach is identified as "*Features Set*." The obtained results have been compared with the approach in which only one *feature* has been used: the Km parameter, strictly related to the energy of the accelerometer signal, proposed and detailed in [10]. Such comparison is proposed since the solution reported in [10] is one of the reference architectures applicable to co-morbid patients monitoring scenarios.

The training signals employed in the tests have been acquired by four volunteers. Each volunteer acquired approximately one hour signal for each of the classes listed above. In order to determine the performance, the accelerometer signal has been acquired by a fifth volunteer not involved in the training phase.

Table 2 shows that "*Features Set*" allows obtaining a more accurate and precise classification of the patient's movements with respect to "*Km*." The average accuracy is approximately 80 percent if the "*Features Set*" is employed, while it is approximately 52 percent if "*Km*" is used.

Conclusions

This article describes the main characteristics of a smartphone-centric Ambient Assisted Living (AAL) platform aimed at monitoring, at home, patients suffering from a set of physical and mental limitations, called co-morbidities. The article highlights that smartphones have both short-range and long-range communication capabilities; information processing capabilities; and sensing capabilities implemented by internal and external sensors. The specific case of co-morbidities management implies the following needs: to acquire data from a set of sensors that monitor different health parameters; to transmit the acquired values remotely; and to control the action and configuration of single sensors. Moreover, an efficient communication architecture for co-morbidity monitoring and management should also assure the possibility of healthcare staff to interact with each other and with the patient remotely, and should guarantee the power to know if the patient is alone or not and who are the caregivers, to localize the patient, and to identify the physical activity performed by the patient. As a consequence, this article is focused on the information processing capabilities of the smartphones with particular emphasis on audio, network interfaces, and accelerometer information processing. These kinds of information can help monitor co-morbid patients remotely. The presented solutions have been designed and practically implemented by using off-the-shelf smartphones. In more detail, the following solutions have been presented: an audio processing-based approach, aimed at recognizing the identity of people who are with the monitored patients at a given time, which implicitly helps to monitor if a patient is alone; a place recognition method where the required information is obtained from multiple sources such as the smartphone WiFi interface, in the case of indoor localization, and the GPS receiver, in the case of outdoor localization; and a physical activity recognition method based on raw data directly acquired from the smartphone accelerometer. In all cases a brief presentation of the performance has been provided. The obtained results allow concluding that the employed information processing solutions are reliable and suitable to be employed in the described AAL smartphone-centric platform for co-morbidity monitoring.

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Biographies

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