J Med Syst (2015) 39: 185
DOI 10.1007/s10916-015-0344-x

MOBILE SYSTEMS

A Semantic Big Data Platform for Integrating Heterogeneous Wearable Data in Healthcare

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Received: 21 November 2014 / Accepted: 7 September 2015 / Published online: 21 October 2015

Abstract Advances supported by emerging wearable technologies in healthcare promise patients a provision of high quality of care. Wearable computing systems represent one of the most thrust areas used to transform traditional healthcare systems into active systems able to continuously monitor and control the patients' health in order to manage their care at an early stage. However, their proliferation creates challenges related to data management and integration. The diversity and variety of wearable data related to healthcare, their huge volume and their distribution make data processing and analytics more difficult. In this paper, we propose a generic semantic big data architecture based on the "Knowledge as a Service" approach to cope with heterogeneity and scalability challenges. Our main contribution focuses on enriching the NIST Big Data model with semantics in order to smartly understand the collected data, and generate more accurate and valuable information by correlating scattered medical data stemming from multiple wearable devices or/and from other distributed data sources. We have implemented and evaluated a *Wearable KaaS* platform to smartly manage heterogeneous data coming from wearable devices in order to assist the physicians in supervising the patient health evolution and keep the patient up-to-date about his/her status.

Keywords Healthcare · Wearable computing · Heterogeneity · Big data · Data integration · Scalability

Introduction

With the development of information and communication technologies (ICTs), wearable computing has the potential to revolutionize the healthcare sector by reducing the physical interaction barriers with patients [1]. "Wearable" corresponds to the use of a miniature, body-borne computer or sensory device worn within clothing and accessories [2]. These devices aim at improving the healthcare outcomes by changing the way medical data is collected, and accelerating this process by remotely reading data. The development of wearable computing in healthcare witnesses an important increase. ABI Research [3] estimates that the global market for wearable devices in health and fitness could reach 169.5 million devices by 2017. These devices are conceived not only to monitor patients' daily activities and fitness by using for instance Nike+iPod Sport Kit [4] and BikeNet [5], but also to detect sleep patterns and emotions [6], and to measure patients' vital signs [7] such as blood pressure, glucose level, heart rate, etc.

Many applications [8–12] have been developed based on wearable data to detect and predict patient health anomalies, to study the human behavior, and to manage therapy. However, these solutions are related to well-defined data structures; and they are not scalable enough to support the integration of new devices. Wearable data comes from multiple sources and arrives with multiple formats depending on the manufacturer, and on the algorithms used to encode the transmitted data. Embedding new wearable technologies into existing healthcare systems requires developing its proper monitoring application, which is challenging due to the rapid growth of the wearable market. Data heterogeneity is still an open

This article is part of the Topical Collection on *Mobile Systems*

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challenge that needs to be addressed to leverage from available data and provide accurate analytics. According to the International Data Corporation (IDC) [13], in 2013 less than 5 % of information was analyzed because very little was known about the data. Thus, a semantic enrichment of data coming from embedded systems will bridge this gap. Moreover, the plethora of wearable adoption in healthcare accentuates the big data paradigm [14], not only through the huge volume of data, but also through its diversity and the speed at which it must be managed. Traditional data mining algorithms are not able to cope with both the scale and the heterogeneity of wearable data in healthcare [15].

Recent advances in cloud computing and big data respectively provide highly scalable distributed data storage platforms that offer computational resources as services [16]; and novel approaches, methods and techniques that exceed the storage and analysis capability of current or conventional systems [17]. Thus, coupling cloud computing with big data allows the system acquiring the ability to manage large scale data, and increase analytic accuracy and performance capabilities that cloud computing alone does not support [18]. Additionally, the development of Semantic Web technologies offers opportunities to cope with semantic data heterogeneity that hampers big data analytics when converting scattered medical data into valuable information. Based on ontologies [19], which constitute a formal conceptualization of a specific domain, a common vocabulary takes place to explicitly provide the meaning of data and enhance reusability, independent of the type and format of the data.

Consequently, in this paper, we introduce a semantic big data architecture that extends the basic NIST Cloud and Big Data reference architectures with smart mechanisms based on ontology to give meaning to the silos of heterogeneous data. Hence, we propose a Wearable Healthcare Ontology (*WH_Ontology*) that facilitates the aggregation of the distributed heterogeneous data coming from wearables to make better-informed health related decisions and create new valuable information. The objectives of this architecture are: (1) providing a scalable solution for storing the large volume of healthcare data generated by multiple sources, (2) supporting data sharing and integration for better decision making, and (3) extracting valuable information (knowledge) from heterogeneous data.

