Ontology-Based Personalized Telehealth Scheme in Cloud Computing

Keke Gai[1(✉)], Lei Zou[2], and Liehuang Zhu[1]

[1] School of Computer Science and Technology, Beijing Institute of Technology, Beijing 100081, China
{gaikeke,liehuangz}@bit.edu.cn

[2] Institute of Computer Science and Technology, Peking University, Beijing 100871, China
zoulei@pku.edu.cn

Abstract. *Cyber Physical Social Systems* (CPSS) has been rapidly developing in recent years because of the dramatic growth of mobile techniques and Internet-based technologies. As an emerging novel technical paradigm, cloud computing is becoming an efficient mechanism that has been broadly implemented in multiple fields with using Internet-enabled devices. Telehealth system is one of the crucial domains in applications of *Cyber Physical Systems* (CPS), which is also considered an important component in smart city. However, *Personalized Cloud-based Telehealth* (PCTH) is still facing a great challenge due to restrictions deriving from various perspectives, such as cloud resource allocations and real-time information transfers. This paper concentrates on the issue of optimizing the performance of the resource allocation for achieving smart tele-health with obtaining and analyzing real-time data within the dynamic application environment in cloud computing. The dynamic data environment is mainly associated with social connections generated by physicians or health organizations. Along with this focus, we propose a novel approach, entitled *Smart Cloud-based Telehealth Cyber Physical Social Systems* (SCT-CPSS), to enable mobile CPSS to offer users a real-time health information service based on the social networking behaviors and inputs. Main algorithms used in this proposed mechanism include *Real-Time Matching with Dynamic Programming Algorithm* (RTM-DPA) and *Monte Carlo-based Real-Time Analysis Algorithm* (MC-RTAA). Our experiment examination has evaluated the performance of the proposed paradigm.

Keywords: Cyber Physical Social System · Personalized telehealth
Cloud computing · Ontology · Dynamic programming

This work is supported by Beijing Institute of Technology Research Fund Program for Young Scholars (Dr. Keke Gai).

H. Jin et al. (Eds.): ICWS 2018, LNCS 10966, pp. 49–64, 2018.
https://doi.org/10.1007/978-3-319-94289-6_4

1 Introduction

As an emerging technique deriving from *Cyber Physical Systems* (CPS), *Cyber Physical Social Systems* (CPSS) is considered an efficient approach that integrates CPS features with humans' inputs and interconnections [1]. The penetration of the humans' behavior and social networks can enable a dynamic operating environment, in which smart services are generated. Currently, implementing CPSS in smart tele-health is still a new realm that is desired to increase service quality and create new values in the system. One of the crucial benefits is to acquire personalized tele-health or personalized medicine [2]. However, the matching process that pairs symptoms or pathogeny with diagnoses is one of the most timing consuming components when executing CPSS-based tele-health systems.

The interrelationship between entities can provide the matching operation with theoretical supports as a technical tool. The critical issue is that pairing healthy conditions with medical advices for personalized medical care is a great challenge, in which the matching operation requires to count the maximum-matchable edges with dynamic inputs in a restricted time period [3]. To overcome this problem, we propose a social networking-based model that concerns two main aspects, including the maximum matching problem and stochastic data computations. Our proposed paradigm, *Smart Cloud-based Telehealth Cyber Physical Social Systems* (SCT-CPSS) model, is designed to assist tele-health users to secure *Personalized Cloud-based Telehealth* (PCTH) services when using mobile CPSS.

The main social connection derive from both tele-health clients and physicians, which bridges up users' healthy conditions with medical advice. The critical inputs in the system are consistently dynamic, which are generated by both tele-health clients and the physician-side. Being aware of the complexity of the dynamic operating circumstance, our approach aims to provide tele-health clients with periodic outputs obtained from real-time data inputs. In addition, we propose two crucial algorithms for implementing the model, which are *Real-Time Matching with Dynamic Programming Algorithm* (RTM-DPA) and *Monte Carlo-based Real-Time Analysis Algorithm* (MC-RTAA). First, RTM-DPA is a dynamic programing algorithm that is designed to solve the *Multiple-Layer Matching* (MLM) problem with the timing constraints. An ontological approach is used to efficiently obtain the result of MLM problem, so that it avoids dealing with a NP-hard problem [3,4]. The other algorithm, MC-RTAA, is proposed to calculate the random dataset for the purpose of the efficient calculation when the dataset size is large.

Figure 1 exhibits the framework of the proposed SCT-CPSS. As shown in the figure, there are mainly two inputs, namely tele-health clients and physicians. Real-time healthcare data are collected from tele-health clients by using medical sensors and are delivered to the cloud-side database via *User Interface* (UI). The collected data are extracted according to symptomized characteristics and are used for *Matching Processing* (MP) on cloud-side database. Details of MP are given in Sects. 3 and 4. On the other side, physicians' inputs are collected by

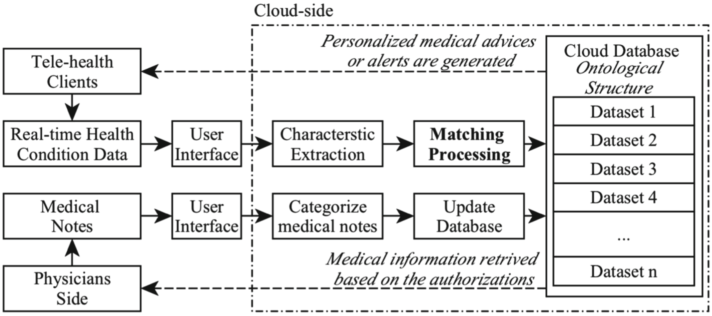

Fig. 1. Framework of Smart Cloud-based Telehealth Cyber Physical Social Systems (SCT-CPSS).

the system and are attached to the knowledge pool of database, which is also utilized for MP. The continuous updating mode enables the execution of the smart tele-health CPSS by generating personalized medical advice or alerts for tele-health clients.

