Remote Healthcare System based on AIoT

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Abstract. Life expectancy in recent years has sensibly increased and age related problems in elderly people have followed a similar trend. Being able to find innovative solutions to enable senior population to maintain their quality of life despite the presence of chronic illnesses has become crucial for high quality ageing. The opportunities offered by the technological advancement with remote assistance applications, wearable devices, and *Artificial-Intelligence-Of-Things (AIoT)* architectures are of paramount importance to improve the services in healthcare facilities by adding the power of Artificial Intelligence to Internet-Of-Things devices. An experimental framework has been deployed to two residential homes in collaboration with two italian companies to collect and analyze data in order to actively monitor the vital signs of their guests, predict critical situations and identify significant clusters or communities.

Keywords: remote assistance, healthcare, Artificial-Intelligence, Internet-of-things, smart devices

1 Introduction

In developed countries, average life expectancy has sensibly increased in the last few years thanks to improved healthcare services, active prevention of diseases and pathologies and the availability of new drugs. The result of these combined factors is the increase in geriatric population which consequently affects the spreading of a whole group of diseases that are directly related to ageing. As reported in [1], the extension of life span has led to an exponential growth of elderly population who suffer from chronic or degenerative diseases that require life-long treatment that, at the time being, can be effectively supported by innovative smart devices and technologies. In fact, new portable or wearable devices which integrate disparate monitoring sensors are nowadays available for everyone at low cost, making it possible to constantly assess patients' health status through a Health Monitoring System (HMS) that not only limits hospitalization and medical staff intervention but also cuts the waiting lists improving the consultation effectiveness while reducing the overall healthcare expenditure [2].

When the HMS makes use of smart devices to record and track patients' status it is termed Smart Health Monitoring System (SHMS) and can be general purpose (GHMS) when multiple generic vital signs are recorded or Remote (RHMS) if data are collected at a remote location and transferred to healthcare facilities for medical follow-up analysis. Another non-negligible benefit comes from the availability of mobile devices that can provide reliable network connections and computational power to perform data collection and timely onsite preliminary analysis via direct interaction with the medical staff. The advent of IoT devices is fostering the availability of new assets for the development of a brand new personalized care that can improve the quality of life for elderly people. The rest of the document is organized as follows: section 2 presents the state of the art on HMSs; in section 3 the IoT architecture of our data collection system is detailed while section 4 discusses the findings related to data analysis. Finally, section 5 reports closing remarks and future extensions of this work.

2 State of the Art

As presented in [3], various bluetooth wireless devices, such as blood pressure monitor or pulse oximeter for oxygen saturation, were used in combination with an IrDA (Infrared Data Association) connected blood glucose meter and an electronic thermometer to gather patient's data into a set-top-box, responsible for data transmission over a secure network connection. An integrated Wearable and Mobile HMS was setup to record vital signs that were manually checked by registered personnel and evaluated according to standard ward procedures, whereas the researchers were responsible for chasing inaccuracies and time delays. A fuzzy logic system where the significant physiological parameters are properly weighted for a particular condition severity, was used to interpret heart rate, blood pressure, pulse rate, temperature and oxygen saturation (SpO2) and detect cases of bradycardia, labeled with two possible levels of priority growing from P2 to P1. For instance, in case of hypotension the following fuzzy rules were defined:

- Low BP, High HR and High Pulse rate $\Rightarrow$ P2 Hypotension
- Very Low BP, Very High HR and Very High pulse rate $\Rightarrow$ P1 Hypotension

Hypotension is primarily consequent to low BP values but the clinical severity of the condition depends also on high heart rate as well as high pulse rate, as shown above. The authors of [4] propose the adoption of tabled-based applications to make their patients' data timely accessible to caregivers and provide the basic routine functions to clinicians; the application, which is required to be simple, is organized into five sections:

1. Profile, containing patient related information;
2. Vital Signs, reporting the biomedical parameters collected by the adopted bluetooth devices, also available to the medical staff;
3. History, which holds the historical records about medications, mental status, etc.;

4. Medical Notes, where the patient's status is summarized along with any medical notes;
5. Contact, to exchange clinical information with caregivers and/or registered medical staff in case of emergency or support.

