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Ontology Middleware for Integration of IoT Healthcare Information Systems in EHR Systems

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Abstract: Healthcare sectors have been at the forefront of the adoption and use of IoT technologies for efficient healthcare diagnosis and treatment. Because healthcare IoT sensor technology obtains health-related data from patients, it needs to be integrated with the electronic healthcare records (EHR) system. Most EHR systems have not been designed for integration with IoT technology; they have been designed to be more patient-centric management systems. The use of the IoT in EHR remains a long-term goal. Configuring IoT in EHR can enhance patient healthcare, enabling health providers to monitor their patients outside of the clinic. To assist physicians to access data resources efficiently, a data model that is semantic and flexible is needed to connect EHR data and IoT data that may help to provide true interoperability and integration. This research proposes a semantic middleware that exploits ontology to support the semantic integration and functional collaborations between IoT healthcare Information Systems and EHR systems.

Keywords: IoT; EHR; healthcare IT; ontology; semantic integration; middleware

1. Introduction

Technological advancements are realizing the vision of interconnected objects (things) as smart objects which can sense each other according to the environment and deliver information to a variety of innovative applications and services [1]. These sensing objects constitute the Internet of Things (IoT) that can offer enormous potential for high-quality automation in many different industry sectors. IoT has attracted interest from various research communities and industries. Examples of IoT applications include environmental monitoring [2], healthcare services [3], smart cities [4], smart homes [5], firefighting system [6], and security systems [7].

The IoT, as the most advanced trend in internet technologies, has a variety of application domains, including healthcare servicing. Healthcare sectors have been at the forefront of the adoption and use of IoT technologies for efficient healthcare diagnosis and treatment. Medical devices integrated into the IoT that are used effectively for treatment and diagnosing constitute the objects in an IoT healthcare ecosystem. Heart rate sensors, blood pressure monitor, blood glucose meter, and thermometer can be given as examples for IoT in healthcare. IoT-based healthcare services are expected to help with the monitoring of patient data, make emergency medical decisions, reducing costs in the process, and increasing the patient's quality of life by monitoring the patient's lifestyle (Figure 1).

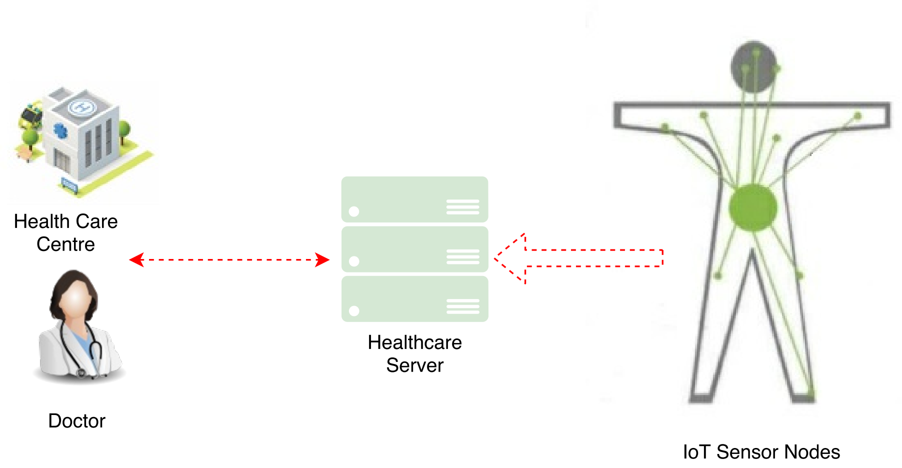

Figure 1. IoT Healthcare System.

IoT technology makes wearables and other monitoring devices more efficient by enabling them to track the patient's health status more accurately. Because a sensor obtains health-related data from patients, it needs to be integrated with electronic healthcare records (EHR) systems. EHR systems have become more advanced in the process of data collection, management and sharing of patients' health information [8]. Most EHR systems have not been designed to integrate with IoT technology; they have been designed to be more patient-centric management systems. The use of the IoT in EHR remains a long-term goal. Configuring IoT in EHR can improve patient healthcare, enabling health providers to monitor their patients outside the clinic.

The health data from connected devices ultimately need to land in the EHR environment. EHR needs to rely on the healthcare IoT which helps a health provider to monitor a patient's health status related to several chronic and acute conditions such as hepatitis C, mental health risks, medication adherence, and diabetes, among others. However, currently, the EHR industry is unable to use IoT data for clinical decision-making.

One of the major challenges to implementing the IoT is that many devices have sensors that collect data; they use data formats that are typically locked into uni-modal closed systems. To assist physicians to access data resources efficiently, a data model that is semantic and flexible is needed to connect EHR data and IoT data that may help to provide true interoperability and integration. For this purpose, the Semantic Web technologies can be used to define the data collected from the IoT healthcare devices and sensors, and to define and normalize the structures and relationships of the complex and unstructured health data obtained from EHRs.