The significance of this research is applicable for both researchers and practitioners in the field. Many tele-health solutions only provides users with healthcare data representations without giving medical advice assistances. Compare with most current employed tele-health CPSS, the critical merit of our model is to obtain smart healthcare solutions by solving a NP-hard problem considering timing constraints as well as ontological restrictions. Main contributions of this paper include:

1. We propose a novel approach for achieving real-time tele-health services with diagnoses advice offerings in a dynamic manner.
2. A multi-layer matching problem is solved under practical restrictions.
3. This paper introduces a new mechanism by building up the social connections between healthcare clients and physicians in CPSS.

The remainder of the paper is organized as the followings. In Sect. 2, we review and summarize the related work in the field. Main concepts used in the model are represented in Sect. 3. Our crucial algorithms are given in Sect. 4. We exhibit the experiment configuration and the results in Sect. 5 and the conclusion is drawn in Sect. 6.

2 Related Work

This section presents the main recent academic works of CPSS in tele-health domains. A number of dimensions are covered to formulate a holistic view of the relevant knowledge structure, such as CPSS implementations and explorations, smart tele-health development, and cloud-based tele-health approaches.

As an innovative term, CPSS is still at an exploring stage in which there is limited prior work done by the prior research [5]. Most previous work had addressed the implementation of CPS in building up a social connection in a perspective of functionality enhancement, such as strengthening *Global Position System* (GPS) with applying social networks [6]. Another attempt of increasing performance was using social networks for CPS to achieve interference mitigations [7]. This approach detected and predicted social interactions when deploying *Wireless Body Area Networks* (WBANs). However, this research direction had limited work on the system improvement in a perspective of services.

Meanwhile, another perspective of exploring CPSS was to propose novel framework or architecture for future utilizations. For instance, CPSS-based security architecture was proposed for future *Internet of Things* (IoT) with a secure social management control [8–10]. The information and human cognitions were two key aspects that could impact the physical security from the external context and internal infrastructure. The technique of CPSS could be also applied in smart home through deploying multi-level self-organization CPSS [11]. The adoption was based on the ontological information model to identify interactions between entities in smart home. Nevertheless, most prior work addressing this research domain seldom examined the implementation of CPSS in the smart tele-health field.

Moreover, recent spreads in smart health discipline had a great growth in multiple dimensions. Some researches paid attentions to adopting smart home in emergency management and telemedicine for aging people, which involved social networks in CPS [12]. Smart home techniques used sensor technologies to collect users' real-time medical data and transfer the information to remote servers via wireless networks [13]. Some implementations of smart tele-health solutions enabled the remote controls for the employed equipment [14]. As a medium of the data collection, sensors were considered an aspect for increasing treatment quality, such as consistent operations with higher-level accuracy [15]. Nonetheless, most previous researches rarely concerned to implement social networks.

Furthermore, there were a variety of approaches for data collections in tele-health systems [16]. Integrating e-health monitoring systems [17] was an approach that used multiple devices to gather real-time data for purpose of healthcare monitoring. A smart-oriented integrated tele-health system features a few characteristics, such as flexibility [18] and compatibility [16]. Meanwhile, the wearable devices with sensors were another group of systems that could be used to achieve a consistent data collection [19,20]. Next, the implementations of *Wireless Sensor Networks* (WSN) [21] and *Body-Area-Networks* (BAN) [22] are efficient choices for smart tele-health systems to fetch data. However, most prior researches hardly had ventures in social networks between stakeholders in the system.

In addition, as a type of embedded system, tele-health systems had been expanded in a perspective of hardware optimizations and *Personal Digital Assistant* (PDA) [23]. For instance, a reliable high performance resource scheduling was proposed for gaining higher-level efficiency of remote rescue with using *Virtual Machine* (VM) in the clouds [24]. Implementing VM technologies is an efficient approach for integrating tele-health services with other existing infrastructure or systems, such as TV systems [25]. Meanwhile, embedded *Digital Signal Processor* (DSP) tele-health was also a realm explored by the prior research, such as using radar facility to detect unexpected in-door behaviors. Along with the utilization of the healthcare equipment, such as *Electrocardiogram* (ECG), [26,27], healthcare data could be gathered and processed by various technologies, such as WSN, cloud computing [28], and DSP. Nonetheless, the mechanism of performance enhancements by multiple dynamic inputs in social networks had been seldom addressed by the recent researches.

In summary, despite recent academics had done diverse researches in tele-health CPSS fields, most previous researches had not concentrated on the involvements of social networks in the system. This paper focuses on enabling social interactions in tele-health CPSS to achieve real-time personalized medical services.

