INTERNATIONAL RESEARCH JOURNAL OF MULTIDISCIPLINARY TECHNOVATION (IRJMT)

http://www.mapletreejournals.com/index.php/IRJMT
Received 19 August 2019 ISSN 2582-1040
Accepted 23 September 2019 2019; 1(6); 87-97
Published online 02 November 2019

Remote Patient Monitoring with Health Care Records Using Iot

J. Valan Abisha[1*], C. Abisha[1], S. Abirami[1], J. Reziga Susia[1]

[1] *UG Student, ECE Department, DMI Engineering College, Aralvoimozhi, Kanyakumari District, Tamil Nadu, India.*

**Corresponding author E-Mail ID: abishachellappanviji@gmail.com,*

Doi: https://doi.org/10.34256/irjmtcon12

ABSTRACT

For a medical treatment with IoT-based facilities, physicians always have to pay much more attentions to the raw medical records of target patients instead of directly making medical advice, conclusions or diagnosis from their experiences. Because the medical records in IoT-based hospital information system (HIS) are dispersedly obtained from distributed devices such as tablet computer, personal digital assistant, automated analyzer, and other medical devices, they are raw, simple, weak-content, and massive. Such medical records cannot be used for further analyzing and decision supporting due to that they are collected in a weak-semantic manner. In this paper, we propose a novel approach to enrich IoT-based medical records by linking them with the knowledge in linked open data. A case study is conducted on a real-world IoT-based HIS system in association with our approach, the experimental results show that medical records in the local HIS system are significantly enriched and useful for healthcare analysis and decision making, and further demonstrate the feasibility and effectiveness of our approach for knowledge accessing.

Keywords: Internet of Things, Medical Records, Health Care, Smart Devices, Health determination.

1. INTRODUCTION

Hospital Information System (HIS) is designed as a comprehensive, integrated information system to manage all the aspects of a hospital’s operation, such as medical, administrative, financial, and the corresponding processing of services. It is almost used by every hospital for daily operations. With the rapid development of mobile and IoT technologies in health-care system [1], [2], HIS does not only record data from physicians but also receives data from a mobile computer or IoT devices such as personal digital assistant, tablet computer, medical analyzer and other devices. IoT based HIS collects the data in different manners with complete format and large volume but much less knowledge. The features of IoT data they are structured but heterogeneous in format and massive but straightforward with less Knowledge.

In summary, the contributions of our work are highlighted as follows:

- A feasible way is provided to build a bridge between local structured data environment and LOD known as the biggest open knowledge network.
- A valuable application is raised by taking advantages of IoT and LOD technologies on real-world hospital data source.

Relational databases (RDB) scattered over the web are generally opaque to regular web crawling tools and other knowledge accessing applications. To address this concern, many RDB-to-RDF approaches have been proposed over the last years. There are mainly two types of approaches to transform RDB into RDF. One is R2RML[3] mapping language-based approaches. The others are non-R2RML approaches. In detail, Morph-RDB [10], RDB2RDF [11], Ultrawrap [12], [13] and Virtuoso [14] are the implementation of R2RML. In contrary, D2RQ [15], [16], DB2OWL [17] and R2O [18] have its own mapping language. The Table 1 given below gives the summary of state-of-art RDB to RDF transformation approaches.

Table 1. Summary of State-of-Art RDB to RDF Transformation Approaches

	Mapping Language	Compliance of R2RML	Status	Comme-rcial
Morph-RDB	R2RML	54/62	Active	No
RDB2RDF	R2RML	50/62	update to 2012	No
Ultrawrap	R2RML	62/62	Active	Yes
Virtuoso	R2RML	33/62	Active	Yes
D2RQ	DM	/	Active	No
DB2OWL	Customized	/	update to 2007	No
R2O	XML-based	/	update to 2011	No

I. THE METHOD

1.1. Overview of the Method

As showed in Fig 1, the pipeline of the approach is started from the various data sources such as IoT-based medical devices, physicians, system records, etc. The three modules, RDB Transformation, Entity Extraction and Knowledge Accessing, process the input data sources to connect with LOD. The output of the approach is the enriched HIS records with corresponding knowledge from LOD.