Semantic Web is defined as the extension of the current Web in which the meaning of information is given in a well-defined manner, enabling better collaboration between computers and people [9]. The Semantic Web technologies provide enhanced capabilities that allow data to be processed in a more effective and accurate way, create the framework enabling interoperability between healthcare systems and integrate data from IoT sources by means of their semantic meaning. Ontology structure, which is a core of Semantic Web, is an excellent tool for the representation of knowledge and semantics between systems.

In this research, a semantic middleware exploits ontology to support the semantic integration and functional collaborations between IoT healthcare information systems and EHR system. The envisioned goal of this research is to provide semantic interoperation middleware for IoT data and EHR data that will facilitate data interoperability, integration, information search and retrieval, and automatic inference. This research paper addresses the following questions:

- How can IoT healthcare information and EHR be represented using a semantic knowledge base?
- What are the functions that need to be implemented in a semantic middleware for IoT data?

- What are the challenges facing the implementation of semantic interoperation middleware?

The proposed architecture will benefit the community and the healthcare sector in the following ways:

- Patients can improve their quality of life by being enabled to continuously monitor their health beyond the doctor's office.
- Physicians, by accessing real-time data regarding a patient's health status, can intervene and act appropriately to improve a patient's well-being when alerts are triggered by the system during the monitoring.
- Hospitals and insurance companies, by increasing "pay for value" services to patients, can avoid extra medical services costs, capacity and additional hidden compensation.

The rest of the paper is organized as follows: Section 2 presents background information relevant to the research area and a small survey of IoT architectures/platforms and applications in the healthcare field. In Section 3, we describe semantic ontology middleware architecture. The subsequent sections describe the main components of the model architecture. Section 4 shows an example and introduces both investigated and unexplored challenges associated with IoT healthcare services. The paper concludes with several suggestions for future research and development.

2. Background and Related Work

This section presents background knowledge relevant to the research area. It includes biomedical ontologies and terminologies that have been introduced to describe comprehensively a particular domain in medicine. Also, we present existing and emerging ontologies designed for the domain of Internet of Things. Also, we offer some background information about EHR systems and the components of a semantic ontology knowledge base. We also present a small survey of IoT architectures/platforms and their applications in the healthcare field.

2.1. Biomedical Ontologies and Terminologies

In past years, several biomedical ontologies and terminologies have been introduced to provide comprehensive descriptions of specific medical and biological domains. Among these are: the Foundational Model of Anatomy (FMA) [10], SNOMED-CT [11], Unified Medical Lexicon System (UMLS) [12], International Classification of Diseases (ICD)-11 [13], and OpenEHR [14].

FMA [10] is a domain ontology that describes the knowledge about human anatomy. FMA contains more than 75,000 classes covering human anatomy from sub-cellular components to the main body parts and the entire organism. It also contains approximately over 120,000 terms, and over 2.1 million relationship instances which are grouped in more than 200 types of spatial structural and non-structural relationships. FMA was developed by the Structural Informatics Group (SIG) from the University of Washington and is currently at version 4.12 and its format is OWL.

SNOMED-CT (Systematized Nomenclature of Medicine-Clinical Terms) [11] provides the core terminology for the Electronic Health Records (EHR). The goal of SNOMED-CT is to encode the meanings that are used in health information to improve the effective clinical recording of data and patient care. The use of SNOMED-CT in health informatics systems can lead to consistent information interchange and to an interoperable electronic health record; hence, it can facilitate the interoperability of different health information systems.

The United Medical Language System (UMLS) [12] is a repository of many biomedical vocabularies and ontologies that have been developed by the US National Library of Medicine. The UMLS covers most biomedical terminology and it integrates over 2 million names for some 900,000 concepts and over 12 million relationships among these concepts. The majority of vocabularies that are integrated in UMLS are SNOMED-CT, ICD-10, the Medical Subject Headings (MeSH) and others.

ICD [13] is the standard diagnostic for all general epidemiological issues, and includes many health management and clinical uses. ICD was originally designed to record cause of death, but has been extended to include the analysis of the general health situation of population groups and other health problems in relation to other variables such as morbidity classification, reimbursement, and other specialty areas such as oncology and primary care.

OpenEHR [14] provides an open-standard specification in health informatics that is designed to facilitate the interoperability between health information systems and healthcare organizations. The openEHR describes the management, storage, retrieval and exchange of EHR health data. The openEHR is based on two data models: the archetype model (AM) that consists of archetypes and templates, and the reference model (RM) that defines logical structures of an EHR.

2.2. Ontologies in the IoT Domain

There are several existing and emerging ontologies designed for the IoT domain-W3C SSN ontology [15], IOT-A information model [16], IoT.est ontologies [16], IoT-Lite ontology [17] and SensorML [18].