3 Concepts and the Model

3.1 Concepts

There are a variety of entities in SCT-CPSS for the calculation of matching process due to comparing interrelationship patterns. An *Interrelationship Pattern* refers to a chain of relations defined by an ontology that connects or interacts a set of entities in the system. In a pattern, an *Entity* refers to a group of objects having the same categorial features or similar attribute scopes by which output labels are generated. Next, an entity type determines the means of layer-based computations. Main entities include *Restricted Elements* (RE), *Data Collected by Sensors* (DCS), *Symptoms or Disease Signs* (SDS), and *Pathogeny or Disease* (PD).

Throughout this paper, we define the concept of main entities used in SCT-CPSS as follows:

- **RE** refers to the different variables that are used as parameters during the data gathering process, such as time, humidity, and lapse rate.
- **DCS** is a group of data collected by users' devices with sensors, which will be analyzed and allocated by the pre-defined medical ontology.
- **SDS** are entities that describe users' health conditions deriving from analyzing, depicting, or calculating the collected health data.
- **PD** is a pool of knowledge describing the pathogeny or disease by using ontological models, by which a health alert is determined.

In SCT-CPSS, the model supports multiple dimensions for matching pairs in ontology. We extract multi-dimensional structures from knowledge-based ontologies so that an MLM problem is formulated. The MLM problem is defined in Definition 1.

Definition 1. *Assume* $\exists$ *multiple disjointed sets* $\mathbb{E}^{Dim_i}$ *associating with different dimensions. Then* $\forall$ *sets* $\mathbb{C}$ *as input datasets DCS;* $\exists$ Dim_i *as feature sets* *with the ith dimension;* $\exists$ *the set* $\mathbb{T}$ *as pre-stored taxonomy in ontology. Define* $\mathbb{M} \subseteq \mathbb{T}$ *is an MLM problem while any patterns in* $\mathbb{M}$ *follow the ontologies stored in set* $\mathbb{T}$*.* $\forall$ *any two patterns* $\mathbb{M}_1$ *and* $\mathbb{M}_2$ *in* $\mathbb{M}$*,* $\exists\ \mathbb{M}_1 \neq \mathbb{M}_2$*. Define* $\mathbb{P}$ *is a subset involving interrelationship patterns between entities, then* $\exists \mathbb{P} \subseteq \mathbb{M}$*.*

As defined in Definition 1, the crucial component of MP is completing matching operations on multi-layers. Considering varied application scenarios and practical demands, the number of layers is uncertain and dynamic; thus, it is generally associated with the time complexity and space complexity. Applying our propose scheme can dramatically reduce both complexities. Proofs are given in Sect. 4.

Furthermore, solving MLM problem is designed for implementing matching processes, in which the set $\mathbb{M}$ will be comparing with the knowledge-based ontological model. Entity taxonomies are interrelated in an ontological approach with multiple dimensions. For the purpose of simplifying ontological structures, we consider various dimensions layers, at which conceptualize the computations addressing the entities The following section presents a knowledge-based ontological model in SCT-CPSS.

3.2 Proposed Knowledge-Based Ontological Model

SCT-CPSS adopts a knowledge-based ontological model that uses semantic features and relationships as restriction selections. The mechanism of the restriction selection is following a set of rules described by taxonomies. For the purpose of label generations, we represent two definitions to trigger the activities of output labels in the perspective of interrelationship sets, including $\mathbb{P}^{Dct}$ and $\mathbb{P}^{Ind}$. The definitions of $\mathbb{P}^{Dct}$ and $\mathbb{P}^{Ind}$ are given in Definitions 2 and 3, respectively.

Definition 2. $\exists$ *set* $\mathbb{P}$*, in which there are a set of subsets* $\mathbb{P}_i$*, represented as* $\mathbb{P} = \{\mathbb{P}_1, \mathbb{P}_2, \mathbb{P}_3, \ldots, \mathbb{P}_n\}$*,* $n \in N$*. Define the set* $\mathbb{P}^{Dct}$ *by which the* $Output_{alert}$ *can be directly created.* $Output_{alert} \Leftarrow \mathbb{P}_i^{Dct}$*.* $\forall$ *unions of* $\mathbb{P}_i \subseteq \mathbb{P}^{Dct} \subseteq \mathbb{P}$*.*

As defined in Definition 1, it formulates those interrelationship pattern sets that directly involve PD. An output label $Output_{alert}$ has a direct relationship with a $\mathbb{P}^{Dct}$. It means that an alert will be generated when a $\mathbb{P}_i^{Dct}$ is matched, represented by $Output_{alert} \Leftarrow \mathbb{P}_i^{Dct}$. Distinguishing from the $\mathbb{P}^{Dct}$, another crucial pattern in SCT-CPSS is $\mathbb{P}^{Ind}$.

Definition 3. $\exists$ *set* $\mathbb{P}$*, in which there are a set of subsets* $\mathbb{P}_i$*, represented as* $\mathbb{P} = \{\mathbb{P}_1, \mathbb{P}_2, \mathbb{P}_3, \ldots, \mathbb{P}_n\}$*,* $n \in N$*. Define the set* $\mathbb{P}^{Ind}$ *by which any elements in set* $\mathbb{P}^{Dct}$ *can be activated.* $Output_{alert} \Leftarrow \mathbb{P}^{Dct} \Leftarrow \mathbb{P}_i^{Ind}$*.* $\forall$ *unions of* $\mathbb{P}_i \subseteq \mathbb{P}^{Ind} \subseteq \mathbb{P}$*.*

Definition 3 conceptualizes those $\mathbb{P}_i$ that have relationships with $\mathbb{P}^{Dct}$. However, activating $\mathbb{P}^{Ind}$ cannot directly determine whether a $\mathbb{P}^{Dct}$ is matched. It depends on interrelationship types between $\mathbb{P}^{Ind}$ and $\mathbb{P}^{Dct}$. Only those relations supporting $\mathbb{P}^{Ind} \Rightarrow \mathbb{P}^{Dct}$ can trigger an alert, $Output_{alert}$.

