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Towards An Uncertain Integration and Composition Approach of Data from Heterogeneous WoT Health Services

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Abstract

Over the past few years, the use of electronic health records (EHRs), wearable devices and health apps has grown in popularity. Due to the abundance of collected and integrated data, self-management of health becomes more practical. Among the challenges facing the current health system are intelligent homes and intelligent workplaces made possible by the Internet of Things. The Web of Things (WoT) is a subset of the Internet of Things that aims to connect everyday things to the Internet and manage interoperability. Furthermore, collaboration of health data with data from various devices at home and at work, as well as open data on the Internet, is critical for successful and accessible health self-management. Unfortunately, shared health data may be untrustworthy for a variety of reasons. Uncertainty can be caused by heterogeneity, incompleteness, unavailability, and data inconsistency. To address the problem of health data uncertainty, we provide a probabilistic approach for composing uncertain Health Connected Data and computing the probabilities to deliver the final degree of uncertainty. We also present a method for parsing typical WoT objects into a new programmatic form that mimics the uncertainty of health data. Using a health care use case, we show how our technique successfully integrates uncertain health data with home, work, and sport environment data for the WoT domain.

Keywords: Uncertainty; WoT; uncertain IoT; REST Data; Integration; Probability

Nomenclatures

WoT: Web of Things.
EHR: Electronic Health Record.
P: Probability.
MUX: Mutual exclusive node.
IND: Independent node.
IoT: Internet of Things.
XOR: Exclusive formula.
OR: Independent formula.

Introduction

In today's modern information systems, individuals, networked devices, and businesses may create and publish vast amounts of data on the web via web APIs and public endpoints [15, 19]. The data is then aggregated from multiple sources and used in mashups to provide value [19]. Data may come from disparate, inconsistent, or incomplete sources, disrupting the integration process [10]. The Web of Things (WoT) has revolutionized people's lives in recent years. Since 2020, the number of connected devices and apps has outnumbered the world's population, reaching more than 50 billion [8]. Furthermore, the emergence of the Internet of Things (IoT) has supported the creation of smart homes, smart work, and other smart technologies. Furthermore, in [5] medical care and health care systems are among the most enticing application areas for the WoT. As a result, the application of IoT technology in healthcare simplifies and improves people's lives [7]. Long-term and frequent treatment of chronic diseases by individuals and healthcare providers is necessary for successful and simple self-management.

Wearable gadgets, health apps, and EHR for healthcare monitoring have enabled more people to take charge of their own health. Many healthcare professionals have utilized EHR systems. Smart home, work, and health gadgets that are WoT enabled create a seamless environment for recording patient data and vital signs. The aforementioned devices, applications, and systems generate huge amounts of health data from the patient. The Collaborative health data, home and work environment data have the potential to support chronic disease patients with more effective and convenient self-management. However, the collaborative health data with home and work data and activity daily can provide a comprehensive overview and an increased understanding.

Unfortunately, all the data generated risk to become data silos and in heterogeneous format because most of the things used different network protocols. Interoperability plays an important role in smart healthcare, providing connectivity between different devices using different communication technologies. Hence, to resolve the above problems [9] uses WoT standards to bring up interoperability between things. The composition of this varied and unpredictable data is required by health data services. For a variety of reasons, the WoT services can be unpredictable. The results produced by various WOT health devices, for example, are not equivalent since they are positioned in distinct situations. The control of data uncertainty is required for reliable integration of health data with home and work resource environments, which is the goal of this research. Several types of uncertainty have been discovered in the evaluation of emerging IoT applications in healthcare, notably in WoT. Parameter uncertainty, structural uncertainty, methodological uncertainty, variability, heterogeneity, and decision uncertainty are all examples of uncertainty. Every day, an increasing number of devices join to the WoT connection. A smart healthcare network is made up of billions of devices and a massive quantity of data and information that can be analyzed. Can only succeed if it can give capabilities for dealing with heterogeneity and uncertainty. The aim of this work is to address the issue of Uncertain Health Data Composition in the context of WoT.

This paper is organized as follows: Section II covers the related works that dealt with the uncertainty of integration and composition. Section III describes our technique for coping with the unpredictable composition of WoT health data. Section V provides a use example that demonstrates the uncertain composition. Finally, we get to the conclusion of our paper.

Challenges

When dealing with data uncertainty in WoT health service compositions, such as the one in the motivating example, the following challenges arise:

- How can the heterogeneity of values provided by different WoT devices, which are not equal because they exist in different contexts, be managed?
- How should the values supplied by the various WoT devices be handled if they're not equivalent since they are situated in separate places (home and workplace) and have varying measurement accuracies?
- How should data that represents the same device be handled in terms of redundancy, contradiction, and incompleteness?