The W3C Semantic Sensor Network (SSN) ontology [15] is one of the most significant and widespread models used to describe sensors and IoT related concepts. The SSN ontology is a domain-independent ontology that describes the notion of sensor and physical devices in general, actuators, observations, and related concepts.

The IoT-A model [16] is the project that extend the SSN ontology to represent other IoT related concepts such as services and objects in addition to sensor devices. The IoT.est model extends the IoT-A model with extended service and test concepts. The IoT-A model is complex for fast user adaptation. IoT-Lite ontology [17] is a lightweight ontology to represent (IoT) resources, entities and services, which is an instantiation of the SSN ontology.

The Sensor Model Language (SensorML) [18] was developed by the Open Geospatial Consortium (OGC), which provides syntactic descriptions using XML to describe sensors, and observations and measurements. While SensorML provides an XML schema for defining sensors, it lacks the expressibility provided by ontology languages such as OWL.

2.3. Electronic Health Record

EHR systems facilitate the management and sharing of patients' health information among healthcare providers. EHRs collect patient health records related to medications, diagnoses, hospital admissions, operations, imaging, laboratory tests, and pathology data. The main benefit of an EHR is that it improves the quality of healthcare delivery. Since the EHR concept seems to be complex, companies commercializing EHR have been implementing established standards. Several international organizations for standardization that have provided standard solutions for EHR are:

- International Organization for Standardization,
- European Committee for Standardization,
- Health Level Seven accredited by American National Standards Institute in the US.

International Organization for Standardization (ISO): the ISO established the Technical Committee ISO/TC 215. This committee introduced several standards related to health informatics. One of these standards, (ISO/TR 20514), defines the structure and context of a basic/generic EHR [19]. The ISO also published the ISO 13606-reference model which is used to improve EHR communication [20,21].

The European Committee for Standardization (CEN): the European Committee for Standardization of Health Informatics (CEN/TC 251) presented a reference model, an archetype interchange specification, reference archetypes, security features, and exchange models. Also, the CEN/ISO 13606 is a European standard approved by ISO, and was designed to achieve semantic interoperability in electronic health record communication. The ISO/CEN 13606 standard is based on a dual-model architecture: archetypes to provide semantic meaning and the reference model structure [22,23].

Health Level Seven (HL7) in the US: the term 'HL7' refers to both the organization and to a set of messaging standards. HL7 are the health-messaging standards that support two messaging protocols: HL7 Version 2 and HL7 Version. HL7 Version 3 has developed the Clinical Document Architecture

(CDA) for exchanging health data such as progress notes, discharge summaries, and results of physical examinations across healthcare systems [24–26].

EHR systems have three architectures: basic, universal and distributed. In a basic EHR architecture, a centralized EHRs database is developed in one organization (i.e., a hospital) and collects data from all healthcare systems operating in the hospital such as the laboratory system, radiology information system and others. In a universal EHR architecture, a centralized EHR database is developed from several national/regional EHRs databases. In a distributed architecture, each healthcare organization (i.e., a hospital) has its own EHR with its own data model and its own terminology standards [27].

2.4. Ontology Based Structured Knowledge Base

The Semantic Web is a vision for the future of the World Wide Web where information is given well-defined meaning, providing logical connections of terms. Regarding the Semantic Web, the W3C recommends an RDF (Resource Description Framework) for semantic interoperability [9,28–30]. RDF provides a powerful triple-based representation language for Universal Resource Identifiers (URIs). RDF Schema (RDFS) provides data-modelling and structured vocabularies for RDF data. Web Ontology Language (OWL) provides greater expressivity of objects and relations when describing domain knowledge than does RDFS [31,32]. The Semantic Web adopted description logic (DL) as a formal knowledge representation of the ontology language. The DL offers a good trade-off between expressivity, complexity and efficiency in knowledge representation, and reasoning about structured knowledge.

Definition 1. *An ontology-structured knowledge base is comprised of (I, E) where*

- *I is an intentional knowledge (**T-Box**), which defines the concepts and properties, as well as the axioms of the logical theory.*
- *E is an extensional knowledge (**A-Box**), which defines the membership of individuals (instances) and couples to concepts of individual relationships.*

Definition 2. *I states that individuals (instances) belong to one concept as also belonging to another concept in the form of* $C \sqsubseteq D$.

Definition 3. P: $C_i \times C_j$ *a binary relationship (property) describes how concepts are related.*

The Intentional (terminological, "T-Box") knowledge is used to describe a conceptualization, assertions about classes, assertions about properties and property hierarchies. The extensional (assertional, "A-Box") knowledge describes property assertions between individuals and membership assertions. Figure 2 shows an example of these conceptual components. SPARQL is a semantic query language for semantic data, and has become a W3C standard that is able to retrieve and manipulate data stored in semantic triplestore [33–35].