Similarly, wireless sensors are used by [5] to relieve chronic patients from the burden of intrusive instruments. The authors propose a three stage system based on an Arduino board for sensing, filtering and transmitting the signals over internet and later display the relevant results with a computer-based or mobile-based application. The authors of [6] assert that a decrease in health related quality of life (HRQoL) is correlated to frailty or pre-frailty status, which is why they recommend an HMS capable of achieving remote continuous monitoring without active patient's intervention by integrating Artificial Intelligence with *Internet of Things* (AIoT). IoT features in medical systems should be designed in a human-centric perspective, considering human beings as critical *components* of the system and focusing on two use cases (remote elderly monitoring and smart ambulance) that combine emerging technologies with best healthcare practices. Patients and caregivers become *actors* in the new cyber-physical system, with specific context-driven tasks and critical issues. One recurrent goal of most papers in literature, such as [3, 8], is the adoption of devices that do not interfere with patient's regular life, which is becoming more and more possible with smart bracelets and other integrated sensors.

3 System architecture

Our project involved multiple *actors*, playing different roles in the operational interaction with the selected hardware devices for data sensing and collection. The patients are housed in two residential home-like accommodation (RSA Minoretti and RSA Valpolcevera) that provide special medical assistance for people who cannot be cared at home. These residential homes, based in Genoa (Italy), are managed by a medical staff specialized in geriatric care and therapies for people with physical, mental and sensory disability. Each room can accommodate two or three patients and the total number of patients involved in the present study is 25, with 10 males and 15 females. The technological infrastructure was provided by Hassisto srl, a spin-off of the National Research Council (CNR), that developed an innovative software platform for e-Health, connecting multiple bluetooth devices to a specialized hub that transmits the anonymized patients' data to a central database for continuous monitoring. Patients undergo an active control procedure that collects data during daily activities which will be utilized to automate routine check-ups thereby reducing the cost of indoor healthcare management. This platform integrates a wide variety of professional medical devices, such as ECG or EEG, but also commercial wearable sensors that can measure heartbeat, blood pressure, SpO2, blood glucose level, physical activity and quality of sleep. Moreover, other specialized devices can also be supported for real-time fall detection, monitoring the weight or tracking the rehabilitation exercises. The primary sources of data were the IoT devices worn by each patient who was identified by a unique anonymous code to comply with the European General Data Protection Regulation (GDPR). Despite the multiplicity of smart devices supported by the hardware platform, in this initial project we adopted only two sensors and the transmission hub, not to be too invasive in the elderly patients' lives.

3.1 Spovan H03 wristband

Unlike other smartwatches , the primary aim of this waterproof wristband is the collection of health data: it is and advanced fitness and health tracker which provides on-wrist ECG, blood oxygen metering, blood pressure, sleep and heart rate variability (HRV) monitoring. It is based on the Nordic 52832 multiprotocol SoC with Si1182 ECG sensor and electrode on the watch body; photoplethysmography and electrocardiography methods are used acquire vital signs [9]. With its 1.14 inches high definition screen and its 150mAh rechargeable battery, the selected wristband can operate up to 5 days in low energy bluetooth mode. All data collected by the smartwatch can be transferred to a remote database server through a mobile application released by Hassisto.

3.2 The sleeping band

The sleeping band is a non-invasive device, which is positioned between the sheets and the mattress, at the level of user's rib cage, to monitor the quality of sleep, breathing and heart beats when the patient is in bed. Made with hypoallergenic plastic materials, it makes use of polyvinylidene fluoride (PVDF) sensors to detect pressure values associated to the vital signs of the subject. It can also identify some specific movements or situations that might require the caregiver intervention, such as in case of seizure, prolonged sleep apnea or sudden chaotic movements. Real-time monitoring is also supported via a dedicated application and sends data to the remote server through the internet box. Presently, due to its BLE technical limitations, only one sleeping band at a time can be connected to the box.

3.3 The communication hub

The communication hub, namely the *Hassisto Gateway*, is based on a customized Android TV box that provides the necessary bluetooth interface toward monitoring devices and hosts an HTTP Web server, which allows for the remote connection to the collected data [6]. It requires a working internet connection, either by LAN or WiFi, and should be located close to the monitoring devices in range for BLE communication.

