Exploring the Notion of Context in Medical Data

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Abstract Scientific and technological knowledge and skills are becoming crucial for most data analysis activities. Two rather distinct, but at the same time collaborating, domains are the ones of computer science and medicine; the former offers significant aid towards a more efficient understanding of the latter's research trends. Still, the process of meaningfully analyzing and understanding medical information and data is a tedious one, bound to several challenges. One of them is the efficient utilization of contextual information in the process leading to optimized, context-aware data analysis results. Nowadays, researchers are provided with tools and opportunities to analytically study medical data, but at the same time significant and rather complex computational challenges are yet to be tackled, among others due to the humanistic nature and increased rate of new content and information production imposed by related hardware and applications. So, the ultimate goal of this position paper is to provide interested parties an overview of major contextual information types to be identified within the medical data processing framework.

Keywords Context • Metadata • Medical data analysis • Knowledge management

1 Introduction

Computer science and health care are two domains of great interest over the recent years. The two diverse—at first glance—disciplines have merged and researchers have been devising algorithms that search useful new patterns in data produced by medical equipment and used in medical trainings and exams. In this process it is rather true that researchers look for clinically useful correlations in the middle of huge piles of information. At the intersection of medicine and computer science, the notion of context plays a crucial role in disambiguating complex data and clarifying underlying trends. Still, the capacity of contextual information to take

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multiple meanings is widely acknowledged, thus hindering the adoption of a single unyielding definition that covers its usage within most medical data processing efforts.

Under the broader scope of computer science, interest in contextual information is of great importance in relevant fields like artificial intelligence, information search and retrieval, as well as medical image and video analysis [1–3]. Still, effective use of available contextual information within such structures remains an open and challenging problem. After almost 50 years of informatics it is rather common knowledge that information does not occur in isolation. In particular, when dealing with human-produced or consumed information, a broader environment needs to be taken into consideration, namely the so-called *context* [4]. The notion of context is generally of great importance in the identification of the semantic meaning of data, thus by definition plays a crucial role in the medical domain. Within the latter, context is considered to be pivotal for correct diagnosis, accurate prognosis, and appropriate treatment.

In principle, contextual information may be considered as any information about the situation, circumstances and user state when a user is either producing or consuming digital content items [4, 5]. In this framework, medical data are fundamentally context-dependent, and cannot be properly interpreted outside of their specific contexts [5]. Therefore their analysis based on data mining techniques must incorporate contextual information in the process. In an early effort to identify the information needs in clinical settings, Forsythe et al. [6] conducted a related study. Still, the highly contextual nature of medical information is apparent in tasks like data mining of electronic patient records [7]. The vast amount of patients' data collected for screening, diagnosis and evaluation of treatment may and need to be viewed as resources to be exploited in related data mining tasks, as it contains valuable data and metadata. Aiming at extracting interesting information from large collections of data, data mining has been widely used as an effective decision making tool. Mining medical data datasets in the presence of context factors may improve performance and efficacy of data mining by identifying underlying unknown factors that are not easily detectable in the process of generating an expected outcome. Still, context itself appears in various forms and modifications and is not a single and uniform notion. Thus, researchers commonly emphasize distinctions between different types of context. In this paper we shall provide an overview on the definition of the basic aspects of context exploited within the medical data processing systems and applications.

The structure of the rest of this paper is as follows: in Sect. 2 we explain in more detail the motivation behind investigating context in the medical field. In Sect. 3 we provide a brief overview of an identifiable distinction of context in the medical domain, whereas Sect. 4 is devoted to context in medical data processing and related contextual approaches within the medical data analysis field. Section 5 deals with context-aware medical applications and Sect. 6 tackles briefly approaches from the electronic patient and health records domain. Section 7 discusses the utilization of context within intelligent hospital applications, whereas Sect. 8 concludes this work by briefly introducing our final comments on the topic.