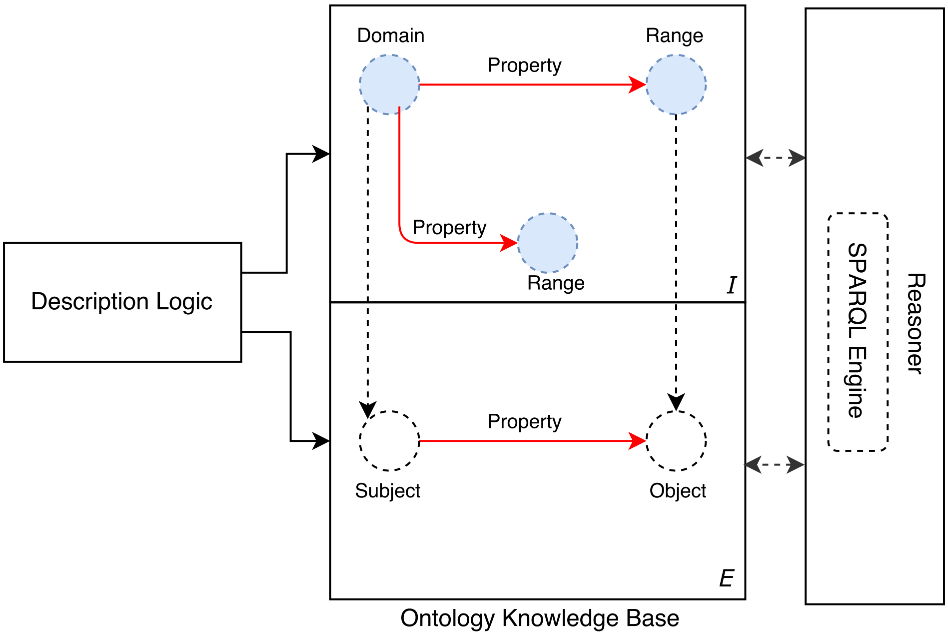

Figure 2. Components of Semantic DL Ontology.

2.5. IoT Healthcare Services and Applications

An increasing number of researches have been conducted on the use of IoT technology in the healthcare field. Fortino et al. (2018) [36] presented the INTER-IoT systemic approach that is being created within the INTER-IoT project to provide interoperability between heterogeneous IoT systems across the communication/software stack, including: middleware, devices, networks, application services, data/semantics. Gyrard et al. (2018) [37] devised a Personalized Healthcare Knowledge Graph (PHKG) that takes into consideration a patient's health condition and enriches that with contextualized knowledge from environmental sensors and Web of Data. Andročec et al. (2018) [38] showed an overview on how Semantic Web technologies are used in IoT interoperability related research.

Santos et al. (2016) proposed IoT-based mobile gateway solution integrated with an Intelligent Personal Assistant IPA platform for a physician to give real-time information about the observed patients [39]. Vazquez-Briseno et al. (2012) suggested an IoT-based m-health service to raise childcare's awareness by tracking their food intake and sending appropriate notifications and messages based on their food choices [40].

Dohr et al. (2010) proposed a modular architecture for ambient assisted living (AAL) to support the daily activities of elderly people [41]. M. Zhang and N. Zhang (2011) suggested an open platform based on the IoT and cloud computing for ambient assisted living and telemedicine [42]. Jara et al. (2010) proposed a drugs checker based on IoT technology and a knowledge-based system to detect Adverse Drugs Reaction (ADR) and allergy interactions. Accurately, the patient's terminal identifies the drugs by means of barcode/NFC-enabled devices [43].

Xu et al. (2014) offered a ubiquitous data-accessing model that can interoperate IoT data for emergency medical services [44]. Guan, 2013 proposed a device for blood pressure data collection and transmission over an IoT network [45]. Lijun (2013) proposed an IoT-based multi-parameter medical acquisition detector that can be used for health monitoring [46]. Istepanian et al. (2011) suggested an m-IoT in non-invasive glucose level sensing and an m-IoT-based architecture for diabetes management [47]. Furthermore, for more details on the IoT-based healthcare technologies and the state-of-the-art network architectures/platforms, applications, and industrial trends in IoT-based healthcare solution, see for example the survey undertaken by [3].

Most of the studies have proposed IoT architectures and middleware trying to solve the interoperability problems applied to e-health. However, an integration between IoT data and EHR data is still an issue. In this paper, we propose a semantic interoperation middleware for IoT data and EHR data that will enable data interoperability, integration, information search and retrieval, and automatic inference. The proposed model is based on OWL which allows automatic inference functionality and offers a good trade-off between expressivity, complexity and efficiency in knowledge representation, and reasoning about structured knowledge.

