Trends and challenges in smart healthcare research: A journey from data to wisdom

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Trends and Challenges in Smart Healthcare Research: A Journey from Data to Wisdom

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***Abstract*—Smart Healthcare is a relatively new context-aware healthcare paradigm influenced by several fields of knowledge, namely medical informatics, communications and electronics, bioengineering, ethics and so on. Thus, many challenging problems are related to smart healthcare but in many cases they are explored individually in their respective fields and, as a result, they are not always known by the smart healthcare research community working in more specific domains.**

The aim of this article is to identify some of the most relevant trends and research lines that are going to affect the smart healthcare field in the years to come. To do so, the article considers a systematic approach that classifies the identified research trends and problems according to their appearance within the data life cycle, this is, from the data gathering in the physical layer (lowest level) until their final use in the application layer (highest level). By identifying and classifying those research trends and challenges, we help to pose questions that the smart healthcare community will need to address. Consequently, we set a common ground to explore important problems in the field, which will have significant impact in the years to come.

Keywords—Smart Healthcare; Context-awareness; Data Gathering; Data Mining; Behavior Analysis

I. Introduction

The healthcare industry is very dynamic and incorporates technologies to their processes so as to improve the quality of life of patients (*e.g.,* by speeding diagnostic procedures up and personalizing treatments) and to increase efficiency (*e.g.,* by reducing management costs and releasing patients earlier). This adoption of information and communication technologies (ICT) within the healthcare industry gave birth to the so-called electronic health (e-health) [1], which aimed to address organizational problems such as the management of healthcare records, and opened the door to telemedicine and the remote collaboration between medical professionals and patients. Later, with the spread of mobile devices and their integration within the healthcare sector, the concept of mobile health (m-health) appeared [2]. Thanks to the ubiquity of such devices, remote and continuous monitoring of patients became a reality and a bunch of new possibilities for data gathering emerged. However, most of those data are context-dependent [3] (*i.e.,* the same value for a given variable could have different meanings/interpretations depending on the context – for example, depending on the location). Hence, a new paradigm of healthcare that put together the capabilities of mobile devices and the sensing and networking infrastructures of context-aware environments was a natural evolution proposed by Solanas et al. [4] and took the name of Smart Health (s-health). Although the initial definition of smart health emerged from the role of Smart Cities, the paradigm has been generalized from smart cities to any context-aware smart environment such as smart hospitals, smart homes and so on.

Regardless of the healthcare paradigm that we would like to embrace or the specific flavor that we would like to confer to their definitions, there is a general agreement on the fact that advances in sensors technology, computer science, and telecommunications enable an unprecedented capacity to gather huge amounts of data (*e.g.,* medical data, mobility data, contextual data, etc.). Notwithstanding, these data are no longer homogeneous and well-structured but, on the contrary, they are variate. In addition, they flow at sickening speeds and accumulate rampantly. Hence, although we have the ability to gather data effortlessly, obtaining benefits from those data is not easy. In the words of B. Harris (1987):

> *"Seduced by the effortless gathering of data, we discount the costs of turning data into information, information into knowledge and knowledge into wisdom."*

Indeed, the transformation of data into wisdom is a tough journey and it becomes even tougher in the medical area, where very sensitive data are managed and lives could be at stake. In this article we explore some of the challenges and research opportunities that, in our humble opinion, will stay on the table of smart health researchers in the years to come. We have organized those challenges according to the moment in which they appear in the data life cycle. Thus, in Section II we initiate our journey identifying the challenges that have to be faced in the phase of gathering data (from the physical layer). Next, in Section III we elaborate on the difficulties arising from the storage and retrieval of such a tremendous amount of data and, in Section IV we discuss several avenues to analyze the data at hand to obtain knowledge. Section V elaborates on the applications that the previous processes enable and, the article concludes in Section VI with some final thoughts and remarks. A graphical summary of the challenges and opportunities that we have identified and classified are shown in Figure 1.