2 The Motivating Perception of Context

A fundamental problem tackled via access to and processing of contextual information is the bridging of two fundamental gaps in the literature; the *semantic* and *sensory gap* [8]. The *semantic gap*, an issue inherent in most computerized applications, is described as the gap between high-level semantic descriptions humans ascribe to digital content like medical images and low-level features computers may automatically parse. The *sensory gap* is described as the gap between an object and the computer's ability to sense and describe this object. At this point computational systems may indeed be able to bridge both gaps under conditions, but only if incorporating contextual knowledge in the process. With the advent of all kind of new medical devices, applications and systems, new opportunities arise to infer the necessary related semantics, whereas contextual metadata are capable of playing the important role of the "semantic mediator". Information from low-level sources, such as sensors, acquired in mass quantities without any further interpretation, may be meaningless, trivial, vulnerable to small changes, or uncertain, after all [9]. As a side-effect, limitation of low-level contextual cues when modeling human interactions and behavior, risks reducing the usefulness of context-aware medical applications. On top of that and as observed early enough by Schilit et al. [10], context is considered to encompass a rich set of information, because other related things of interest are also changing at the same time or pace.

As an additional motivation to this work, it is rather common knowledge that context itself appears in various forms and modifications. Even semantically the term *context* does not have a unique definition resulting sometimes in ambiguous interpretations. The Merriam-Webster online dictionary[1] defines context as "the situation in which something happens: the group of conditions that exist where and when something happens" or "the interrelated conditions in which something exists or occurs". The Free On-line Dictionary of Computing[2] defines context as the thing that "surrounds and gives meaning to something else". Consequently, the term may be used under various different meanings. In a previous work [11] we have identified context as any information that might be used to specify the situation of an entity; the latter being a person, a place or an object that is relevant to the interaction between the user and the software system. In the medical framework this identification has to be adjusted accordingly, to tackle the nature of medical data that focus heavily on the temporal aspect of information (especially with respect to electronic medical records and biomedical information systems).

[1] http://www.merriam-webster.com/dictionary/context.

[2] http://foldoc.org/context.

3 A Distinction of Context in the Medical Domain

According to the so far discussion the type of knowledge required for medical data analysis is by definition thought to be context-sensitive. Consequently, to define and identify the appropriate type of context to be utilized in the process is a very important and complicated task. It is rather tempting to follow a breakdown approach whose initial task would be the definition of the suitable aspect of context at hand. As already introduced in our previous work in the multimedia domain [12], we may identify two relevant types of context in medical data analysis:

a. the *context of medical content analysis*, and
b. the *context of use*.

The first type, i.e., the *context of medical content analysis*, refers to the context exploited during preparatory medical content analysis tasks and aids the extraction of semantic metadata. These may take the form of plain low-level semantic concepts (such as the name of a patient), or composite ones (such as medical events like an ischemic stroke and/or high-level concepts like the patient herself/himself). The latter forms clearly a composite concept, since its instances are related to instances of basic nature, like name, age, or gender. In the particular framework of medical image analysis such interpretation maybe used to detect whether a picture or video sequence represents a tumor or not; an obviously crucial decision with respect to many applications.

When low-level visual features are employed to globally analyze medical multimedia content and classify it in one of a number of pre-defined categories, e.g., within a cancer staging system, we have the so-called "top-down" case of classification. Quite on the contrary, the "bottom-up" approach that focuses on local analysis to detect and recognize specific objects in limited regions of an image, without explicit knowledge of the surrounding context, e.g., recognize the presence of a growing tumor, characterizes the task of object detection/recognition. Classical attempts worth mentioning in the area include Saber et al. [13], where low-level color classification is utilized and Smith and Li [14] dealing with the context of content-based image retrieval. Still and as depicted in [15], utilizing context orientation information in generic object class detection algorithms should in principle be avoided, due to the fact that such contextual information is not always present especially in the case of medical images.

On the other hand, the *context of use* is focused on collecting and analyzing detailed information about a computational system's intended users, their tasks, as well as the technical and environmental constraints present. In the medical domain such data may be gathered using personalized interviews, site surveys, observational studies, etc. Its main goals are to ensure that all factors relating to the use of a medical application or system are identified before its design work starts and to provide a basis for future usability tests [16]. As a result all information about context of use is an essential input to the problem definition, goals, requirements, conceptual and detailed design, as well as the planning of other usability methods to follow and is heavily exploited by search/retrieval and personalization applications [17].