To determine an eventual output label, identifying holistic concepts of interrelationships is significant for knowledge-based ontological model. In SCT-CPSS,

Table 1. Examples of interrelationship types in SCT-CPSS

Interrelationship types	Definition
Part of	Being involved in the object (reverse involve)
Involve	Involves the object (reverse part of)
A type of	Being a type of the object (reverse categorize)
categorize	The object is a type of subject (reverse a type of)
A sign of	Being a sign of generating the object
Is	A statement of the object
Lead to	A reason resulting in the object (reverse consequence)
Consequence	A result caused by precedent entity (reverse lead to)

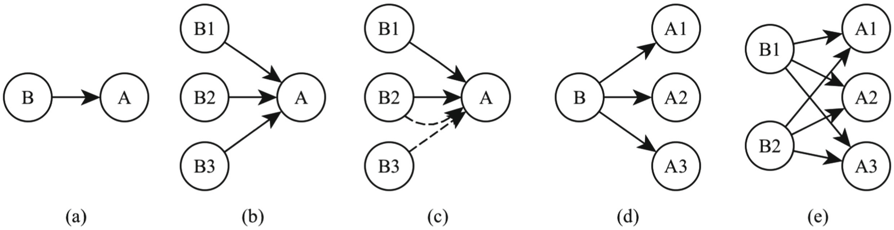

Fig. 2. Basic relation manners in SCT-CPSS. (a) One-to-One relation manner from B to A; (b) Multiple-to-One relation manner from {B1, B2, B3} to A; (c) Multi-Multi-to-One relation manner illustrating two manners, from {B1, B2} to A and from {B2, B3} to A; (d) One-to-Multiple relation manner from B to {A1, A2, A3}; (e) Multiple-to-Multiple relation manner from {B1, B2} to {A1, A2, A3}.

an *Interrelationship* describes relations between entities. It can be a double-direction relation that is described by two reverse statements in a directed graph. For instance, the relation *Part of* refers to *Being involved in the subject*, which can be reversed by the relation *Involve* that refers to *Includes the subject*. Table 1 exhibits a few important interrelationship types used in SCT-CPSS.

Moreover, there are a few relation manners between entities and it implies that activating $\mathbb{P}^{Dct}$ may have multiple ways. A *Relation Manner* refers to the method of reaching an entity described by taxonomy-based interrelationships. We propose four relation manners implemented in SCT-CPSS, include *One-to-One* (O2O), *Multiple-to-One* (M2O), *Multi-Multi-to-One* (MM2O), *One-to-Multiple* (O2M), *Multiple-to-Multiple* (M2M), and *Mixed-Manner* (MdM). Scopes of these four manners are represented as follows:

- **O2O:** One entity is the only preceding entity of one succeeding entity.
- **M2O:** Multiple entities are preceding entities of one succeeding entity.
- **MM2O:** Multiple groups of entities are preceding entities of one succeeding entity. A preceding entity can be shared by different groups of preceding entities.

- **O2M:** One entity is the preceding entity of multiple succeeding entities.
- **M2M:** Multiple entities are preceding entities of multiple succeeding entities.
- **MdM:** An advanced relation manner that is a mixture of other basic relation manners.

Figure 2 shows five basic relation manners, including O2O, M2O, MM2O, O2M, and M2M. In the figures, we use a B to represent the preceding entity and an A represents the succeeding entity. Figure 2 demonstrates five basic relation manners from B side to A side, based on relation manners. Following the above relation manners is a fundamental of implementing the proposed ontological approach. The following section presents main algorithms in SCT-CPSS.

4 Algorithms

Addressing the critical hemispheres of the proposed model, we propose two critical algorithms adopted by the proposed paradigm. They are *Real-Time Matching with Dynamic Programming Algorithm* (RTM-DPA) and *Monte Carlo-based Real-Time Analysis Algorithm* (MC-RTAA). Main notations and the corresponding definitions are listed in Table 2.

Table 2. Main notations and definitions

Notations	Definitions
δ	An input dataset of Algorithm 4.1 with ontological structure on clouds, which is a set of $\mathbb{R}_i$; an output dataset of Algorithm 4.2
δ^o	An input dataset that is original δ when applying Algorithm 4.2
δ^{MT}	Intermedia dataset when applying Algorithm 4.2
δ_i^m	Intermedia table, $i \in \{1, 2\}$
λ^p	Users health data captured in a certain period p
$Label_{alert}$	Type of output alert, $Label_{alert} = \{0, 1\}$, 0 refers to non-alert, 1 refers to alert creations
$Label_k$	Labels in $\mathbb{R}_j$, $k \in N$
$Labels$	A set of $Label_k$ for outputs
$\emptyset$	Empty set
$\mathbb{F}_i$	A feature in λ^p, $i \in N$
$\mathbb{R}_j$	A record that is set of $\mathbb{F}_i$, $j \in N$
$Max_p(n)$	The critical point reaching the maximum performance when calculating n sized dataset

4.1 Real-Time Matching with Dynamic Programming Algorithm (RTM-DPA)

RTM-DPA algorithm is designed to solve the MLM problem by using dynamic programming. The pseudo codes of RTM-DPA is presented in Algorithm 4.1. The algorithm is based on implementing the ontological structure and the aim is to reduce the complexity of computations and increase the computing efficiency.