The remainder of this paper is structured as follows. Section 2 portrays our generic semantic big data architecture. Section 3 details our proposed *WH_Ontology*, which is the foremost element that copes with the heterogeneity of wearable data, and provides a scenario dealing with diabetes to illustrate the added value of the ontology in harmonizing data. Section 4 presents existing works addressing the integration of wearable devices in healthcare systems and compares them with our proposal. Conclusions and future work are presented in Section 5.

Generic semantic big data architecture for data integration

We propose a generic semantic big data architecture adopting the *Knowledge as a Service (KaaS)* approach to deal with data heterogeneity and system scalability challenges. The KaaS was defined, in an earlier work [20], as an extension of the NIST Cloud Computing reference model [21]. It aims at generating new knowledge from heterogeneous data stored in the cloud and makes it available as a service. In this work, the basic KaaS architecture is extended to support big data and semantic data enrichment in order to deal with the volume, variety and velocity of data coming from sources sharing the same context.

Multiple sources generate heterogeneous data that can be stored in relational databases, RDF, NoSQL, etc. or in the KaaS clusters through the implemented application (e.g., wearable application). Transforming these heterogeneous datasets into understandable and sharable knowledge requires services that collect, prepare and process these datasets. To this end, we adopt the NIST Big Data reference architecture [22] defined by the NIST Working Group, where 5 abstract components are identified: data collection, data curation, analytics, visualization and access control. Our contribution relies on extending and enriching the NIST Big Data reference architecture with the Semantic Web (1) to cope with the heterogeneity of data and (2) to transform the result of the analytics into sharable and reusable knowledge.

As depicted in Fig. 1, the proposed architecture is composed of three layers: the *Data Storage Layer* where the large datasets are stored in the cloud, more precisely in the Platform as a Service layer *(PaaS)*; the *Big Data Layer* that includes the NIST Big Data components associated to scalable technologies for data processing; and the *Semantic Knowledge Layer* that offers the common understanding of data. This architecture allows preparing data to be interpreted and reused by computers, and to be easily integrated with external information systems, independent of its structure and its representation.

Each data provider needs to explicitly inform the KaaS about its characteristics (e.g., the kind of data that is generating, its meaning, its storage location, etc.). This is done through the "*Semantic Data Source Annotation*" service that allows providers using a common knowledge representation (based on ontology) that formalizes a domain specific context, as advocate in Fig. 1. Then, data can be collected in real-time, imported from external databases and/or retrieved based on query languages such as SPARQL and SQL (cf. *Data Collection* component in Fig. 1). The collected data is stored in distributed big data clusters deployed in the *Data Storage Layer (PaaS)*.

The next step is to harmonize the collected data to be processed by the domain analytic services. The *Data Curation*