4 Context in Medical Data Processing

In an effort to merge the two worlds of computer science and medicine a categorization of health-care related context-aware applications according to subjective criteria has been tried out almost a decade ago [3]. Among the first data-oriented approaches we may identify the context modeling survey of Bolchini et al. [18] or the classic work of Dojat and Pachet [19] defining an object-oriented context model in the medical domain. In this early pioneer work, authors described two types of contextual information, the so-called *situational* and *set-of-beliefs*. The situational context provided three aspects, namely the patient one (in terms of her/his patient's history, the type of patient's disorder and patient's response to treatment), the temporal one (in terms of the course of the patient's disorder), and the clinical one (in terms of specific clinical guidelines, expertise, and experience). The second context type provided a set of underlying assumptions made by the clinicians, e.g., excluding a specific disorder based on the absence of specific symptoms. Other early research efforts in the area include a fuzzy-based system to combine objective biomechanical data with subjective medical data [20].

In [5], authors focus on five contextual dimensions, namely goal orientation, interdependency of data, time sensitivity, source validity, and absent value semantics. They demonstrate context-dependent modeling based on examples of clinical data used for screening, diagnosis, and research of a serious respiratory disorder. Furthermore, they present a conceptual framework for representation of related contextual information. Transforming unstructured data into a readily accessible format enables many different uses for contextual information, whereas defining those use cases is critical to identifying appropriate text analytics tools [21]. In a recent study, Massey et al. [22] addressed the text analytics challenge of medical reports in a rule-based approach. Table 1 provides a detailed overview of the discussed context research efforts by categorizing them according to their task incorporated, illustrates their advantages and disadvantages and reasons on their suitability within the broader research field.

5 Context-Aware Medical Applications

As expected, the majority of computational health-care initiatives focus on the application domain. This remark coupled together with the fact that one of the major domains in which context currently receives growing attention is the one of mobile

Table 1 Context in medical data processing

Work	Task(s)	Description	Pros	Cons	Dataset
[3]	Context-aware categorization, trends	Survey, overview	Pioneer work	Outdated (2007)	–
[18]	Data-oriented context modeling, features	Data-oriented survey	Evaluation framework, comparison	Outdated (2007)	–
[19]	Medical context representation	Object-oriented context model	Pioneer study, definition of situational & set-of-beliefs context	Outdated (1995)	–
[20]	Contextual interpretation of biomechanical data	Fuzzy-based system	Real-life dataset, mathematical notation	Outdated (2006)	96 fuzzy trees, 1330 rules
[5]	Medical context modeling	Five contextual dimensions, fuzzy approach	Conceptual context framework	Robustness of conceptual model	Several real-life datasets
[21]	Contextual organization of medical data	Text analytics and data management integration	Recent work (2015)	Lack of evaluation	–
[22]	Medical reports text analytics	Rule-based approach	Applied approach (utilizing commercial software), visualization	Evaluation size and comparison	Pathology reports

computing, leads to interesting observations in the medical domain. But, first, let us understand the impact of aforementioned tasks and position context-aware medical applications in this framework. In principle, mobile computing involves two pylons, namely computing and mobility. In computer applications, and as depicted early enough in [23], context is acquired either explicitly by requiring the user to specify it, or implicitly by monitoring user and computer-based activity. In mobile computing on the other hand, application usage is set in different environments at different times, constituting changing contexts that lie outside the human-computer system in the environment. For acquisition of this kind of context there are two possible options:

a. to prepare a so-called "smart environment", which provides an infrastructure for obtaining context and for providing context to mobile applications.
b. to embed sensors in mobile devices to acquire context related to the physical environment.

The second option does not rely on the underlying infrastructure and is applicable to almost any type of environment. Still, a primary concern of context-awareness in mobile computing is awareness of the physical environment surrounding a user and their mobile device; early adopters go back to [24] by sensing locality of mobile users to adapt applications to people's whereabouts. In this framework only few early efforts considered context beyond location and among these are context-aware information capture and retrieval systems that use time in addition to location [25].

In principle, context awareness refers to the ability of systems to react based on their environment. Devices and computer systems may have information about the circumstances under which they are able to operate and based on rules, or an intelligent stimulus, react accordingly. A good overview of the issues in the context-awareness domain may be found in context-awareness computing surveys, like the ones conducted by Chen and Kotz [26] and Korkeaaho [27]; in addition, most of the general papers on context-awareness indicate health care as an important and promising field of research. Thus, several research and applied approaches attracted interest, such as the Vocera communication system [28], which forms a communicator badge system for mobile users. It is a wearable badge with a push-to-call button, a small text screen and versatile voice-dialing capabilities based on speech recognition, whereas it is biometrically secured with speaker verification and delivers information directly to the users. In a different approach, Munoz et al. [29], tackle the idea of empowering mobile devices to recognize the context in which hospital workers perform their tasks. In particular the authors propose an extension of instant messaging to add context awareness as part of the message. Contextual elements used include location, delivery timing, role reliance, artifacts, location and state.