Algorithm 4.1. Real-Time Matching (RTM) Algorithm

Require: δ, λ^p
Ensure: $Label_{alert}$, $Labels$
Input δ and λ^p
$\delta_1^m \leftarrow \delta$, $\delta_2^m \leftarrow \emptyset$
for each targeted $\mathbb{F}_i$ in λ^p **do**
  if $\delta_1^m == \emptyset$ **then**
    $Label_{alert} = 0$
    return $Label_{alert}$
  end if
  for each $\mathbb{R}_j$ in δ **do**
    if $\mathbb{R}_j \ni \mathbb{F}_i$ **then**
      Add $\mathbb{R}_j$ to δ_2^m
    end if
  end for
  $\delta_1^m \leftarrow \delta_2^m$
  $\delta_2^m \leftarrow \emptyset$
end for
$Labels \leftarrow \emptyset$
for each $\mathbb{R}_j$ in δ_1^m **do**
  Get $Label_k$ from $\mathbb{R}_j$
  Add $Label_k$ to $Labels$
end for
$Label_{alert} = 1$
return $Labels$, $Label_{alert}$

The main phrases of Algorithm 4.1 include:

1. Input dataset with ontological structure as well as users' health data collected by the sensors during the certain period. Initialize two temporary dataset. Assign the original input dataset to δ_1^m and assign an empty set to δ_2^m.
2. Filter records in the δ using each feature in the user' health data. If a feature is involved in a record in the δ, add this record into intermedia dataset. If intermedia dataset is empty in this process, a non-alert label will be returned.
3. Use an empty set to initialize the output dataset of the alert label.
4. Get labels from records in the intermedia dataset and add them to the set *Labels*.
5. Return the set *Labels* and an alert label.

Algorithm 4.2 . Monte Carlo-based Real-Time Analysis Algorithm (MC-RTAA)

Require: δ^o, $Max_p(n)$
Ensure: δ
Input δ^o, $Max_p(n)$
if $\delta^o \leqslant Max_p(n)$ **then**
  $\delta \leftarrow \delta^o$
else if $\delta^{MT} \leftarrow \emptyset$ **then**
  for i from 1 to $Max_p(n)$ **do**
    Random select $\mathbb{R}_j$ from δ^o
    Add $\mathbb{R}_j$ into δ^{MT}
  end for
  $\delta \leftarrow \delta^{MT}$
end if
return δ

The principle of Algorithm 4.1 is using $\mathbb{F}_i$ to filter the $\mathbb{R}_j$ in δ. Assume there are m features in each record on average, $\mathbb{R}_j$, and it is desired that the records can be filtered by half at each time on average. For each feature, $\mathbb{F}_i$, the average of computation times is m/2. Since there are n records, the time complexity can be approximately calculated by Eq. (1). Time Complexity =

$$\frac{m}{2} \times n + \frac{m}{2} \times \frac{n}{2} + \frac{m}{2} \times \frac{n}{4} + \cdots + \frac{m}{2} \times \frac{n}{2^{m-1}}. \tag{1}$$

Deriving from Eq. (1), we further formulate the equation shown in Eq. (2). Time Complexity =

$$m \times n \times \sum_{i=1}^{m} \frac{1}{2^i}. \tag{2}$$

Since $\sum_{i=1}^{m} \frac{1}{2^i} \in [1/2, 1)$, the time complexity of Algorithm 4.1 is $\mathrm{O}(\mathrm{m} \times \mathrm{n})$ and the space complexity is O(n).

4.2 Monte Carlo-Based Real-Time Analysis Algorithm (MC-RTAA)

MC-RTAA algorithm is designed to deal with over-sized dataset, which is represented in Algorithm 4.2. The output of MC-RTAA algorithm will be the input dataset of RTM-DPA algorithm. The main purpose of implementing MC-RTAA is to ensure that SCT-CPSS can provide real-time services. Applying *Monte Carlo Model* [29] aims to reduce the dataset size when the input dataset is too large to be operated in a short period.

As shown in Algorithm 4.2, the main phrases in the algorithm include the following steps.

1. Input the original dataset and the critical point reaching the maximum performance when calculating n sized dataset.

2. Output the original dataset if the size of the original dataset is not larger than the critical point, by which the system can well handle.
3. Otherwise, enter a for loop and random select $Max_p(n)$ records from the original dataset and run n times. Add the records into an intermedia dataset δ^{MT}.
4. Assign the set δ^{MT} to the set δ and return the set δ.

The next section demonstrates our experimental examinations with the implementation of the proposed algorithms.