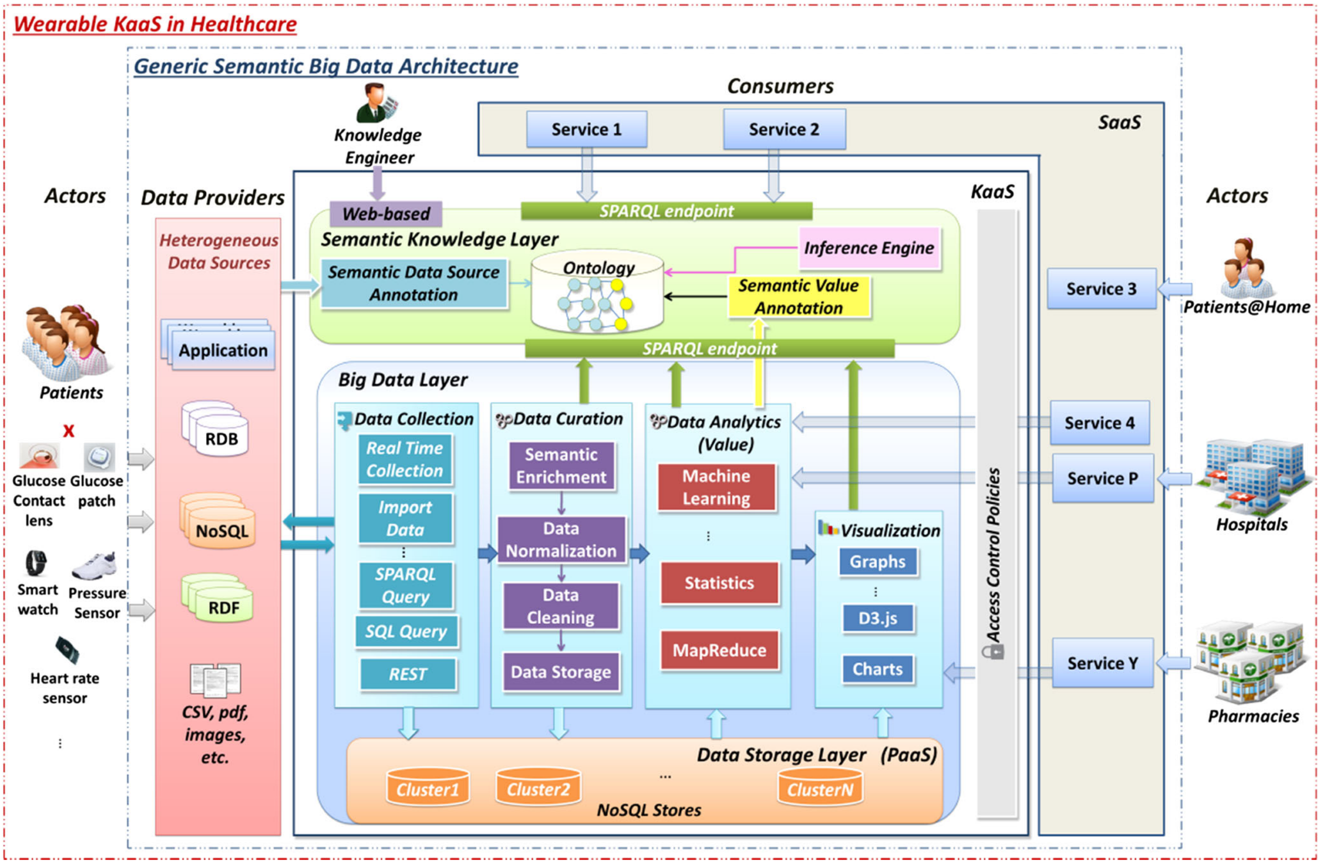

Fig. 1 The generic conceptual semantic big data architecture

component operates over the semantic layer and the distributed storage layer in order to enrich the generated data with context information. It is mainly composed of four services: (i) the semantic enrichment that adds meaning to the data based on the ontology; (ii) the data normalization that unifies the data values related to the same observed parameters; (iii) the data cleaning that plays an important role in improving the quality of data by removing corrupt or inaccurate records such as those resulting from the misbehavior of sensors; and (iv) the data storage that stores the prepared data in big data clusters to be exploited by the analytics and the visualization services.

The analytic services operate over the harmonized datasets to discover new knowledge related to the domain from the available data based on scalable machine learning algorithms, MapReduce jobs and other big data technologies for distributed large datasets processing. It is worth mentioning that the results of the analytic services will be annotated using the "*Semantic Value Annotation*" service, as presented in Fig. 1, in order to be shared and reused by the appropriate consumers. The semantic knowledge is stored in an RDF triple store and queried through SPARQL which is a standard recommended by the W3C. Our KaaS offers also visualization services to graphically represent data and the analytics results in order to facilitate the interpretation of data for domain experts. The access to our KaaS services is based on access control policies.

In the next section, we provide an illustrative scenario in which we instantiate our proposed architecture to manage heterogeneous data generated by wearable devices.

Wearable knowledge as a service in healthcare

In this section, first, we detail the Wearable Healthcare Ontology (*WH_Ontology*). Then, we present a patient-centric prototype which allows monitoring the patient health based on heterogeneous wearable data.