A context-aware data mining framework is proposed in [30], by which contexts are automatically captured to maximize the adaptive capacity of data mining. In this process contextual information may consist of any circumstantial factors of the user and domain that may affect the data mining process. A platform for performing proper medical content adaptation based on context-awareness is also introduced in [31]. Proper coding and transmission of medical and physiological data is coupled together with sensors used to determine the status of a patient being monitored through a medical network. Additional contextual information regarding the patient's environment (e.g., location, data transmission device and underlying network conditions, etc.) are represented through an ontological knowledge base model. A similar model is followed in [32], where context is captured using an ontology formally modeling the concepts within the health-care domain, together with their relations and properties. More specifically, the authors introduce a self-learning, probabilistic, ontology-based framework, which allows context-aware applications to adapt their behavior at run-time. In [33] the authors present an image search system that allows search by a multitude of image features, metadata (demographics, patient's medical history, clinical data) and context in the form of an ontology towards efficient dementia diagnosis.

In search of applications and systems that would aid the improvement of people's quality of life, a new trend is the utilization of users' biological signals via wearable and even implantable wireless sensors that implement context-aware solutions, so as to adapt to changes in the users' mood, mental states, biological signals and environment. A recent survey on the issue is proposed by [34] and presents an overview of context-aware solutions wrt body area networks. In a similar but more specific sense, Miao et al. [35] propose a wearable, low power context-aware ECG monitoring system integrated with built-in kinetic sensors utilizing a smartphones' processing capabilities, in order to recognize physical activity and automatically detect arrhythmias. Mitchell [36] describes the rapidly expanding capabilities of modern smartphones that enable the creation of new classes of health- and wellness-related applications by utilizing data collected from on-board sensors, web services, social media and external biosensors and combined contextual information in the sense of the context of the device, user, and environment.

On another approach, RecFit [37] takes into account contextual information and suggests physical activities to users based on the users' environmental and behavioral context (e.g., their risk tolerance, their budget, their location, or even the surrounding weather). The latter forms a rather novel approach in the sense that it augments activities with metadata of ideal performance context (namely: popularity, sociability, risk, location, expense, time, and weather).

Trying to combine two distinct trends, i.e., the Internet of Things [38] interrelated computing devices world and the computationally rich health-care sector, [39] introduce a new concept of smart health, which according to the authors forms a context-aware complement of mobile health within smart cities and provide an overview of the main fields of knowledge that are involved in the process of building this new concept. In addition, Doukas et al. [40] investigate the potential of Future Internet-based architectures for enabling context-aware content adaptation and specialized delivery of health-related information in assistive environments. Focusing on the concept of medical cyber-physical systems that enable automatic medical device coordination for patient protection, Lia et al. [41] propose to utilize contextual information to improve them and tackle their limited capabilities detecting human errors that result into late device coordination in the case patients have already developed adverse physiological reactions. Finally, following Table 2 presents the herein discussed context-aware medical applications according to their type and illustrates each one's main features.

6 Electronic Patient and Health Records

Electronic patient records (EPR) are considered to be the electronic upgraded version of traditional paper-based patient records [42]. They typically contain a patient's medical history, including her/his diagnoses, medications, immunizations, family medical history, etc., as well as her/his contact information. In the biomedical sub-domain, the rapid adoption of such electronic patient and health records with the parallel growth of narrative data in electronic form, along with the needs for

Table 2 Context-aware wireless medical applications

Work	Task(s)	Description	Pros	Cons	Dataset
[23]	Context definition	Wide notion of context, context modeling	PDA prototypes, sensor-related study	No strict medical impact	–
[24]	Context-awareness definition	Indoor context-aware applications	Novel sensor system	No strict medical utilization/impact	–
[25]	Context in wearable computers	4 contextual capabilities, Contextual Information Service	Prototype application	No medical application	–
[26]	Context-awareness computing survey	Analysis of types and models of context	Detailed literature analysis, point of reference	Outdated (2000), no medical focus	–
[27]	Context-awareness computing survey	Focus on temporal and spatial context	Detailed literature analysis, point of reference	Outdated (2000), no medical focus	–
[28]	Mobile pervasive computing	Health care wearable context-aware application	Pioneer mobile real-life application	Outdated (2003)	–
[29]	Context-aware mobile communication in hospitals	Context-aware mobile system	Mobile device context exploitation	Outdated (2003)	–
[30]	Context-aware data mining framework	Application model	Use context to maximize data mining's adaptive capacity	Outdated (2003)	Public medical datasets
[31]	Medical content adaptation, semantics	Platform, ontological framework	Semantics utilization, sensors, ontological framework, SWRL rules	No evaluation	–
[32]	Context modeling	Self-learning, probabilistic, ontology-based framework	Ontology-based context model, rule-based context-aware algorithms	–	5 data values, +1000 instances SIRS dataset