4 Data analytics

All data collected by the selected devices are stored on a remote software platform that provides a dashboard to manage patients, devices and the relevant measurements which can be supplemented by the residential home personnel with additional medical information about each patient. Moreover, measurement data can be imported from a second portal which represents the primary source for project data retrieval via a REST API, available at https://api.hassisto.com/swagger, to perform various machine learning tasks, such as statistical analysis. The API provides three different sections for data exchange:

- *lookup* allows to inquire the internal reference codes for several platform categories,
- *output* section refers to the *get* method requests for patient's recorded data,
- *input* section offers the *post* method requests to store and modify patient's health status.

The API was accessed using Python Requests module [10], which is the simplest way to make HTTP requests, and then processed and analyzed in a Pandas DataFrame [11], that offers easy access and visualization tools. The following columns were specified in the DataFrame:

- *patientcode*, containing the patient's unique identification code,
- *instant*, where the timestamp is recorded,
- *measurename*, holding the name of the vital sign being recorded,
- *value*, containint the values for the corresponding measure,
- *idpatient*, is the indentifier associated to a patient,
- *measurementsource_id*, is the measurement source identifier.

The medical staff requested to aggregate patient's data at weekly, hourly and daily resolutions therefore the collected measurements were averaged over the requested time span, also to take into account the different measurement time intervals of each sensor device. Our focus was set on six sensors: breath, heart rate, maximum and minimum blood pressure, saturation and steps. It is difficult for us to find patterns or communities by looking at the numerical data, therefore we leveraged graphical visualization techniques to find relevant information within the recorded data and possibly detect abnormal situations in the health status of our patients. For this purpose, in order to visualize the overall status of a patient and compare it with other patients having similar health conditions the radar plots were selected as they are highly informative tools to visualize high dimensional datasets and compare them on a two-dimensional plane when more than one track is displayed on the same plot. To have and informative insight of patients' health status from the collected data, we implemented a cluster analysis to get a general estimate of which category a patient belongs to. Clustering allows to group subjects by similar symptoms and assess the presence of possible deviation from the community profile: this was achieved by means of the graded possibilistic clustering algorithm [12], which can iteratively track outliers and adapt to concept shifts and drifts in non-stationary data.

4.1 Clustering algorithms

Clustering is a family of unsupervised learning algorithms whose aim is automatic discovery of similarities among data. There are hard and soft clustering

algorithms which differ by the degree of membership to the clusters that each data point may have. Specifically, in hard clustering a data point can be assigned to one cluster only with binary membership $\mu_i \in 0, 1$, whereas in the soft one each data point can have a $\mu_i \in [0, 1]$ with the optional additional probabilistic constraint that $\sum_i \mu_i = 1$. The elbow method [13] was initially used to estimate the optimal number of clusters k but it did not yield a significant result, therefore an empirically determined value $k = 3$ was set.
Four different algorithms, two hard and two soft methods, were considered and assessed against our dataset:

- *k-means*, is a hard partitioning method that iteratively groups the data points into k distinct clusters, typically based on a Euclidean distance metric [14].
- *k-medoids*, is another hard clustering method, similar to k-means, where the centroids are selected amongst the data points, instead of averaged, and supports alternative distance metrics [15].
- *Fuzzy C-means*, is a soft method where each data point is associated to clusters in terms of a membership vector, which denotes the similarity of a data item to the cluster centroid [16].
- *Graded Possibilistic Clustering*, is a soft clustering model derived from Fuzzy C-means where the probabilistic constraint on the membership is removed thus allowing to distinguish between moderately and extremely atypical data points [17].