3. Semantic Ontology Middleware Architecture

As healthcare IoT sensor technology becomes more efficient in term of wearables, and EHR systems become more advanced in data collection, management and sharing of patients' health information, the next logical step is to integrate wearables and other monitoring devices in EHR for enhancing healthcare. The core goal of the proposed model is to improve care by configuring IoT in EHR to collect actionable data that can be used for treatment or other interventions. To achieve the research goal, a semantic middleware is proposed which has three main components: semantic EHR triplestore, semantic IoT triplestore, and semantic integration process.

The architecture of the proposed model is shown in Figure 3. Below, the main components of the proposed architecture are described. Algorithm 2 is the complete algorithm for the semantic middleware architecture.

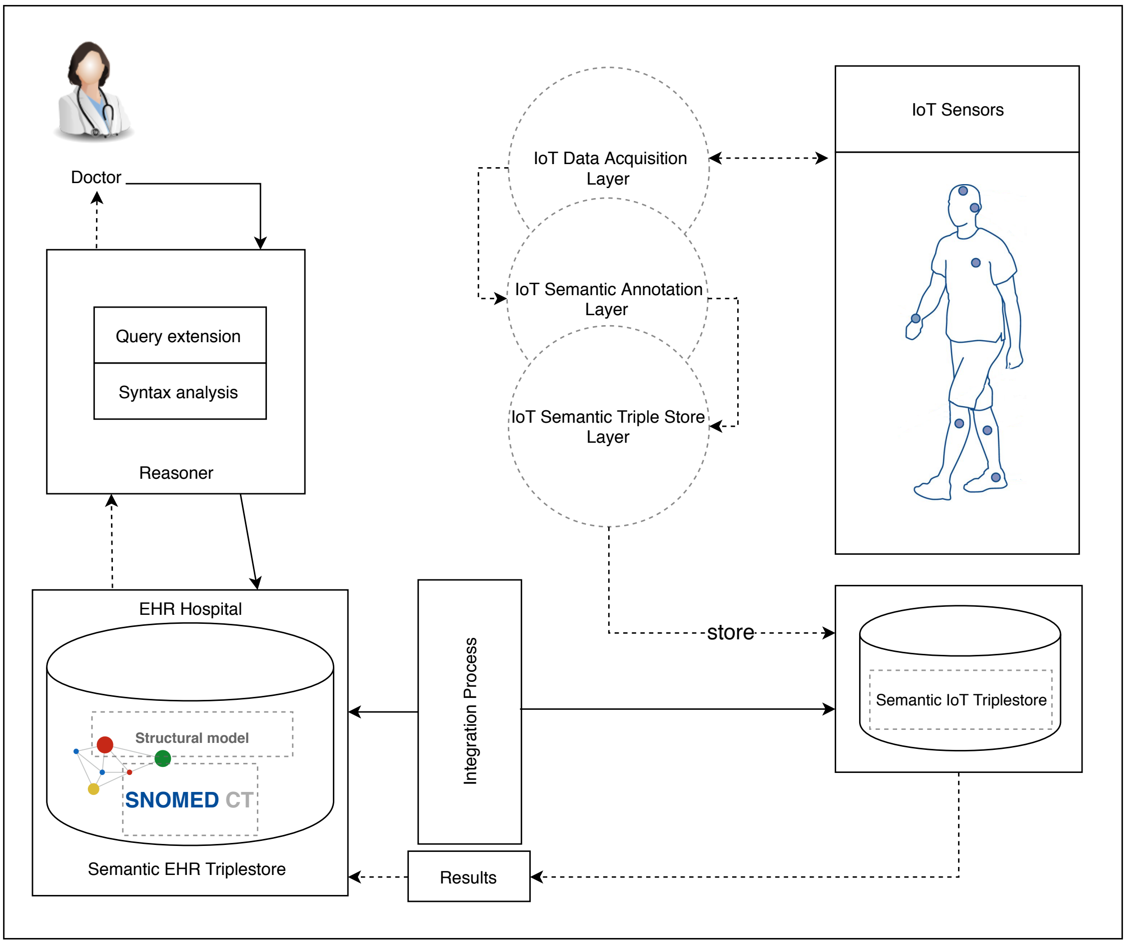

Figure 3. Semantic Middleware Architecture.

3.1. Semantic EHR Triplestore

Ontology structure, a core of Semantic Web, is an excellent tool for representing rich and complex knowledge and semantic visualization. The semantic middleware exploits ontology to support the semantic integration and functional collaborations between IoT healthcare information systems and EHR systems. For this process, a semantic triplestore is designed to manage and store EHR data. The ontology domain is represented using the Web Ontology Language (OWL), thereby obtaining the formal knowledge representation for the store. Our model uses the OWL version of a SNOMED-CT [48], due to its increasing relevance as a comprehensive international terminology that represents a wide variety of clinical information that appears in EHRs with an increasing number of mappings to other classification systems. It consists of upper-level and domain ontology. Upper-level ontology represents very abstract and general concepts that are common across all domains. A domain ontology, SNOMED CT content, will be placed under upper-level classes. Querying and reasoning is performed on stored semantic EHR data with SPARQL language. Figure 4 depicts the knowledge structure of an EHR triplestore.

