

Wireless Sensor Networks for Personal Health Monitoring

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Abstract-*The theme of the project is to monitor the human health parameters like Heart beat, spirometer pressure and ECG. Heartbeat, ECG, Spirometer and pressure sensor is used to monitoring working blood pressure, heartbeat, heart and respiration of the patient and sends to the doctor's PC with the address. From the PC the doctor can monitor and guide the patient according to the values received from the patient. Then any critical in patient health condition alert will be given by buzzer.*

1. 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, and may help tackle these challenges.

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 Smartphone for the collection of medical data in online-databases concerning vital data monitoring services.

Unfortunately, these solutions often lack of 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.

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. 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. 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.

2. COMMUNICATION ARCHITECTURE FOR CO-MORBIDITIES

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 acting as management will be composed of different devices one healthcare system to provide management will be composed of different devices 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. 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.

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

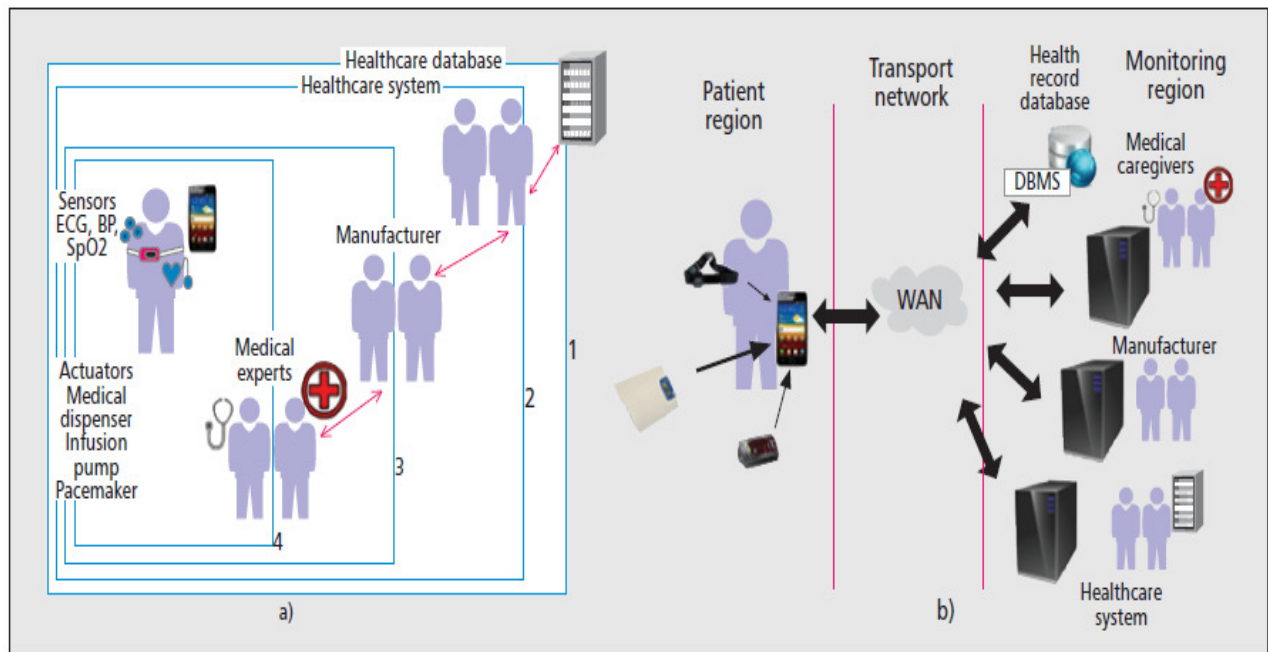


Figure 1. a) Integrated healthcare system; b) the smartphone-centric AAL platform for co-morbidities monitoring.

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).

3. INFORMATION PROCESSING

CAPABILITIES

In 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.

4. NETWORK INTERFACE INFORMATION PROESSING

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) 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,

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. 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 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. 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.

5. REQUIREMENTS FOR WIRELESS MEDICAL SENSORS

Wireless medical sensors should satisfy the main requirements such as *wear ability*, *reliability*, *security*, and *interoperability*.

Wear ability. To achieve non-invasive and unobtrusive continuous health monitoring, wireless medical sensors should be lightweight and small. The size and weight of sensors is predominantly determined by the size and weight of batteries. But then, a battery's capacity is directly proportional to its size. We can expect that further technology advances in miniaturization of integrated circuits and batteries will help designers to improve medical sensor wearability and the user's level of comfort.