5 Experiment and the Results

5.1 Experiment Configuration

In this section, we present our experiment configuration used in evaluating our proposed approach. We conducted experiments by our own simulator-based environment in which simulates the cloud-based tele-health system. We use two local servers to simulate the cloud server and dataset server, respectively. The cloud server is a HP server with Xeon E5 2.4 GHz 6-core CPU, 16 GB memory, and running Ubuntu 15.04. The dataset server is a HP server with AMD Opteron 2.4 GHz 8-core CPU, 8 GB memory, and MySQL 5.7. We use the Disease Ontology [30] as the dataset of our ontology knowledge database. For the purpose of evaluations, we compare our algorithm (M1) with two approaches, which are a traditional matching approach without using ontology (M2) and the naive ontology-based matching approach (M3).

The traditional matching approach used real-time corrected information to match exact values in dataset. The naive ontology-based matching approach was traversing all the terms in ontology dataset to find the matched result. Our approach was to use our own algorithms, RTM-DPA and MC-RTAA algorithms, to match the real-time records to the ontology dataset. The experiment was split into two steps. First, we used ontological optimization approach to redefine health records in traditional dataset. Second, we used real health records from various users to evaluate our approach. We compare the performance and accuracy between our approach and others.

Moreover, we improved the *Disease Ontology Dataset* (DOD) by defining new terms to describe symptoms. For example, referring to the first input health record, we used $Low1$, $Low2$, $Normal$, $High1$, and $High2$ as the status to substitute original exact values. As shown in Table 3, we took the temperature of users, U_1, as an example to introduce our ontology optimization approach. In general, the temperature of U_1 was from 36.9 to 37.8. We defined the temperature from 34.0 to 35.4 as the $Low1$ and from 35.4 to 36.9 as the $Low2$, while from 37.8 to 38.8 as $High1$ and from 38.8 to 42.0 as $High2$. Furthermore, we defined a few different cases, including sleep, after food, sport, and walk, to make our approach close to the practice. In different situations, U_1 had various temperatures. Using this approach could greatly save the storage space and the processing speed of the tele-health system.

Table 3. Ontology-based optimization approach for temperature

U_1	Low1	Low2	Normal	High1	High2
Sleep	34.0–35	35.0–36.5	36.5–37.0	37.0–39.0	39.2–42.0
Normal	34.0–35.4	35.4–36.9	36.9–37.8	37.8–38.8	38.8–42.0
AfterFood	34.0–36.1	36.1–37.5	37.5–38.4	38.4–39.6	39.67-42.0
Sport	34.0–37.2	37.14–38.5	38.5–40.0	40.0–41.0	41.0–42.0
Walk	34.0–35.8	35.8–36.7	36.7–37.8	37.8–39.4	39.4–42.0

In the ontology-based disease dataset, some disease was defined as a set of health information with ontology-based descriptions. For example, U_1 had one record when he caught cold and the user's temperature was $Low2$ normally. Along with some other health information, such as $High1$ heart rate and $High1$ blood pressure, the cold can be completely defined. Figure 3 showed the input of our experiments. We selected 100 records from different users under various environments. The amount of features for these records was varied due to the diversity of users. This setting ensured the practical significance of our approach. Generally speaking, we could get about 18 health records from health-oriented mobile devices. However, we only collected few records, as the time 20 and 74 in Fig. 3.

5.2 Experiment Results

First, our ontological optimization approach could dramatically save storage space for users' health information dataset. As shown in Table 4, the *Original* column indicated the original approach in which every exact value of users' health information was stored. The *Ontology* column showed our ontology optimization approach, in which we defined some value intervals referring to users' history health information. The average space cost of traditional approach was appropriate 1 GB, while the average space cost of our approach was around 20 KB.

Addressing two crucial concerns, our experiment evaluations had examined the performance in timing consumptions and accuracy rates under various operating scenarios. The experiment results were represented by figures, from Figs. 4, 5, 6, 7 and 8. Figures 4 and 5 illustrated comparisons of the performance between our proposed scheme (M1) and non-ontological approach (M2) from different perspectives. Figure 4 exhibited an evaluation of time consumptions between M1 and M2, which proved that our proposed method had a great advantage of saving computation time comparing to the non-ontological method. Next, Fig. 5 depicted the comparison of the accuracy performance between M1 and M2. According to the distribution shown in the figure, our ontological approach had a much higher-level of accuracy rate than the non-ontological approach.

Table 4. Comparison of users' health datasets using different approaches

	Original	Ontology
U_1	1.127 GB	21 KB
U_2	0.975 GB	19 KB
U_3	0.76 GB	18 KB
U_4	0.938 GB	19 KB
U_5	1.084 GB	20 KB
U_6	1.451 GB	26 KB
U_7	1.378 GB	25 KB
U_8	1.187 GB	22 KB
U_9	1.271 GB	22 KB
U_{10}	1.04 GB	20 KB

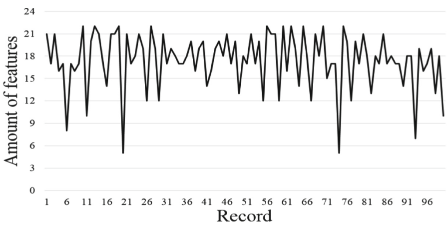

Fig. 3. Experiment inputs from selecting 100 records of different users under various environments.

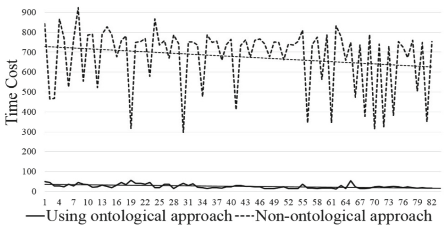

Fig. 4. Comparison of time consumptions between using ontological (M1) and non-ontological (M2) approaches.