A significant advantage of Graded Possibilistic Clustering (GPC) is its ability to detect outliers by properly tuning the algorithm parameters, which is crucial in recognizing any irregularities in the patient's health. Raw data are loaded into a Pandas DataFrame, that supports averaging and pivoting to aggregate the measurements at the desired time span, removing unwanted sensors data and replacing the missing values with average values. Moreover, in order to compensate the different ranges of the measured quantities a min-max scaler was applied to normalize the dataset. Finally, since our dataset mostly represents real patients, it was important that the cluster center be a true patient, which in principle makes the *k-medoids* clustering method favorable against the other presented algorithms.
With regard to visualization, radar plots were implemented via D3 - Data Drive Documents - library taking into account three main goals:

- activity based profile, for specific hours during the day
- daily profile of a single patient
- weekly profile of a single patient
- clusters on average profile, for a population of patients over a defined time span

The reported vital signs have different ranges that cannot be displayed in a single radar plot, hence alternative informative solutions were agreed with the medical staff as follows:

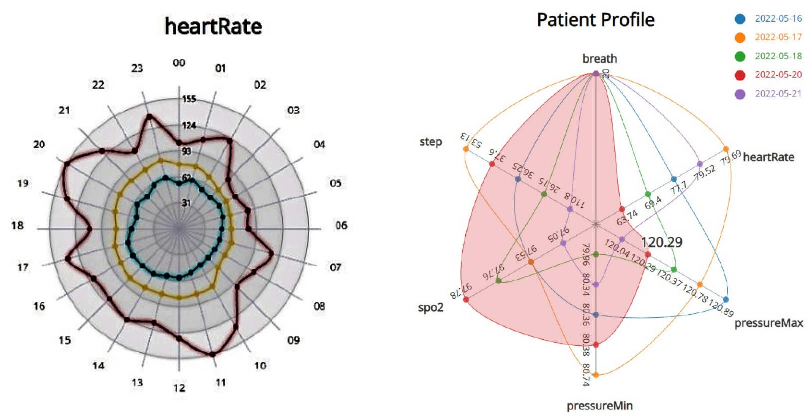

Fig. 1. Hourly radar plot of a patient's hearth rate (left); comparison of the selected vital signs for a patient's profile over five days (right

– profile of hourly data of the patient for individual measures during a specified period, a single day or week,
– complete patient profile of all vitals for daily average values over a certain period,
– profiles of selected number of patients, for a selected period of time, for specific number of measures, evaluated by clustering algorithm

Examples of the generated radar plots can be seen in Figure 1.

4.2 Results and discussion

During the test phase, data from a four week period was selected, furtherly divided into two blocks of two weeks each to be able to appreciate any possible change in the centroids. Standard scaler normalization was performed before running the tests and two clustering techinques, commonly used in similar problems, were used: Fuzzy C-means for soft clustering and K-means for hard clustering. In Figure 2, it is evident that both algorithms produce nearly identical results over the two considered periods respectively. The limited number of patients in this study represents a serious limitation on the reliability of the results but we could demonstrate the usefulness of the adopted radar plots in conveying significant information about patient's communities to the medical staff who will in future be able to deliver more targeted therapies to their elderly guests.

5 Conclusions

This paper presented a preliminary study of an AIoT system aimed at active monitoring of vital signs for frail and elderly people hosted in residential homes.

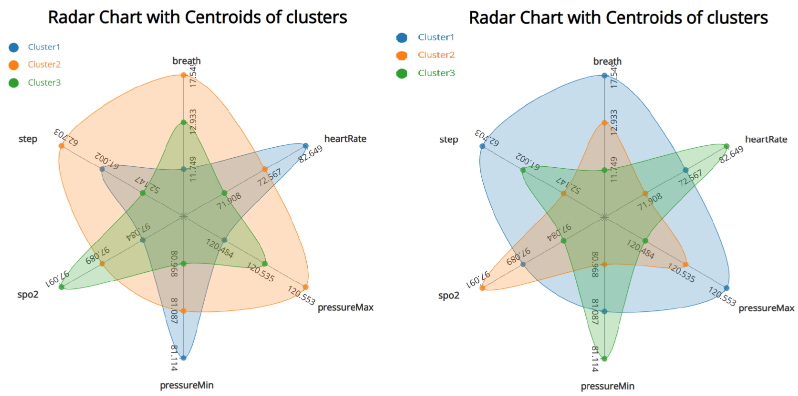

Fig. 2. Comparison of clustering models built for Fuzzy C-means (left) and k-means (right

We used wearable sensors and sensored beds to continuously collect streams of data for a long period and perform clustering analysis over several time frames. The medical staff and caregivers can visualize a set of radar plots enabling a synoptic view of a single patient or groups of similar patients.

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