Wearable healthcare ontology

Our proposed *WH_Ontology* is designed to deal with the heterogeneity of wearable data to ensure semantic interoperability and to allow creating more accurate knowledge about the patient such as detecting and/or predicting anomalies. The *WH_Ontology* characterizes the wearable devices and their generated data to provide a smart system for patient care management, independent of the disease. Figure 2 shows the main

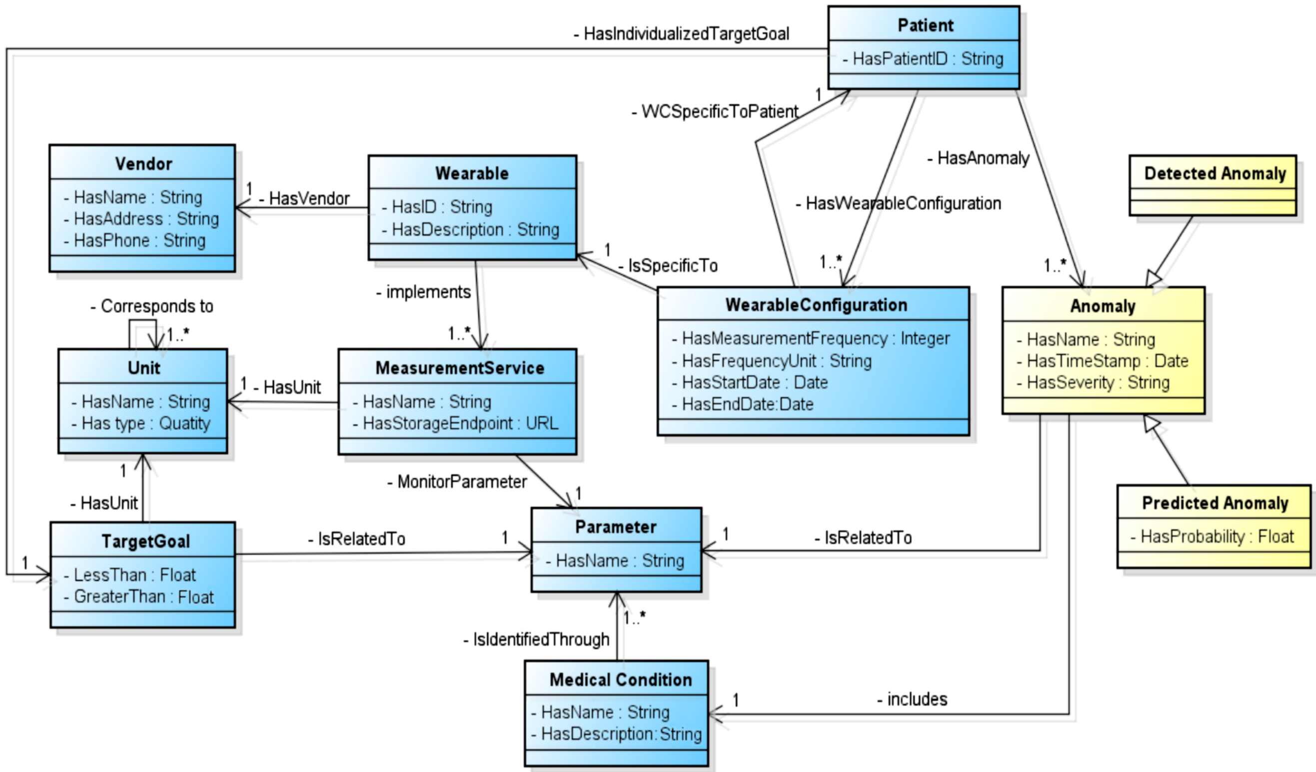

Fig. 2 Depiction of the main classes and relationships of the WH_Ontology

classes of the *WH_Ontology* providing a common representation and sharing the same meaning among the different wearable devices.

The *WH_Ontology* introduces a generic class named "Parameter" that represents the nature of the monitored data. This class is generalized to include sub-classes such as "Glucose", "Blood Pressure", "Heart Rate", "Step", etc. that will be instantiated later. Each medical condition (disease, symptom, etc.) is identified through a set of parameters. For example, the "Hypertension" is associated to monitoring the "Blood Pressure". Semantically characterizing this piece of information will help on discovering and deducing new diseases that may affect the patient. The *WH_Ontology* also characterizes the "Wearable Configuration" class which has a 'StartDate' and 'EndDate', and describes the frequency of measurement (e.g., '1 measurement per day'). Each configuration is specific to only one "Wearable" device which has a reference ID attributed by its "Vendor". Each wearable implements at least one "*MeasurementService*" which is responsible for observing the monitored parameter and expressing the generated value with a specific unit. The monitored data will be stored in distributed datasets identified by their endpoints.