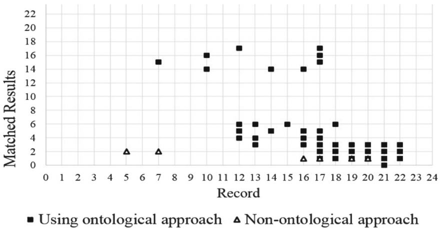

Fig. 5. Comparison of accuracy performance between using ontological (M1) and non-ontological (M2) approaches.

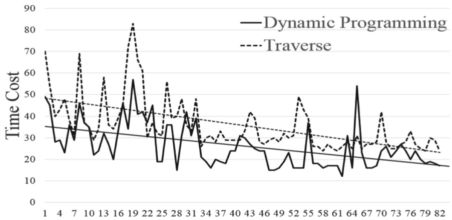

Fig. 6. Comparisons of time consumptions between our algorithm (M1) and traverse algorithm (M3).

Furthermore, we evaluated time consumption levels between M1 and M3, which both were ontological approaches. These two methods had the same level of accuracy rates since both were ontology-based. However, the time consumptions of M1 and M3 were varied. Figure 6 represented a comparison of time costs between M1 and M3 by counting the number of implementations. On average, the solid line was higher than the broken line, which meant that our proposed method M1 had a better performance than M3 in time saving.

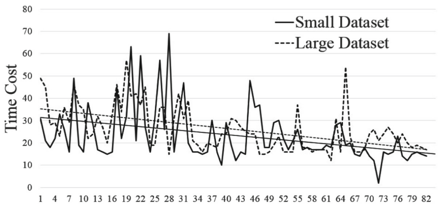

Fig. 7. Time saving performance comparisons of the proposed scheme (M1) with different sized datasets.

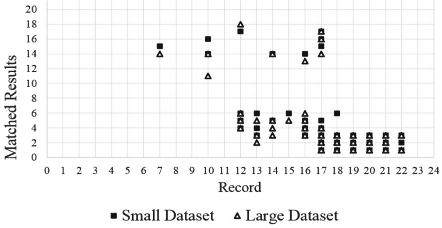

Fig. 8. Comparison of accuracy performance by using the proposed scheme (M1) under different sized datasets.

Moreover, we examined the performances of our scheme when dealing with different sized datasets from both perspectives of time costs and accuracy rates. Figure 7 represented a performance comparison for time consumptions. The solid curve exhibited executions for smaller sized dataset and the broken curve represented the implementation of the large dataset. According to our evaluation results, our scheme had a better performance in time saving when the dataset was smaller, as the broken curve positions were higher than the solid curve in the figure. In addition, Fig. 8 exhibited a distribution of the accuracy rates when the proposed scheme was implemented under different sized datasets. As shown in the figure, our scheme had similar performance under these two scenarios.

In summary, our experiment evaluation has proved that our system has an advantage of increasing computation capability and increasing the pairing rates in most situations. The implementations of SCT-CPSS can fit in real-time demands in the target tele-health field.

6 Conclusions

This paper proposed a novel paradigm, SCT-CPSS, for achieving personalized cloud-based tele-health solution based on implementing CPSS. The proposed approach could be adopted in smart city. The main motivation of implementing our mechanism was obtaining real-time information services and overcoming the challenge of real-time smart data processing in the dynamic cloud-based context. The proposed two crucial algorithms were RTM-DPA and MC-RTAA. Our experiment examinations had proved that the proposed scheme was efficient in time saving and ensuring accuracy.

References

1. Fouquet, F., Morin, B., Fleurey, F., Barais, O., Plouzeau, N., Jezequel, J.: A dynamic component model for cyber physical systems. In: Proceedings of the 15th ACM SIGSOFT Symposium on Component Based Software Engineering, Bertinoro, Italy, pp. 135–144 (2012)
2. Wang, S., Wang, D., Su, L., Kaplan, L., Abdelzaher, T.: Towards cyber-physical systems in social spaces: the data reliability challenge. In: IEEE Real-Time Systems Symposium, Rome, Italy, pp. 74–85 (2014)