State of the art

The applicability of WoT in healthcare is critical for a variety of applications. Clinical therapy, remote monitoring, and situational awareness are the three phases of this criterion. The use of an autonomous medical data collection, integration, and composition technique eliminates the possibility of human error during the data integration and composition of Health Data. This will increase the accuracy of the diagnosis and lessen the possibility of human mistake in the gathering or transmission of potentially life-threatening information. There have been attempts to evaluate healthcare from many perspectives. We cover relevant efforts on two aspects in this section: handling heterogeneity in health data with and without uncertainty.

Many research on integrating health data to help healthcare professionals and patients monitor and make decisions have been undertaken. Kumar et al. described a method for integrating glucose data into the EHR to allow diabetic patients to monitor and assess their health [13]. Dexcom, a sensor technology that detects interstitial glucose levels, was employed to do this. The glucose readings are sent to the device vendor's IOS mobile phone app. Apple HealthKit receives the information. The data is then available for analysis within the HER. Authors in [6] created a mobile healthcare system that addressed connection and interoperability difficulties. The integration of the body sensors is accomplished through the use of the Restful web service. In [17], the e-health ontology is suggested to integrate and communicate health and fitness data from disparate IoT sources. The integration was accomplished by utilizing semantic web technologies to facilitate the integration and interoperability of data acquired from disparate IoT sources. The authors in [20] offered an approach for information fusion. To deal with data from disparate sources, a common format and information fusion paradigm for complimentary log aggregation and abstraction are required. They proposed an information fusion approach that reorganizes personal healthcare activity logs and visualizes them hierarchically in a harmonized fashion while delivering a comprehensible summary, as well as a sensor and activity model that classifies heterogeneous sensors. Other research works con- centrated on integrating health data with semantics Health IoT ontology. Such as authors in [18] they set out to characterize the semantic interoperability of medical items and data. They created an algorithm for analyzing the observed vital signs and providing appropriate therapy.

The authors in [12], suggested a platform for integrating data from disparate source sources The integration of data allows different stakeholders access to clinical decision-making and healthcare delivery. In [4], authors addressed variable composition of resources in the context of the social IoT. In [21], the authors proposed a portal-based home care platform for integrating various assistive devices and their associated online services. There are three layers to the integration: service, information, and device. The integration levels are intended to increase the adaptability of home health care systems. In [2], authors proposed a framework for aggregating health data and context The data collection intended to improve self-awareness, which led to targeted behavior modifications. A community initiative in [14] introduced JSON-LD to standardize Linked Data in JSON, and the syntax is completely compatible with regular JSON. The JSON -LD can be used to develop RESTful services as well as integrate the exposed data into the Semantic Web. These studies are more concerned with specific integration in healthcare.

According to the following sections, to illustrate the uncertain integration of health data. Some approaches consider uncertainty in terms of fuzzy inputs and outcomes. In [1], authors provided a method for assessing decision-making units' performance under uncertainty (DMUs). It incorporates the Data Envelopment Analysis (DEA) approach for cross efficiency. In [11] the authors suggested a model for a healthcare supply chain in an integrated healthcare system with unpredictable product complaints. Authors in [22] suggested a validation model for physical activity, offered in an IoT enabled customized healthcare setting for reducing irregular uncertainties and evaluating data dependability. In [16], the authors presented a dynamic paradigm for prioritizing surgical patients based on risks and uncertainty. Authors in [3], offered a probabilistic method to data synthesis in the context of the Linked Data web only. These publications are more concerned with specific integration in healthcare. According to the following sections, to illustrate the uncertain integration of health data. Unfortunately, these techniques generate a semantic interoperability difficulty because objects cannot interact with them. Furthermore, none of these techniques address the issue of integrating uncertainty in health data with IoT and, in particular, WoT devices.

Uncertain composition of WoT Health Data

We discuss our approach to the unpredictable composition of health data with home and work contexts in this part. Furthermore, the fundamental rationale for integrating health in diverse situations (at home and at work) is to improve the thinking process. The collaborative health data is concerned with supporting chronic disease patients in better managing their symptoms. The management of data uncertainty is required for the trustworthy uncertain composition of data, which is the goal of this research. The health data services sources, API layer, parser layer (JSON-LD to JSON-LDpx(MUX,IND), uncertain composition health data layer, and utility applications layer include our method. Figure.2 outlines the layered architecture for unpredictable health data composition with home and work environments. To integrate uncertain health data, we begin with the first layer, where we must combine health uncertain data from various services. The API layer then simply requests data from services via APIs; for WoT things, we serve data in JSON-LD serialization format (named as TD or Thing description). JSON -LD format is used to showcase each service. In this paper, we will focus on the parsing and composing of health data with WoT devices.