Notice that to provide a personalized management of the patient health, each patient has his/her own parameter goal which depends on the patient medical characteristics and disease stage. This goal, which is fixed by the physician, is the clue for detecting anomalies. By this way, the system supports the specification of personalized anomalies depending on each patient' characteristics and data generated by the wearables without modifying the analytic services. The *WH_Ontology* identifies two main types of anomalies: "Detected Anomaly" such as detecting an "increased glucose level" based on rules, and "Predicted Anomaly" such as predicting "hypertension" based on machine learning algorithms operated over datasets of patient having diabetes (with and without hypertension) [23]. If an anomaly is detected or predicted, it will be automatically populated in the KaaS. According to its severity, notifications will be sent to the appropriate physicians to keep them up-to-date about the patient health evolution and avoid complications by taking preventive and timely interventions.

Wearable KaaS applied to diabetes

Motivated by the rapid growth of people suffering from diabetes [24], and by the complications associated to this disease such as hypertension and obesity [25], we propose to apply our KaaS to integrate the data coming from multiple wearable devices in order to manage the patient health. In this section, we focus on describing the *Semantic Knowledge Layer* of the *Wearable KaaS* platform. From the implementation perspective, we are using Semantic MediaWiki (SMW) [26] with other extensions as a frontend to annotate the wearable devices' characteristics and to visualize the patient profile.

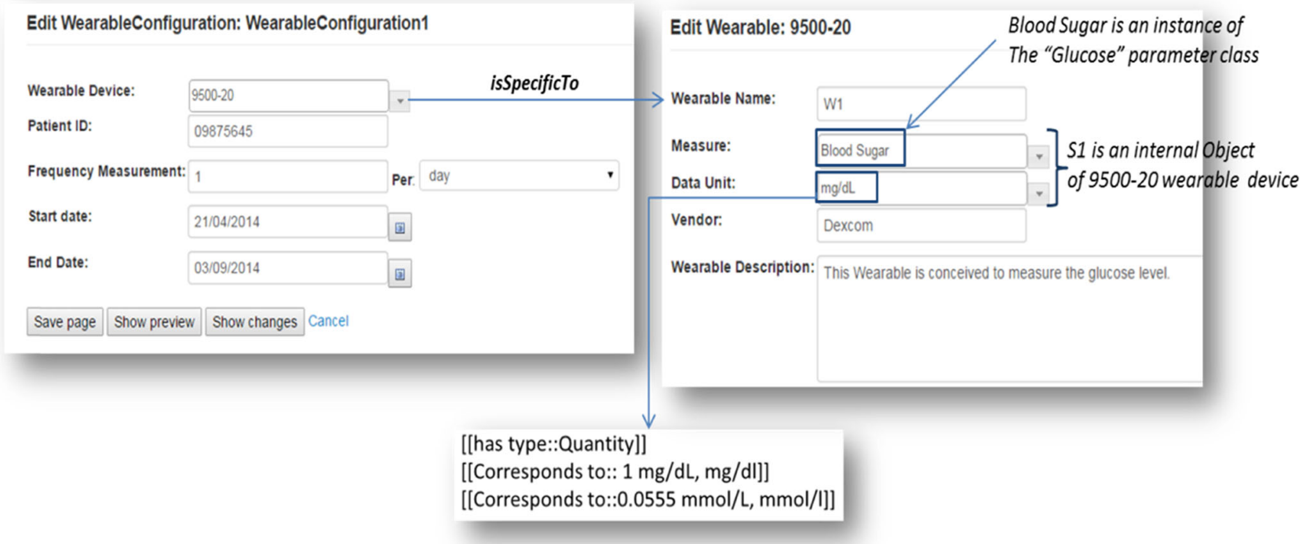

Fig. 3 Excerpt of wearable annotation based on *WH_Ontology*

SMW is an open source Semantic Web technology that enables the collaborative data annotation. We associated SMW with Fuseki,[1] which is an RDF triple store, in order to provide a SPARQL endpoint to retrieve and reuse the semantic knowledge.

In this scenario, we assume that we have two wearable devices (W1 and W2) that monitor the same type of parameter (the "Glucose" class) through two different services S1 and S2, respectively. These services measure data expressed through different units (S1 in "*mg/dL*" and S2 in "*mmol/L*") and using different names of the "Glucose" parameter class (S1 uses "Blood Sugar" and S2 uses "Glucose"). We emulated fake data pertaining to a virtual patient having 09875645 as an ID through implementing S1 and S2. Both wearable devices have been configured to send '*1 measurement per day*'. However, the first one has been used from *21/04/2014* to *03/09/2014* and the second one from *04/09/2014* to *06/11/2014*. All these information are annotated by following the *WH_Ontology*. Other relevant information such as the unit conversion is also characterized to be reused when normalizing data. It is well-known in medicine that "*1 mg/dL*" is equal to "*0.0555 mmol/L*". This later is expressed through the "Corresponds to" property. Figure 3 illustrates an example of annotating the wearable device "W1" in our platform.