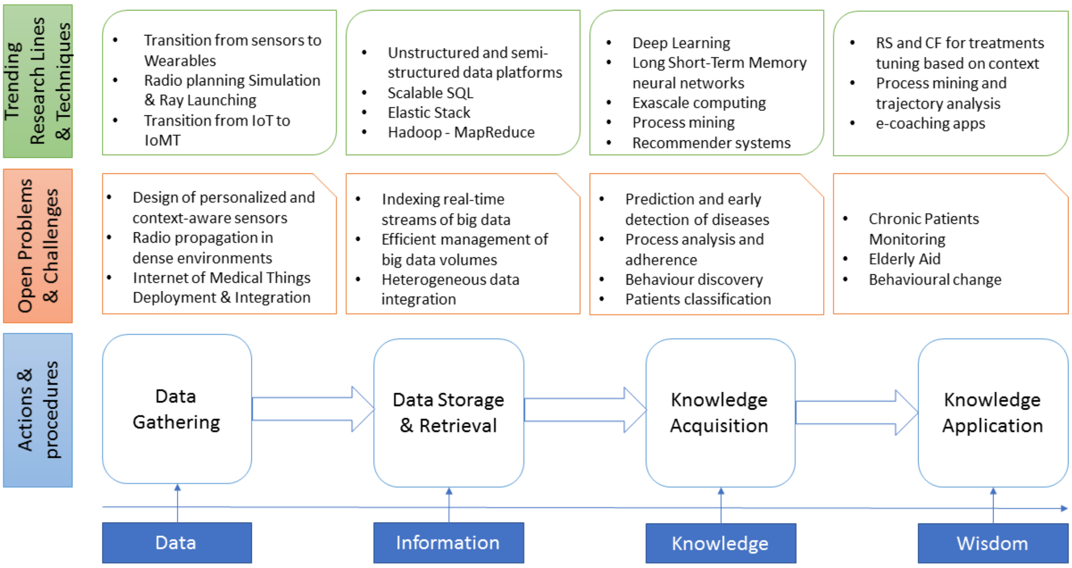


Fig. 1. Summary of actions, open problems, challenges and trending research lines in our data-driven approach to the transformation of data into wisdom.

II. Data Gathering

To obtain wisdom from data first we must gather them. The amount of available data grows so rapidly that it is difficult to estimate the actual amount [5]. However, gathering personalized context-dependent data in participatory scenarios is difficult and the involved processes pose challenges in terms of reliability, energy and cost efficiency, non-intrusiveness and integrability. Generally, sensors form networks and, they transmit data to centralized collectors. Despite its apparent simplicity, transmitting data in densely sensorized environments, in which users/patients contribute with their own data, pose important problems and radio planning is a must. Next, we comment on the transition from classic sensors to wearables, the difficulties and open research lines related to radio planning in dense environments, and the impact of new data gathering platforms such as the Internet of Medical Things (IoMT).

A. From sensors to wearables: A participatory approach

Designing sensors for medical equipment to collect data is a well-known research area of electronic healthcare. Notwithstanding, those equipments are very specific and are mostly located in hospitals and similar healthcare facilities. On the contrary, the sensors used to capture contextual and personalized data, which are contributed by users/patients (*i.e.*, the kind of data inherent to the smart healthcare paradigm), are still an active research area. It is worth emphasizing the relevance of those sensors that are seamlessly integrated in wearable devices. Indeed, wearable technology is playing (and will play) a fundamental role in smart healthcare in the years to come. It is paramount to develop new fabrics and clothes that integrate sensors [6][7] enabled for the continuous monitoring of patients. Also, the integration of sensors within the human body will be an active research area, specially for those directly interfaced with the brain [8], and other non-invasive forms of integration such as tattoos based on new materials [9].