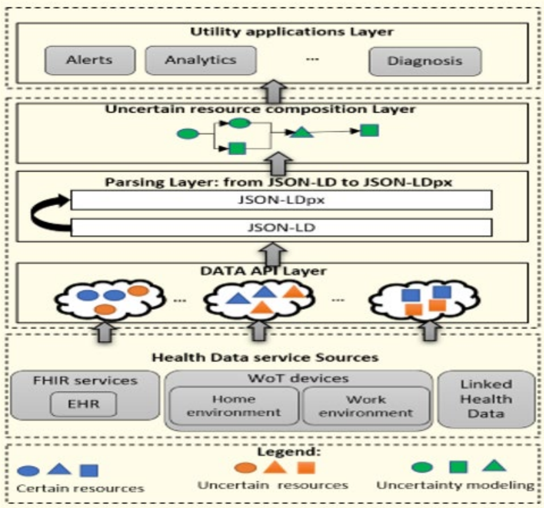

Figure 1: Layered architecture of uncertain Health Data Composition.

- ***The uncertain resource layer***: The first layer includes all of the healthcare domains that come after them. Allowing for a wider range of data and a wealth of information for a more comprehensive analyzing experience. These data are redundant, ambiguous, diverse, and large in scale, making integration, utilization, and composition problematic. The next phase (parsing) is to describe this uncertainty in such a way that data processing, integration, and composition become relevant tasks.
- ***Parsing layer***: We will describe the parsing algorithm (JSON-LD to JSON-LDpx procedure in this layer. This method finds JSON-LD file content that has been modified to probabilistic JSON-LDpx and then parses it into JSON-LD format using the sendTo Parse class to determine whether the JSON-LD format is legitimate or not. If the grammatical syntax is correct, then continue with the process. The file is not parsed if it does not conform to the JSON-LD format. The following is the parsing algorithm:

Algorithm 1 Parsing JSON-LDpx

```
Require: JSON-LD files
Ensure: JSON-lDpx
  JSON − LDpx ← 0
  while JSON − LDfilenotempty do
    if Same attribute and multiple values then
      Attribute ← uncertain − Id
      Dist − IND ← (Uncertain − Id, v, p)
                                        ▷ (value and probability)
      add.JSON-LDpx(Dist-IND)
    else if Same attribute and one value then
      Attribute ← uncertain − Id
      Dist − MUX ← (uncertain − Id, v, p)
                                        ▷ (value and probability)
      add.JSON-LDpx(Dist-MUX)
    elseError                           ▷ Empty file
    end if
  end while
  return JSON-LDpx
```

– ***Uncertain data Composition layer***: Smart home and work environment data are also considered health-related resources since they are tied to a person's health management. We propose an uncertain composition technique in this layer to combine health data services with WoT home and work services in the presence of data uncertainty. In order to accomplish efficient and effective health self-management, it is necessary to integrate and collaborate personal health management data with home and work contexts.

a) The context of home and work are very important to enhance the reasoning process. Figure.1 describes the process of the uncertain health data composition with home and work environment. In the first step we request file JSON-LDpx from health service and WOT device service home and work. Then, we compute the probability in the uncertain sub-distribution IND and MUX. We propose a WoT probabilistic algebra (inspired from [3]) to compute the uncertainty of the final response degree. The computation of the sub-probability response P is as follow:

- the uncertain sub-distribution (IND) with the OR operator:

$$\text{OR} = \prod_{i=1}^{n} p_1 \wedge \ p_2 \ldots \wedge \ p_n \qquad (1)$$

- the uncertain sub-distribution (MUX) with the XOR operator:

$$\text{XOR} = MAX(p1, \ldots, p_n) \qquad (2)$$

Finally, we estimate the uncertainty of the final degree response by aggregating all the probabilities.

$$\text{P} = \prod_{i=1}^{n} p_{IND} \ * \ p_{MUX} \qquad (1)$$

– ***The utility applications layer***: The doctor may use this layer to prescribe an acceptable therapy for the patient as well as to tell the patient about his condition and the necessary treatment.

Use case of uncertain composition

To demonstrate the uncertain health data an example of motivation has been presented in section 1. The motivation example has been presented focuses on the patient in different contexts at home, work, and when practices sport.

In each setting, the WoT devices offers distinct data values. The article's major goal was to answer the issue of data ambiguity and return the final degree of uncertainty in order to make an appropriate decision for health patients in each setting. This outcome will assist doctors in obtaining a relevant result among all the unclear options. The health data are modeled in JSON-LDpx. Table 1 describes the data values during one week provided by WoT device blood glucose (BG), WoT device temperature (T), and WoT device steps(S) in each context.