(continued)

Table 2 (continued)

Work	Task(s)	Description	Pros	Cons	Dataset
[33]	Dementia diagnosis	Image search based on ontologies and contextual information	Context-aware medical image retrieval	Focused on dementia	Real-life imaging data
[34]	Context-aware applications in wireless body area networks	Survey study	Network-oriented approach	Medical and non-medical focus	–
[35]	ECG monitoring system	Wearable context-aware ECG monitoring system	Smartphone sensors exploitation, integrated approach	–	1697, 2320 & 2006 physical activities samples (rest, walking, running, respectively)
[36]	Smartphone-related medical applications	Context and bio-aware mobile applications	Implementation	Weak evaluation	Biosensors, web services, social media, 3 devices
[37]	Physical activity recom-mendation	Environmental and behavioral context, smartphone application	Smartphone application prototype	Limited dataset	137 physical activities database
[39]	Intelligent smart cities/health-care	Smart-health concept	Combination model of Internet of Things and health-care	No evaluation	–
[40]	Cognitive and context-aware assistive environments	Context-aware content adaptation & information delivery	Future Internet technologies utilization	Qualitative evaluation only	–
[41]	Medical cyber-physical systems	Contextual information utilization	Contextual information utilization, prototype system	No real-life evaluation	Emulated dataset

improved quality of care and reduced medical errors are both strong incentives for the development of computational intelligent systems [43]. The huge potential for medical research is also depicted in [44], where authors propose a dynamic consent model based on contextual information such as time and metadata, although they ultimately focus on the social means to maintain public trust. Temporal data mining and exploitation of contextual information is also utilized in [45]. Authors claim that the developed method can be used to extract dose-dependent adverse drug reactions information from already collected EPR data. Taking this a step further, mining of electronic health records has the potential for establishing new patient-stratification principles and for revealing unknown disease correlation as depicted in [46].

In general several methods have been employed in the biomedical literature to extract facts from free text and fill out template slots. For instance, McNaught et al. [47] describe a detailed review of information extraction techniques in the biomedical domain; however, their review does not include the clinical field. In [48] the author studies the ways contextual information in the form of linguistic ethnography may enhance the understanding of EPRs in health care settings. Another approach is pattern-matching, which exploits basic patterns over a variety of contextual information structures, like text strings, tags, semantic pairs, and even dictionary entries [49]. Its main disadvantage is its lack of generalization ability, which limits their extension and adaptation to new domain features. Last but not least, even knowledge-based approaches have been incorporated in the task, by introducing ontology-driven information extraction in order to guide free-text processing [50]. A summary of the aforementioned studies is provided in the following Table 3.

7 Intelligent Hospital Applications

Considering this rather standalone health-care sector, there are also several standalone intelligent hospital applications worth mentioning herein. Being an ongoing implementation field, there are currently a variety of software solutions, platforms and systems enabling smart health-care activities and assisting health-care providers diagnosing and deciding the correct course of actions. In this manner a context-aware prototype is proposed in [51], which includes a context-aware hospital bed with a built-in display that may be used by both patients (e.g., for entertainment) and clinicians (e.g., for accessing medical data). Furthermore, the bed is able to identify the nurse, the patient and the medicine tray, and displays relevant information according to this context, such as a medicine schema or patient record. In another work following a study of the needs of the Royal London Hospital, authors in [52] proposed a variety of usage scenarios (i.e., remote consultation, tracking of patients and equipment, notification of awareness and patient data) and have implemented an experimental prototype. In MobileWARD [53] a prototype is introduced to support morning procedure tasks in a hospital ward; the prototype is able to efficiently display patients lists and information.