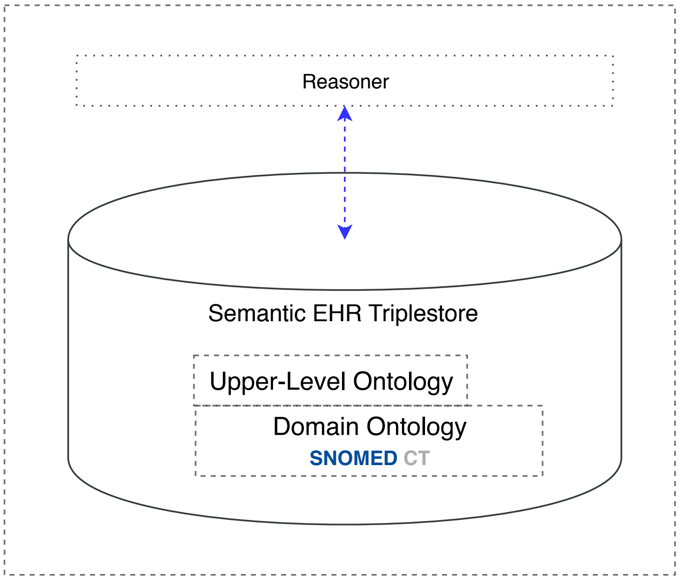

Figure 4. Knowledge structure of EHR triplestore.

3.2. Semantic IoT Triplestore

Semantic triplestore for IoT data in medical service needs to have the following functions: (1) ability to share data with health information systems such as EHR Systems; (2) scalability in order to handle the increasing amount of data being stored. To enable the sharing of data between IoT healthcare information systems and an EHR system, a semantic IoT triplestore is proposed to define the data that is collected from the IoT healthcare devices and sensors. In the proposed model, the ontology design uses some of the existing ontologies and domain models in IoT, in particular:

- SSN ontology is used to represent the sensor resources [49].
- OWL-Time is used to represent the time sub-domain models such as temporal unit and temporal entities [50].
- Geo ontology is used to represent spatial information [51].

Figure 5 shows the subset of concepts and relations, together with a suite of ontologies (i.e., sensor, time, geospatial ontology).

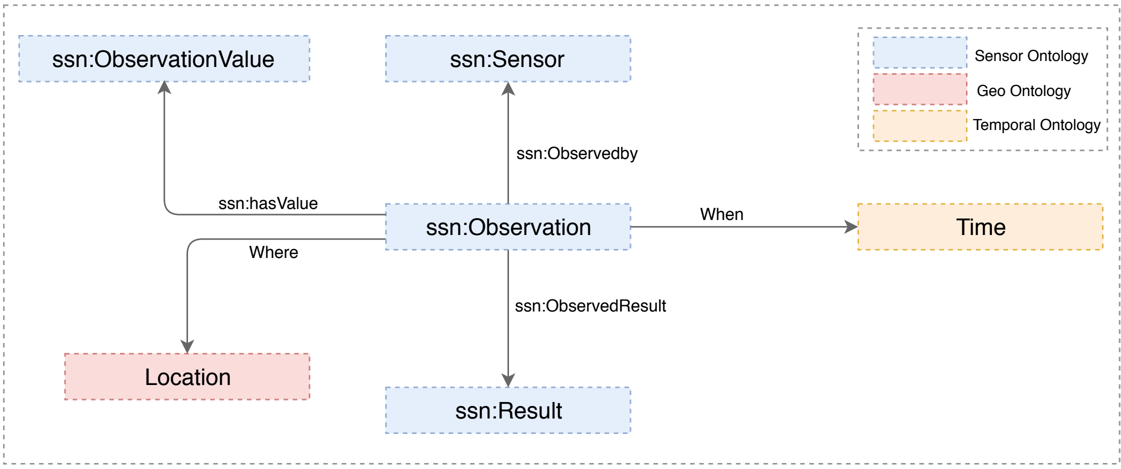

Figure 5. The relations between sensor, time, geospatial ontology.

For persistence and retrieval of sensor observations, our model builds on an RDF database (triplestore). To summarize the features of the proposed model, an abstract semantic IoT triplestore can be modelled as shown in Figure 6; it comprises three layers:

- IoT data acquisition layer;
- IoT semantic annotation layer;
- IoT semantic store layer.