Time Context	***Home Context***	***Work Context***	***Sport Context***
01-10-2020	BG:3.5, T:37.5	BG:4.5, T:36.5	BG:1.00, S:300
02-10-2020	BG:2.5, T:33	BG:2.5, T:35.7	BG:0.99, S:200
03-10-2020	BG:1.5, T:40	BG:1.5, T:40	BG:2.25, S:1000
04-10-2020	BG:4.2, T:36.5	BG:3.5, T:36.5	BG:0.99, S:400
05-10-2020	BG:3.5, T:37	BG:3.5, T:37	BG:1.20, S:600
06-10-2020	BG:2.5, T:36	BG:2.5, T:40	BG:0.98, S:800
07-10-2020	BG:1.25, T:37.5	BG:1.5, T:38.5	BG:2.5, S:100

Table 1: The uncertain value of health data resources in each context.

Figure.2 depicts the BG and T resources of Alex's residence. The representation of probabilistic data is passed to calculate the final degree in order to make an appropriate health patient choice. First, we compute IND's BG resource type. The T type of MUX is then computed. Finally, the final degree is computed. The probability response P(1) is computed as follows:

First, we use the OR operator to compute the probability in the unknown sub-distribution BG (IND) where we take only three possibilities:

$OR(BG) = \prod_{i=1}^{n} p_i = \prod_{i=1}^{n} p_1 \wedge\ p_2 \ldots \wedge\ p_7 = (0.1 * 0.2 * 0.3) = 0.006$

Second, we compute the probability in the uncertain sub-distribution T (MUX) is calculated by the XOR operator:

XOR(T) = MAX(p1, .., pi) = MAX(0.6, 0.2, 0.8, 0.5, 0.6, 0.2, 0.3) = 0.8

The final result: P(Q1) = (0.006 $*$ 0.8) = 0.0020


```
{  "@context": "http://schema/org",
   "@id": "http://hl7.org/fhir",
   "id":"http://iotschema.org/tempeture",
   "blood glucose": "@300",
   "tempeture":"@301",
   "dist":{
   "dist1":{ "iddist": "@300", "type":"IND",
   "val":[3.5,0.1,2.50,0.2,1.50,0.3,4.20,0.1,3.50,0.1,2.50,0.1,1.25,0.1]},
   "iddist": "@301", "type":"MUX",
   "val":[37.5,0.6,33,0.2,40,0.8,36.5,0.5,37,0.6,36,0.2,37.5,0.5]} }
```


Figure 2: JSON–LDpx (MUX, IND) data at home; BG and T.

Figure.3 depicts the data values of Alex's BG and T resources. The representation of probabilistic values is passed to determine the final degree for making an appropriate health patient choice. First, we compute IND's BG resource type. The T type of MUX is then computed. The probability response P(2) is computed as follows: First, we use the OR operator to compute the probability in the uncertain sub-distribution BG (IND) where we take only three possibilities:

$OR(BG\ ) = \prod_{i=1}^{N} p_i = 0.3 * 0.1 * 0.1 = 0.003$

The XOR operator is then used to compute T probability in the uncertain sub-distribution (MUX):

XOR(T) = MAX(p1, .., pi) = MAX(0.6, 0.2, 0.8, 0.5, 0.6, 0.7, 0.6) = 0.8

The final result: P(Q2) = (0.03 ∗ 0.8) = 0.0328


```
{  "@context": "http://schema/org",
   "@id": "http://hl7.org/fhir",
   "id":"http://iotschema.org/tempeture",
   "blood glucose": "@200",
   "tempeture":"@201",
   "dist":{
   "dist1":{ "iddist": "@200", "type":"IND",
   "val":[4.50,0.3,2.50,0.1,1.50,0.1,3.20,0.17,3.50,0.16,2.50,0.15,1.50,0.02]},
   "iddist": "@201", "type":"MUX",
   "val":[36.5,0.6,35.7,0.2,40,0.8,36.5,0.5,37,0.6,36,0.2,40.5,0.5,38.5,0.6]} }
```


Figure 3: JSON–LDpx (MUX, IND) data at home; BG and T.

Finally, the total degree of uncertainty for all resources is calculated using P(3) as follows:

P(Q3) = (0.002 0.0328) = 0.0000656

According to the computation, the data values in each context differ. We have a better understanding of the patient's health in each situation, which helps us to improve our thinking and give the patient with suitable therapy. The ultimate outcomes in P1, P2, and P3 varies since the patient is in different conditions. Understanding health patients requires the calculating of probability. Furthermore, the unpredictability of health data from home, work, and sports WoT devices provides clinicians with a comprehensive perspective of patients' health for the most accurate analysis.

Conclusions and Perspectives

In this research, we provided an uncertain approach to compose health services that is incorporated in WoT standards. The capacity to integrate various categories of health services and WoT services has the ability to assist in self-management of health, particularly for those with chronic conditions. Contexts is an attempt to increase cognition in a variety of contexts while also providing appropriate therapy for the patient. We proposed a method for parsing conven tional data into uncertain data in order to provide a probabilistic value to each data set. In addition, we provided an example of patient health in various contexts. Our method gives clinicians a visual overview of data uncertainty as well as a better user experience.

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