When our KaaS is acquiring data from the wearable devices, this data is automatically normalized by referring to the "Corresponds to" property, and stored for further reuse. Visualizing the glucose evolution is an example of services that reuse the prepared data. Thus, the following generic SPARQL query, presented in Fig. 4, is executed to get from the RDF store the list of the wearable devices used by the patient to measure the "Glucose" parameter between *01/05/2014 and 31/10/2014*. Based on the returned wearable IDs, the normalized data during this period are extracted from the clusters and visually represented to display the patient glucose evolution, as shown in Fig. 4.

Related work

Despite the development of standards, interoperability and data integration are still open issues. The work of Kim et al. [27] is an example of research efforts that deal with integrating healthcare standards in order to ensure the interoperability between the HL7 and the IEEE 1451 standards when monitoring the patient data. The heterogeneity of wearable devices impede their integration into existing systems, and require efforts to develop applications from scratch [28]. New approaches based on ontologies have been proposed to deal with this issue. Lasierra et al. [29] proposed an ontology to describe the patient's vital signs and to enable semantic interoperability when monitoring patient data. Following the same direction, Kim et al. [30] proposed an ontology driven interactive healthcare with wearable sensors (OdIH_WS) to acquire context information at real time using ontological methods by integrating external data such as meteorological web site in order to prevent disease. We agree with the authors [29, 30] about using ontology to describe the context and provide a common meaning to the heterogeneous data. However, storing the wearable readings in the ontology has some limitations, since ontologies present scalability limitations when executing rules to detect anomalies if huge quantities of data are stored. Contrary to these works, our platform

[1] Fuseki: http://jena.apache.org/documentation/serving_data/ (last visit, November 10, 2014)