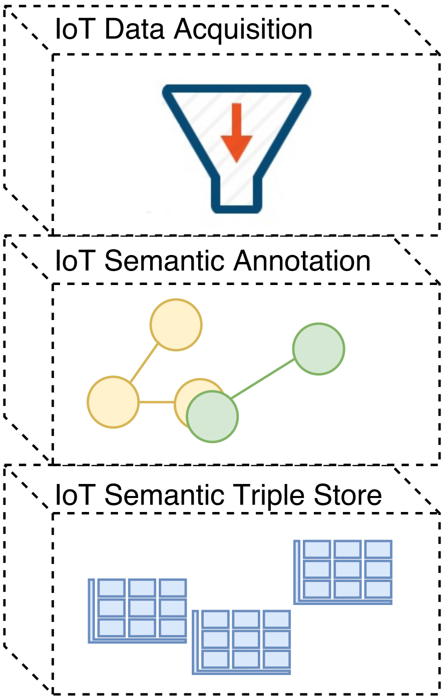

Figure 6. Semantic IoT Triplestore Layers.

The IoT data acquisition layer. This layer has several sensor devices that collect sensor information and observation data. It should transform the acquired data according to the semantic annotation layout defined in the next layer.

The IoT semantic annotation layer. This layer maps sensor data to the form of OWL ontology using SSN ontology, since SSN technology enables data acquisitions.

The IoT semantic store layer. This layer is responsible for storing semantically annotated data in triplestore. Semantic triplestore should store integrated data after being enriched using the model provided by the IoT semantic annotation layer. Given the sensor data as input, the algorithm shows the steps used to map IoT sensor data to semantic triplestore. The pseudo code of the mapping process is depicted in Algorithm 1.

Algorithm 1 Mapping IoT sensor data into semantic triplestore

Input: Sensor data
Output: IoT semantic triplestore

1: DATA IS COLLECTED FROM THE SENSOR RESOURCES
2: STORE IT INTO SENSOR DATA
3: SENSOR DATA ARE MAPPED TO OWL DATA BASED ON SSN ONTOLOGY
4: OWL DATA ARE MAPPED TO SEMANTIC TRIPLESTORE

To ensure scalability in order to handle the increased amount of data being stored, this model adopts a distributed and hierarchical storage architecture that use Jena-HBase [52] which comprises a combination of the Semantic Web framework Jena and HBase to overcome the lack of scalability of single machine RDF-stores.

3.3. Semantic Integration Process

Semantic technologies are adopted to achieve the integration of health data with IoT knowledge. A semantic EHR triplestore is used to define and normalize the detailed structures and relationships of EHR health data. Semantic IoT triplestore is built to store the sensor data that is gathered by the IoT healthcare devices and sensors. To integrate the EHR healthcare information with the IoT healthcare system, integration process is used to transform data subject (patient data) to semantic IoT triplestore. The requesting data subject will be translated into the SPARQL query and executed against semantic IoT triplestore. The query is then evaluated at the triplestore and the results returned to the requester. We introduce the following definitions to formalize this term.

Definition 4. *Formally we define the integration process, map: T1 → T2 if Sim(pa_T1) = pa_T2; Where*

- *T1: EHR triplestore,*
- *T2: IoT triplestore,*
- *pa_T1: Patient in EHR triplestore,*
- *pa_T2: Patient in IoT triplestore,*
- *Sim(pa_T1, pa_T2): Identity function implies that there is a similarity between pa_T1 and pa_T2.*

Definition 5. *A similarity measure between T1 and T2 is denoted by Sim(pa_T1, pa_T1). This function must satisfy the following property:*

- *Identity: Sim(pa_T1, pa_T1) corresponds to the fact that the two data subjects (patient ID) are identical in all respects.*

4. Discussion

To describe the overall system structure, its components, and their interactions, a sample scenario is given (Figure 7). Let us suppose that the physician wants to monitor a patient with symptoms of a heart attack after s/he was discharged from hospital. The patient is connected to a heart monitor electrocardiography (ECG) and photoplethysmography (PPG) to constantly monitor the heart's activity and the blood pressure. The data collected by the IoT healthcare devices and sensors is stored in a semantic IoT triplestore. This data could be integrated with an electronic health records system where data is described with its semantics, which would provide a complete view of patient data. Subsequently, the physician can easily access the patient's record and review the ECG and PPG readings, and then diagnose and treat the patient quickly. The physician can also establish some limiting values for his or her measurements. If a measurement exceeds the defined limit, the system can signal an emergency to inform the physician.