B. Radio planning in dense environments

Real-time monitoring of vital signs of patients can be performed remotely, and data from distributed sensors and wearable devices can be transmitted almost instantly. However, a wide variety of heterogeneous communication systems have to co-exist [10] and might interfere. To reduce interferences and optimally use the propagation channel it is necessary to characterize it in every scenario. In wireless systems, interference control plays a vital role in performance, particularly in 4G and 5G communications [11]. These wireless systems span from short range Wireless Body Area Networks (WBAN) to countrywide mobile communication networks, usually working in a cooperative way [12]. Several approaches to characterize those media exist: from empirical estimations, to full-wave simulation techniques. A midpoint between precision and computational cost could be achieved with Ray Launching (RL) methods [13], which are an active research area. For example, a representative complex smart healthcare situation, where RL can be useful, arises in emergency rooms (*cf.,* Fig. 2), where many users interact with interfering sources such as operating magnetic resonance imaging systems [14][15]. The scenario and the location of transceivers have a direct effect on the overall system performance in terms of quality of service and energy consumption and must be studied carefully [12].

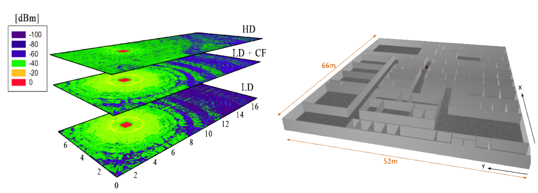


Fig. 2. Emergency floor of the Hospital of Navarre (right). Simulation results of received power level using RL [13] (left).

C. The Internet of things and other data acquisition platforms

The improvements in communications technology discussed above opened the door to the connection of all devices to the Internet and the concept of Internet of Things (IoT) was born. Although IoT was not intended as a data gathering platform, its capillarity and virtual ubiquity, coupled with its communications capabilities have made it perfect to achieve this purpose. The application of the concept of IoT in the healthcare industry led to the appearance of the more specific term Internet of Medical Things (IoMT), which has to overcome the same challenges than IoT but in a more demanding scenario [16]. For example, guaranteeing security in an IoT platform is difficult due to the inner limitations of the very devices (*e.g.,* simple RFID devices [17]). However, it takes especial relevance in the IoMT and many efforts will be devoted to this problem in the years to come. Some other platforms that are more mature (but are yet to be fully developed) and will require the attention of smart healthcare researchers in the near future are smart cities [4][18] and vehicular networks [19]. Also, the irruption of drones into the delivery and surveillance arena could reshape many ideas of healthcare provision in rural areas [20].

III. Data Storage and Retrieval

Knowledge extraction from large data sets requires advanced data management strategies linked to robust data governance models. The volume and nature of big data forces rethinking classical data storage and retrieval approaches to include scalability requirements and to facilitate the transformation of data into knowledge.

A. New storage paradigms

Relational database approaches work well with low-dimensionality data with humble volumes (*i.e.,* up to GB), but their efficiency and response time decrease with the amount of data. The big data revolution requires new storage paradigms such as noSQL databases, optimized to read/write huge volumes of data in an efficient and scalable way, at the price of sacrificing consistency. One of the most accepted computing paradigms used to analyze large volumes of data in a parallel and distributed fashion is MapReduce [21]. This paradigm breaks a big data problem into small sub-problems, each of which are assigned to a processing node. Then, the result is obtained as a combination of the results of the sub-problems (computed by each processing node). The most well-known open-source implementation of MapReduce is Hadoop, which implements its own file system (*i.e.,* HDFS) to deal with replication, fault-tolerance and high availability. The MapReduce implementation provides tools to write data analysis-oriented applications easily. There are other solutions such as Spark, which provides a fast and memory-based alternative to MapReduce, and it is gaining momentum in domains that require big data processing capabilities such as healthcare [22].