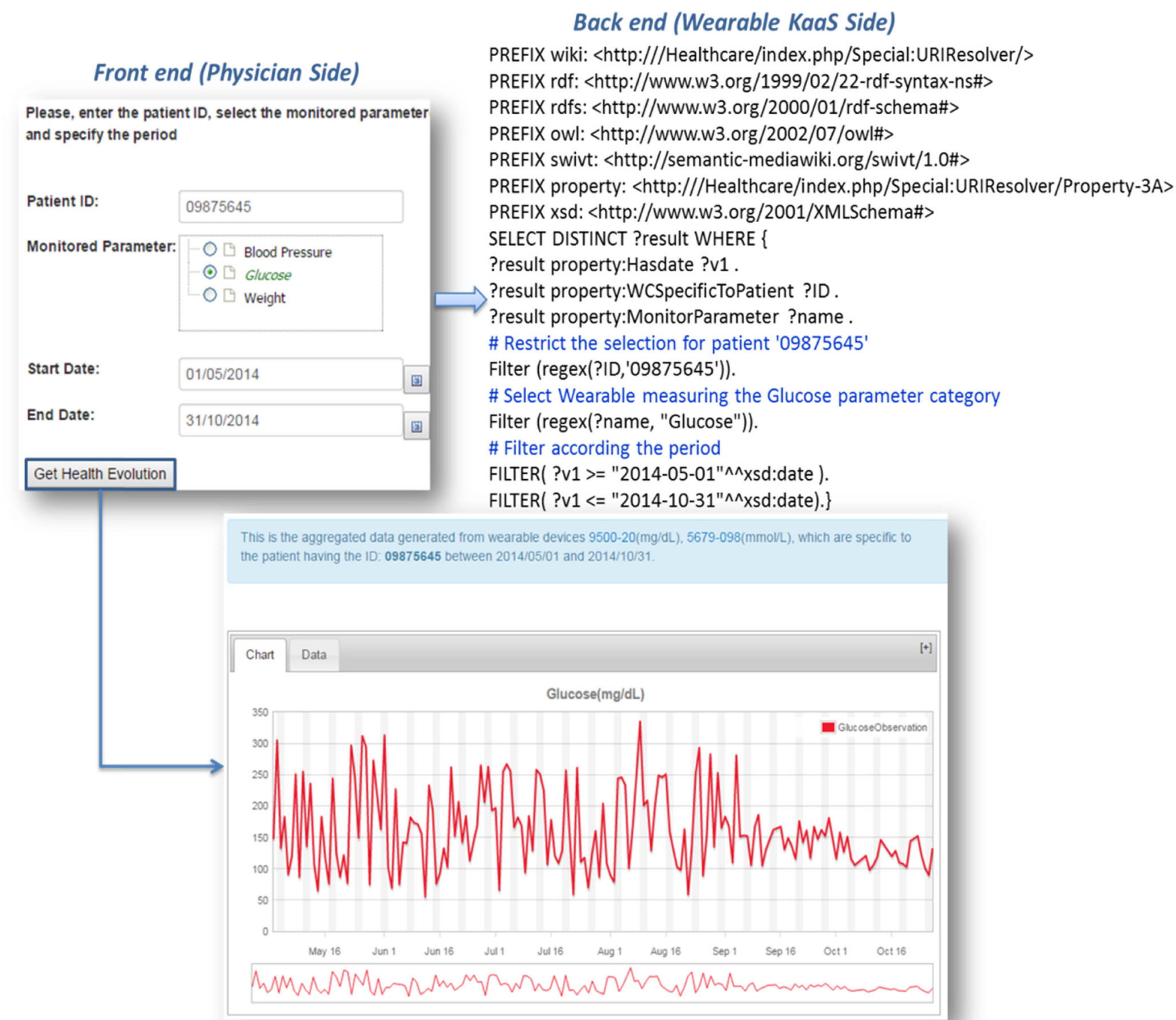

Fig. 4 Visualization of the integrated heterogeneous data measuring the patient Glucose

leverages from cloud computing and big data technologies to store measurements in order to guarantee the system scalability, and uses ontology to tag wearable devices characteristics and data types.

Few researches in this domain concentrate on system scalability from the computational, data storage and reuse point of view. In this context, Forkan et al. [31] proposed a cloud-based context-aware system called CoCaMAAL which covers challenges related to data collection and data processing in ambient assisted living systems. The authors proposed to mitigate the complexity of data computation from sensors to the cloud. They identified an abstract ontology to describe the context including patient information, the environment and devices. Jiang et al. [32] are interested in big data solutions for wearable systems in healthcare. They proposed a wearable sensor system with an intelligent information forwarder that adopts the Hidden Markov Model (HMM) to estimate the hidden wearer's behaviors from sensor readings, and to determine the probability of the patient has a specific health state. Both Forkan et al. [31] and Jiang et al. [32] did not cover the heterogeneity of data units, format, and representation generated by different wearable devices. Contrary to the aforementioned works, our semantic platform integrates and aggregates heterogeneous wearable data stemming from multiple sources by supporting a Cloud and Big Data reference architecture to manage the data volume and velocity, and by identifying the *WH_Ontology* to semantically characterize the wearable devices and services. More importantly, based on the *Semantic Knowledge Layer*, the analytic services and information extraction methods are flexible enough to be reused by different consumers, which is challenging in healthcare monitoring system [15].

Conclusion

Wearable healthcare-related systems are extremely data-intensive and produce huge distributed and heterogeneous datasets. Conventional healthcare systems do not deal with the volume and the heterogeneity of data to bring more accurate analytics. In this paper, we proposed a generic semantic big data architecture that copes with (1) the data heterogeneity through proposing the Wearable Healthcare Ontology, and (2) the scalability via adopting the NIST Big Data reference architecture and storing the wearable data into distributed clusters deployed in a cloud environment. Data processing algorithms are offered as services in the cloud to reduce the computational cost and hide the complexity.

We developed a proof of concept based on semantic web technologies illustrating the ability of our platform to handle the data heterogeneity through a diabetes scenario emulating data coming from heterogeneous wearable devices. The main objective is to share the same semantic of data to ensure a smart interpretation for better decisions. Notwithstanding, the security and privacy remain challenges that need to be considered when transmitting data.

Currently, we are working on the evaluation of the Wearable KaaS scalability using advanced big data technologies such as Hadoop. Our future work will focus on the definition of more elaborated scenarios, and on the implementation of advanced analytics algorithms by collaborating with medical experts.

Acknowledgment This research is entirely funded by the National Research Fund (FNR) of Luxembourg under the AFR project.

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