3. Donoho, D., Tsaig, Y., Drori, I., Starck, J.: Sparse solution of underdetermined systems of linear equations by stagewise orthogonal matching pursuit. IEEE Trans. Inf. Theory **58**(2), 1094–1121 (2012)
4. Li, Y., Gai, K., Ming, Z., Zhao, H., Qiu, M.: Intercrossed access control for secure financial services on multimedia big data in cloud systems. ACM Trans. Multimed. Comput. Commun. Appl. **12**(4s), 67 (2016)
5. Frazzon, E., Hartmann, J., Makuschewitz, T., Scholz-Reiter, B.: Towards socio-cyber-physical systems in production networks. Procedia CIRP **7**, 49–54 (2013)
6. Yu, X., Pan, A., Tang, L., Li, Z., Han, J.: Geo-friends recommendation in GPS-based cyber-physical social network. In: IEEE International Conference on Advances in Social Networks Analysis and Mining, Kaohsiung, pp. 361–368 (2011)
7. Zhang, Z., Wang, H., Wang, C., Fang, H.: Interference mitigation for cyber-physical wireless body area network system using social networks. IEEE Trans. Emerg. Top. Comput. **1**(1), 121–132 (2013)
8. Ning, H., Liu, H.: Cyber-physical-social based security architecture for future internet of things. Adv. Internet Things **2**(01), 1 (2012)
9. Gai, K., Choo, K.K.R., Qiu, M., Zhu, L.: Privacy-preserving content-oriented wireless communication in internet-of-things. IEEE Internet Things J. **PP**(99), 1 (2018)
10. Gai, K., Qiu, M.: Blend arithmetic operations on tensor-based fully homomorphic encryption over real numbers. IEEE Trans. Ind. Inform. **PP**(99), 1 (2018)
11. Smirnov, A., Kashevnik, A., Ponomarev, A.: Multi-level self-organization in cyber-physical-social systems: smart home cleaning scenario. Procedia CIRP **30**, 329–334 (2015)
12. Adib, F., Mao, H., Kabelac, Z., Katabi, D., Miller, R.: Smart homes that monitor breathing and heart rate. In: Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems, Seoul, Republic of Korea, pp. 837–846 (2015)
13. Hu, X., Chu, T., Chan, H., Leung, V.: Vita: a crowdsensing-oriented mobile cyber-physical system. IEEE Trans. Emerg. Top. Comput. **1**(1), 148–165 (2013)
14. Hababeh, I., Khalil, I., Khreishah, A.: Designing high performance web-based computing services to promote telemedicine database management system. IEEE Trans. Serv. Comput. **8**(1), 47–64 (2015)
15. Luprano, J., Carvalho, P., Eilebrecht, B., Kortelainen, J., Muehlsteff, J., Sipila, A., Solà, J., Teichmann, D., Ulbrich, M.: HeartCycle: advanced sensors for telehealth applications. In: 35th IEEE Annual International Conference of the Engineering in Medicine and Biology Society, Osaka, Japan, pp. 6984–6987 (2013)
16. Baig, M., Gholamhosseini, H.: Smart health monitoring systems: an overview of design and modeling. J. Med. Syst. **37**(2), 1–14 (2013)
17. Sorwar, G., Hasan, R.: Smart-TV based integrated E-health monitoring system with agent technology. In: 26th IEEE International Conference on Advanced Information Networking and Applications Workshops, Fukuoka, Japan, pp. 406–411 (2012)
18. Raad, H., Abbosh, A., Al-Rizzo, H., Rucker, D., et al.: Flexible and compact AMC based antenna for telemedicine applications. IEEE Trans. Antennas Propag. **61**(2), 524–531 (2013)
19. Chan, M., Estève, D., Fourniols, J., Escriba, C., Campo, E.: Smart wearable systems: current status and future challenges. Artif. Intell. Med. **56**(3), 137–156 (2012)
20. Hu, C., Liao, J., Jin, P., Lin, W., Wang, G.: A portable telemedicine monitoring information system based on mobile internet networks. In: IEEE International Conference on Robotics and Biomimetics, Shenzhen, China, pp. 2274–2279 (2013)

21. Jimenez-Fernandez, S., Toledo, P., Pozo, F.: Usability and interoperability in wireless sensor networks for patient telemonitoring in chronic disease management. IEEE Trans. Biomed. Eng. **60**(12), 3331–3339 (2013)
22. Quwaider, M., Jararweh, Y.: Cloudlet-based for big data collection in body area networks. In: 8th International Conference for Internet Technology and Secured Transactions, London, UK, pp. 137–141 (2013)
23. Capua, C., Meduri, A., Morello, R.: A smart ECG measurement system based on web-service-oriented architecture for telemedicine applications. IEEE Trans. Instrum. Meas. **59**(10), 2530–2538 (2010)
24. Gai, K., Qiu, M., Zhao, H., Tao, L., Zong, Z.: Dynamic energy-aware cloudlet-based mobile cloud computing model for green computing. J. Netw. Comput. Appl. **59**, 46–54 (2015)
25. Silva, V., Ferreira, V., Viana, N.: Architecture for integrating healthcare services to the brazilian digital tv system. IEEE (Rev. IEEE Am. Lat.) Lat. Am. Trans. **13**(1), 241–249 (2015)
26. Yan, H., Huo, H., Xu, Y., Gidlund, M.: Wireless sensor network based E-health system: implementation and experimental results. IEEE Trans. Consum. Electron. **56**(4), 2288–2295 (2010)
27. Shih, D., Chiang, H., Lin, B., Lin, S.: An embedded mobile ECG reasoning system for elderly patients. IEEE Trans. Inf. Technol. Biomed. **14**(3), 854–865 (2010)
28. Wan, J., Zhang, D., Sun, Y., Lin, K., Zou, C., Cai, H.: VCMIA: a novel architecture for integrating vehicular cyber-physical systems and mobile cloud computing. Mob. Netw. Appl. **19**(2), 153–160 (2014)
29. Browne, C., Powley, E., Whitehouse, D., Lucas, S., et al.: A survey of monte carlo tree search methods. IEEE Trans. Comput. Intell. AI Games **4**(1), 1–43 (2012)
30. Wu, T., Schriml, L., Chen, Q., Colbert, M., Crichton, D., Finney, R., Hu, Y., Kibbe, W., Kincaid, H., Meerzaman, D., et al.: Generating a focused view of disease ontology cancer terms for pan-cancer data integration and analysis. Database **2015**, 1–10 (2015)