B. Data indexing and querying

Volume and variety are the intrinsic features of big data that have significant impact on knowledge extraction processes. Managing large amounts of heterogeneous data requires efficient indexing and search mechanisms capable of dealing with different levels of data organization (*i.e.,* structured, semi-structured and unstructured data). Scalable SQL stores can be used to retrieve information from large structured data sets. However, semi-structured and unstructured data can be retrieved more efficiently using noSQL data stores. A detailed discussion about scalability in SQL and noSQL data stores can be found elsewhere [23]. Future smart health applications will leverage multiple streams of data generated in real-time by sensors, social media, and medical devices. The efficient processing of streaming data requires indexing and searching across large unstructured data stores. In this context, the so-called *Elastic Stack* (Elasticsearch, Logstash and Kibana) provides a high-performance enterprise software stack that can be used to deploy healthcare analytics [24].

IV. Knowledge Acquisition

Once the data are collected and stored, we have to analyze them to obtain information and knowledge. Although classic approaches based on multivariate analysis (*e.g.*, regressions, clustering) are widely used, new forms of data analysis are gaining importance (*e.g.,* trends in the use of programming languages such as Python and R are clear indicators of this paradigm shift[1]). Among all those new approaches, we have selected recommender systems, process mining and deep learning as important representatives of areas of study that will play a fundamental role in healthcare in the years to come.

A. Recommender systems and crowdsourcing

Recommender systems (RS) [25] help to distinguish noise from useful information. With the consolidation of the *Web 2.0*, in which users participate actively and create and share data (*i.e.,* crowdsourcing), RS play an active role. Recommendations based on clients participation are relevant to industries such as e-commerce and healthcare. RS allow clients/patients to discover items and relations and, although the use of RS for healthcare is still in the beginning, their use in e-commerce is vast: Internet users participate in multiple contexts such as the e-commerce field (*e.g.* Amazon), where they evaluate items, and in the audiovisual arena, with sites like Netflix or IMDb. It is worth noting that recommendations from personal acquaintances and opinions posted by consumers on-line are the most trusted forms of advertising today [26]. The most prevalent kind of recommender system is Collaborative Filtering (CF) [27], which involves a large family of recommendation methods. The main aim of CF is to suggest/recommend items (*e.g.* books, films, routes, treatments) based on the preferences/characteristics of users/patients. Recommendations provided by CF methods are based on the premise that similar users/patients are interested in similar items (*i.e.,* they share similar behaviors/tastes/diseases).

In smart healthcare environments, patients act as intelligent and collaborative sensors that share information to improve their quality of life. Therefore, patients are no longer passive information/treatments consumers but also producers of solutions, thus, they become *prosumers* that share information on a wide variety of health-related topics. In the smart health participatory context, RS and CF will develop fast and will play an important role in real s-health applications.

[1] http://spectrum.ieee.org/computing/software/the-2017-top-programming-languages

B. Process mining for smart healthcare

The healthcare industry comprises large and complex processes that usually take place in very dynamic contexts. Healthcare processes (*i.e.,* a set of activities aiming at achieving a certain goal) should be understood to monitor and optimize them, and to manage the organizational control-flow. For traceability purposes, almost every action performed in a healthcare information system generates events, which are stored in log files. Those files are used to verify the correctness, effectiveness and efficiency of the healthcare processes. Indeed, the main challenge of process mining (PM) in the healthcare sector is to exploit huge amounts of event data meaningfully. PM aims to discover, monitor and improve real processes by extracting knowledge from event logs readily available in today's systems [28]. The obtained knowledge enables the identification of bottlenecks and inefficiencies within processes, provides insights about the management of the organizational resources, detects hidden patterns, anticipates problems and enables countermeasures. PM comprises, on the one hand, machine learning and data mining techniques and, on the other hand, process modeling and analysis. PM techniques can be classified into three different groups: (i) discovery techniques producing process models from event log files without any a-priori information, (ii) conformance techniques that compare existing process models with event log files of the same process, and (iii) enhancement techniques that improve existing process models using information about processes recorded in event log files. Although the first group is the most extended in the literature, enhancement techniques will gain importance in dynamic healthcare contexts and will be used to provide context-dependent up-to-date processes.