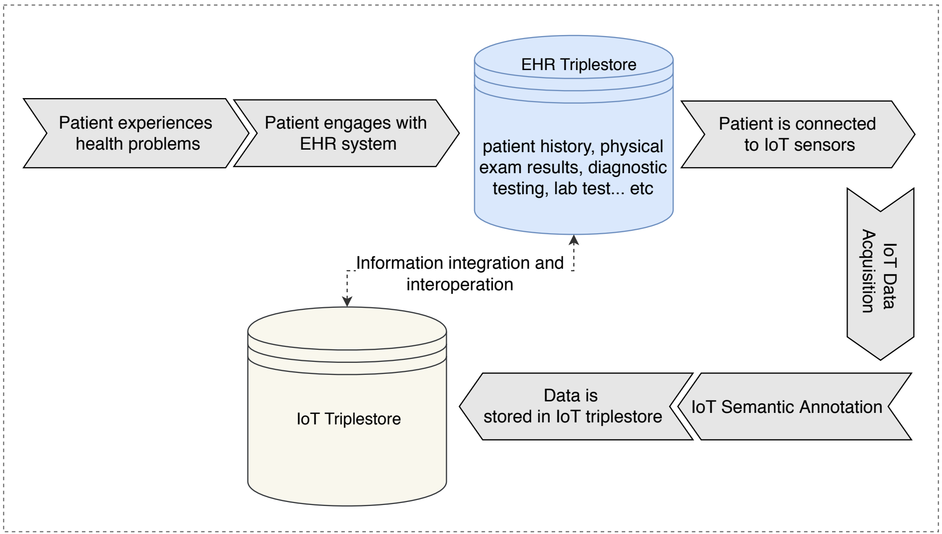

Figure 7. System Interaction.

The inherently sensitive nature of health data, along with the challenges of interoperability, health information exchange, management and sharing of patients' health information, and the poor integration in IoT systems have created opportunities for a semantic environment to make EHR Interoperability and data storage a reliable process. Figure 8 below shows the advantages of our proposed semantic EHR system compared with the traditional EHR system.

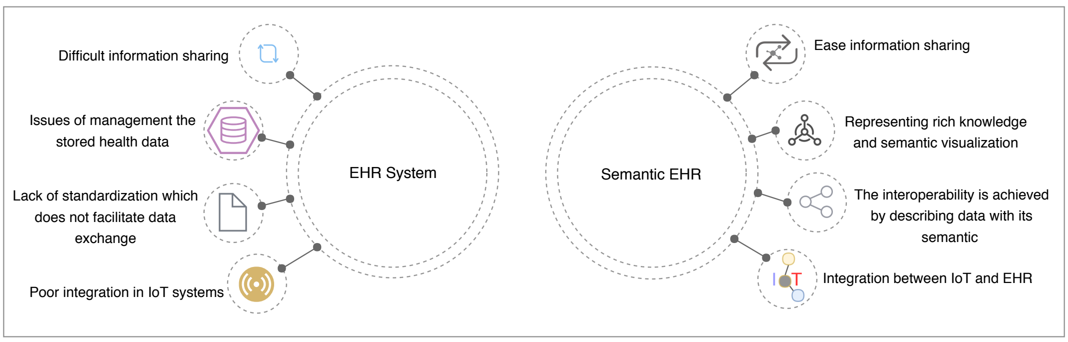

Figure 8. Semantic EHR compared with traditional EHR System.

There are several other challenges that need to be carefully addressed in future work. Below are presented both the investigated and the unexplored challenges associated with IoT healthcare services.

- Data complexity and privacy management. Health information can be very complex; as it originates from various sources that might present information values in an unorthodox way. Hence, the way that information is conveyed must be standardized and rationalized. This sort of challenge involves

privacy protection, data mining, granular access control, cryptography authorized information driven security, exchange logs, secure data repository, data provenance and granular scrutiny.
- Behavioral data security. This sort of challenge includes an increasing number of potential users and health data which further compromise the security of behavioral data.
- Device Sensitivity. This challenge involves the exchange of information outside the dedicated frameworks which presents a significant risk that needs to be addressed and controlled.

Algorithm 2 Semantic Middleware Algorithm

Input: Semantic Query $\mathcal{Q}$
Output: Result Objects

```
Basic Query Syntactic Analysis
Parses Q to identify all the target Terminological knowledge Tk in semantic EHR triplestore
Summarized list of all requested Tk
if Tk.Read() ==1 // user role have access to Tk then
    Generates query subject (Q_T2) that includes patient id from the EHR source
    Send Q_T2 to T2
    if pa_T1 = pa_T2 then
        Return the appropriate matching terminological knowledge
    else
        Return null
    end if
else
    Return null
end if
Transfer results objects from IoT triplestore through the middleware
Generate the final results from EHR with IoT triplestore to the user
```

5. Conclusions

This research proposed semantic interoperation middleware for IoT data and EHR data that will enable data interoperability, integration, information search and retrieval, and automatic inference. The proposed model improves patient care by configuring IoT in EHR to collect actionable data that can be used for treatment or other interventions. Future work will focus on implementing and improving the proposed middleware algorithm.

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