Reliable communication. Reliable communication in WWBANS is of utmost importance for medical applications that rely on WWBANS. The communication requirements of different medical sensors vary with required sampling rates, from less than 1 Hz to 1000 Hz. One approach to improve reliability is to move beyond telemetry by performing on-sensor signal processing. For example, instead of transferring raw data from an ECG sensor, we can perform feature extraction on the sensor, and transfer only information. In addition to reducing heavy demands for the communication channel, the reduced communication requirements save on total energy expenditures, and consequently increase battery life. A careful trade-off between communication and computation is crucial for optimal system design.

Security. Another important issue is overall system security. The problem of security arises at all three tiers of a WWBAN-based telemedical system. At the lowest level, wireless medical sensors must meet privacy requirements mandated by the law for all medical devices and must guarantee data integrity. Though key establishment, authentication, and data integrity are challenging tasks in resource constrained medical sensors, a relatively small number of nodes in a typical WWBAN and short communication ranges make these tasks achievable.

Interoperability. Wireless medical sensors should allow users to easily assemble a robust WWBAN depending on the user's state of health. Standards that specify interoperability of wireless medical sensors will promote vendor competition and eventually result in more affordable systems. It is like a networking device works different communication device operability.

6. 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 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 comorbid 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.

7. 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 comorbidities 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.

REFERENCES

- [1] S. Adibi, “Link Technologies and BlackBerry Mobile Health (mHealth) Solutions: A Review,” *IEEE Trans. Inf. Technol. Biomed.*, vol. 16, no 4, Jul. 2012.
- [2] C. C. Y. Poon, Y.-T. Zhang, and S.-D. Bao, “A Novel Biometrics Method to Secure Wireless Body Area Sensor Networks for Telemedicine and M-Health,” *IEEE Commun. Mag.*, April 2006.
- [3] A. J. Jara, M. A. Zamora-Izquierdo, and A. F. Skarmeta, “Interconnection Framework for mHealth and Remote Monitoring Based on the Internet of Things,” *IEEE JSAC*, vol. 31, no. 9, Sept. 2013.

- [4] R. Carroll *et al.*, "Continua: An Interoperable Personal Healthcare Ecosystem," *IEEE Pervasive Computing*, vol. 6, no. 4, Oct.-Dec. 2007.
- [5] M. Chen *et al.*, "Body Area Networks: A Survey," *ACM/Springer Mobile Networks and Applications*, Feb. 2011, DOI: 10.1007/s11036-010-0260-8.
- [6] L. Pecchia, P. Melillo, and M. Bracale, "Remote Health Monitoring of Heart Failure with Data Mining via CART Method on HRV Features," *IEEE Trans. Biomed. Eng.*, vol. 58, no. 3, March 2011, pp.800–04, doi: 10.1109/TBME.2010.2092776.
- [7] O. R. E. Pereira, J. M. P. L. Caldeira, and J. J. P. C. Rodrigues, "Body Sensor Network Mobile Solutions for Biofeedback Monitoring," *Mobile Networks and Application*, Springer, ISSN: 1383-469X (print), ISSN: 1572-8153 (electronic), vol. 16, no. 6, Dec. 2011, pp. 713-732, doi: 10.1007/s11036-010-0278-y.
- [8] E. Villalba *et al.*, "Wearable and Mobile System to Manage Remotely Heart Failure," *IEEE Trans. Inf. Technol. Biomed.*, vol. 13, no. 6, Nov. 2009, pp. 990–96.
- [9] I. Bisio *et al.*, "A Smartphone-Centric Platform for Remote Health Monitoring of Heart Failure," *Wiley International Journal of Communication Systems*, Article first published online: 14 APR 2014, DOI: 10.1002/dac.2778.
- [10] M. K. Suh *et al.*, "A Remote Patient Monitoring System for Congestive Heart Failure," *J. Medical Systems (JOMS)*, May 2011.
- [11] C.-L. Chen, C.-C. Lee, and C.-Y. Hsu, "Mobile Device Integration of a Fingerprint Biometric Remote Authentication Scheme," *Int'l J. Commun. Systems*; online 28 April 2011 in Wiley Online Library, doi: 10.1002/dac.1277.
- [12] I. Bisio *et al.*, "GPS/HPS- and WiFi Fingerprint-Based Location Recognition for Check-In Applications over Smartphones in Cloud-based LBSs," *IEEE Trans. Multimedia*, vol. 15, no. 4, June 2013, pp. 858–69, doi: 10.1109/TMM.2013.2239631.
- [13] ETSI TS 102.689 V1.1.2, "Machine-to-Machine communications (M2M); M2M service requirements," May 2011
- [14] ETSI TS 102.690, "Machine-to-Machine communications (M2M); Functional architecture," December 2011.
- [15] ETSI TS 102.921 V1.1.1, "Machine-to-Machine communications (M2M); m1a, d1a and m1d interfaces", February 2012.

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