C. Deep learning

Deep Learning (DL) [29] refers to a class of machine learning techniques based on multilayer artificial neural networks capable of discovering data representations. Representation learning is an automated process that transforms raw data inputs into higher-level features (*i.e.,* representations) that can be effectively used in machine learning tasks. Over the last few years, DL models have achieved impressive technological accomplishments exceeding human performance (sometimes referred as *super-human*) in complex tasks such as image recognition [30]. However, with the increasing volume of data and complexity of deep neural architectures, the availability of large-scale computing systems becomes critical to reduce the overall time required for training DL models. Approaches to scale DL algorithms on multi-GPU nodes and large-scale clusters still have limitations (*e.g.,* centralized server approaches or system-wide synchronization requirements) that must be overcome in future exascale computing systems.

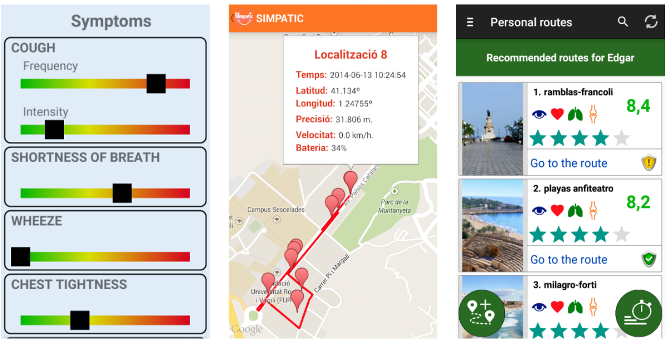
In the health domain, DL enables advanced data analytics in areas such as translational omics and medical imaging [31]. For instance, current DL systems are capable of detecting certain cancer tumors with accuracy comparable to human experts [32]. The development of pervasive sensing technologies and devices will facilitate the application of DL techniques in smart healthcare. Multi-modal data streams provided by wearables and environmental sensors can be used to develop DL systems for activity recognition and for the early detection of behavioral and physiological anomalies (*e.g.,* alterations in vital signs). Long Short-Term Memory (LSTM) neural networks have also been applied in predictive process monitoring [33] and constitute a promising approach for process mining. Given the increased interest on AI-based applications in the biomedical sector, it is expected that DL techniques will play a key role in future personalized medicine and smart healthcare systems.

V. Smart healthcare applications

As previously stated in Section I, the aim of researchers and practitioners in the healthcare industry is to transform data into wisdom. In this section, we show some examples of healthcare applications that put in place the knowledge obtained by means of some of the techniques reported in the article. For the sake of brevity many applications could not be included.

An important field of application of smart healthcare relates to chronic patients. Patients with chronic diseases are affected by a range of potential issues including socioeconomic factors and a decrease in their quality of life. In many cases, environmental factors affect symptoms associated with several chronic diseases, which until now have been hard to consider in treatments. However, this situation is steadily changing due to the emergence of smart environments (*e.g.*, smart cities, smart hospitals, smart homes, etc.). Treatments for many chronic diseases, particularly cardiovascular and respiratory ones, involve physical exercise and rehabilitative activities. In the case of respiratory diseases, a well-known example is Chronic Obstructive Pulmonary Disease (COPD) [34], which was the cause of the 6% of all worldwide deaths (more than 3 million people) in 2012 [35]. Among the most frequent signs and symptoms of COPD, cough, shortness of breath, wheeze and chest tightness stand out from the rest. For this disease, the treatment is defined at multiple levels [36] and, for mild and moderate COPD, physical exercise and rehabilitative activities, such as outdoor walks, are strongly recommended. However, the evolution of the severity of COPD in people is also affected by the context, exhibiting a relationship between environmental factors and diseases [37]. In this sense, the dependence on environmental factors causes that the comfort of people suffering from COPD might be at stake. Thus, their comfort level is translated into a quality of life measure that may be tuned with personalized COPD rehabilitation exercises. For instance, in [37], we find a system that combines the analysis of retrospective data with a recommender system that adapts the therapeutic outdoor activities to the patient profile and the real-time environmental conditions (*cf.,* Fig. 3a).