Effective critical care administration is a very important aspect in health-care. Having the ultimate goal to improve communication capabilities in hospitals, diverse communication mechanisms are also proposed in the literature and some of them do realize the importance of context in the process, like the one introduced in [54], where authors propose a flexible, automated and asynchronous context-aware medical instant message middleware that supports message dispatching based

Table 3 Electronic patient and health records

Work	Task(s)	Description	Pros	Cons	Dataset
[42]	Electronic patient records definition	Electronic patient records definition	Robust term definition	No context exploitation	–
[43]	Electronic health record information extraction	Survey study	Review of electronic health records info extraction techniques	Outdated (2008)	–
[44]	Electronic patient records management	Dynamic consent model based on contextual information	Utilized dynamic consent model	Focus solely on patient trust issues	–
[45]	Temporal data mining of EPRs	Temporal data mining, exploitation of contextual information	Real-life evaluation, novel methodology	Focus solely on limited medical sub-domain	3394 & 43,528 patients datasets
[46]	Electronic health records mining	Overview of related techniques	High-level approach	Weak evaluation	–
[47]	Biomedical information extraction	Review study	Detailed review, in-depth analysis	No clinical field discussion, weak context	–
[48]	EPRs understanding	Context utilization in the form of linguistic information	Detailed analysis and investigation of contextual aspects	Weak evaluation	Real-life dataset
[49]	Contextual information pattern-matching	Contextual data mining for clinical texts	Integrated system architecture	Lack of generalization ability, small dataset	351 documents, 4 topics
[50]	Text mining from biomedical reports	NLP-based knowledge-based approach	Ontology-driven information extraction	Knowledge scalability issues	5000 entries, 4000 concepts and roles, 4973 documents

on context information, so as to improve in-hospital communications. A prototype of this contextual messaging communication system has been implemented in a real clinical setting for evaluation purposes. In an effort to apply context-aware computing using service-oriented architecture in acquiring, analyzing and assisting hospital personnel with necessary information for time-saving decision making, [55] presents an implementation of a set of web services that can be consumed during an intensive care unit (ICU) treatment within a hospital use case scenario. Finally, in [56] a tablet-based system prototype is proposed focused on ICU based workflows that allows for ubiquitous patient monitoring and smart alert generation. Interestingly enough the aforementioned prototype is supported by open source software and hardware platforms. To the reader's convenience following Table 4 provides a brief summary and categorization of the aforementioned research works.

8 Conclusion and Future Work

As discussed herein researchers from the fields of computer science and health-care have developed different approaches to address the medical data processing and related analytics challenges. In this position paper we attempted to summarize briefly the ones that presented and discussed several types of contextual information; the latter being suitable for utilization, exploitation and usage within the medical data framework. Thus, we identified four distinct expressions of such context, namely context in medical data analysis, the domain of context-aware applications, contextual support to electronic patient and health records analysis, as well as context exploitation within intelligent hospital applications. We observed and analyzed why such contextual information may be extremely helpful in computational tasks relating to health-care activities, especially with respect to handling related

Table 4 Intelligent hospital applications

Work	Task(s)	Description	Pros	Cons
[51]	Context-aware hospital bed	Context-aware prototype	Functionalities, variety of users	Installation costs
[52]	Context aware application middleware	Context-aware experimental hospital prototype	Context-sensitive communications, integrated platform	Evaluation
[53]	Intelligent hospital support	Mobile context-aware electronic patient record prototype	Integrated system	Weak real-life evaluation (3 subjects)
[54]	Hospital middleware	Context-aware medical instant messaging middleware	Improved in-hospital communications, prototype real-life evaluation	–
[55]	Hospital decision making	Service-oriented architecture, context-aware computing	Context-aware ICU web-services	Evaluation aspects
[56]	ICU workflow optimization	Tablet-based system prototype	Ubiquitous patient monitoring, open source SW	–

information search, retrieval and utilization problems. The main conclusion of this survey is the fact that context plays a significant role in disambiguating medical data and may be extremely helpful when processing them in the framework of EPRs and/or medical applications.

Based on the aforementioned discussion and interpretation of each analyzed context group, we hope that future useful research directions may be identified by interested fellow researchers. According to the herein presented works tackling a variety of context variations, we may identify a clear effort towards the bridging of the semantics and sensory gaps dominating both computer science and medicine. As a future plan, we intend to extend this survey work towards including a review of additional health-care domains not tackled herein, like for instance health-care big data analytics.

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