Modern healthcare systems foster outpatient therapies, in which the patient is encouraged to take a relevant, participatory role. However, in some cases this role cannot be fully played due to the patients' impairments of fundamental capabilities, which generally increase with age. The unavoidable fact of aging causes the appearance of elderly-related diseases, especially those related to mild cognitive impairments and dementia, which deteriorate cognitive capabilities, and lead to behavioral disorders. Such disorders might drive individuals to disorientation episodes related to wandering, a syndrome of dementia-related locomotion behavior having a frequent, repetitive, temporally-disordered and/or spatially-disoriented nature that is manifested in lapping, random and/or pacing patterns [38]. Since wandering episodes may appear suddenly, relatives and caregivers should pay more attention to the



(a) SmartCOPD (b) SIMPATIC (c) SmartRoute

Fig. 3. Examples of smart healthcare applications.

wanderer's lifestyle. Therefore, in order to ensure the security of wanderers and benefit the quality of life of these people, an early detection of wandering episodes is a must. Some techniques represent wanderer's trajectories as graphs and demonstrate correlations between graph-related features (*e.g.,* length of cycles, direction changes…) and the appearance of wandering behavior [39][40]. To address wandering detection, intelligent systems monitor in real-time the location of wanderers, analyze trajectories, and seek for abnormal patterns. As an example of this kind of applications, we find the SIMPATIC app [41], which proposes an autonomous system (*c.f.,* Fig. 3b) that faces this problem, and included an interesting social perspective involving caregivers, who receive alarms generated by the system upon certain abnormal circumstances.

Although chronic patients are more vulnerable to environmental factors, an active lifestyle should be promoted among the entire population. Many citizens perform physical activities in the city, namely walking, jogging, running, bicycling, etc. Therefore, it would be desirable to count with systems that dynamically adapt to their needs and tastes, promoting healthy habits and fostering smart healthcare. In [42], the authors propose the idea of using recommender systems integrated with the sensing infrastructure of smart cities to provide citizens with routes recommendations that take into account their health conditions and preferences. In addition, the recommendations are adapted in real-time to environmental changes. Moreover, the authors develop and test a mobile application, namely SmartRoute (*c.f.,* Fig. 3c). The application uses real data provided by the sensing infrastructure of smart cities and crowdsourcing-based information provided by citizens [43].

Smart healthcare applications are the icing on the cake, this is, the final embodiment of solutions to problems solved in multiple steps from the data gathering until the final acquisition of knowledge and its application in practice.

VI. Conclusions

Gathering huge amounts of medical data poses difficulties that are progressively begin overcome. However, transforming those data into actionable knowledge and wisdom requires the collaboration of researchers from a variety of fields that, in most cases, do not interact. In this article, we have provided an overview of the main challenges and research lines that will be addressed by the smart healthcare research community in the years to come. Our goal is to provide a big picture of the field that the article does not aim at being comprehensive (this would be impossible in such a short article) but, on the contrary, tries to leave space for additions. We have organized our discussion of topics according to the data life-cycle: from the gathering of data to the final application of the acquired knowledge. This way, researchers can focus on the area that interest them most while, at the same time, they bear in mind a global picture of this wide field of knowledge.

Clearly, it is impossible to consider every research aspect of smart healthcare. Hence, we must skip important topics that, albeit important, are generally more well-known and have been studied deeply for some years now, namely security and privacy [44], ethics, coaching, biomarkers, genetics and personalized medicine, robotic-enhanced environments, human-computer interaction, an so on. Choosing the fields to skip and the ones to include in the article has been a tough task that is necessarily biased towards our knowledge. However, we have tried to emphasize and include those areas that, to the best of our knowledge, will shape the smart healthcare field in the near future and, by doing so, we hope to open constructive, invigorating and challenging discussions.

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