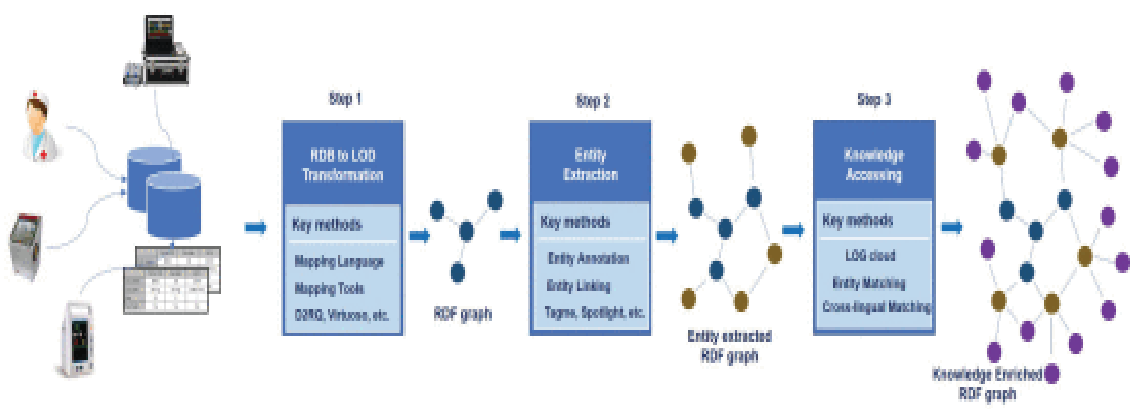

Fig 1. Overview Of TheMethod

The pipeline of the method. The input of the method is various data records from IoT devices, doctors, HIS records, etc. The output of the method is the enriched HIS records with medical knowledge's from LOD. The module "RDB to LOD Transformation" is introduced in section III-A-1. "Entity Extraction" is described in section III-A-2. "Knowledge Access" is proposed in section III-B.

1.1 RDB to LOD Transformation

RDB to LOD transformation has mainly two ways to implement is shown in fig.2. One is the implementation of DM mapping language[5] as well as the other is the implementation of R2RML mapping language.[6] W3C has provided all implementations of currently RDB to LOD transformation on their website.[7] Users could select one of these implementations based on their usages. In work, D2RQ is applied. The reasons D2RQ has been selected are: (a) D2RQ is one of the earliest implementations that many researchers are familiar with and easy to use; (b) Our team used to use DM mapping language which D2RQ has already supported; (b) There is no significant different on the result of transformation by using different implementations from the recommendations of W3C. The input of the transformation is the records of a relational database. The output of the transformation is LOD graph (RDF-triples[8]).

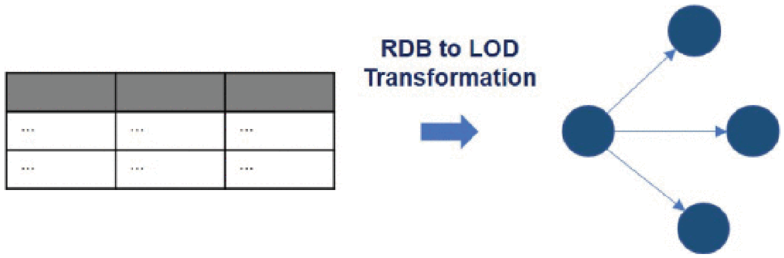

Fig 2. RDB to LOD Transformation

1.2. Entity Extraction

Fig 3 shows the entity extraction method. Currently, entity linking method has been well researched, and the related tools are mature. Most of all these methods are KB-based, such as Wiki-based, DBpedia-based, Wordnet-based, Probase-based, etc. In work, entities need to be linking are all in Chinese. Thus, a public KB-based Chinese entity linking service, CN-DBpedia entity linking service (CN-EL),[9] is applied. The reasons CN-EL has been applied are:

- It provides RESTful API of entity linking that could be easily accessed.
- It is based on the biggest Chinese LOD knowledge base, CN-DBpedia that meets the requirement of the work.
- CN-DBpedia will be used as a bridge to access other open knowledge bases in next step.

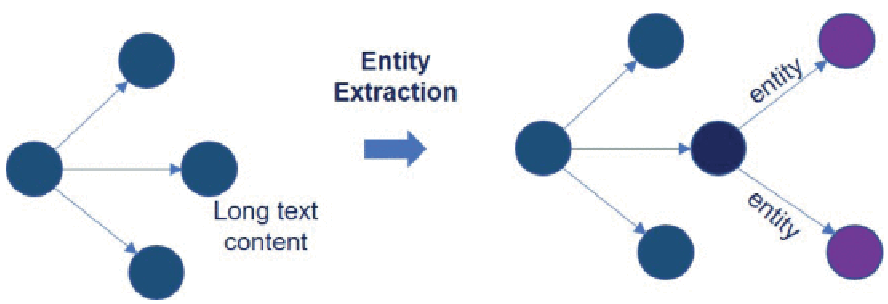

Fig 3. Entity Extraction

1.3. Knowledge Accessing

To obtain knowledge from open knowledge graph with local data environment is, indeed, to find the matching pairs between local data and open knowledge bases.

Thus, we utilize CN-DBpedia as a middleware knowledge base to bridge Chinese entities into LOD data environment. Since medical entities are extracted and linked with CN-DBpedia, the problem then becomes to match entities from CN-DBpedia to Drugbank and DBpedia.

Medical entities are a domain-specific thing that has particular terms, numeric values, abbreviations, identifiers and other specific text contained in their attributes. It is supposed that cross-lingual medical entities may not share common descriptions, comments, names, and labels. But, they tend to share common values on particular terms, numeric values, abbreviations, etc.

How common values affect the same medical entities between CN-DBpedia and DBpedia. So we randomly select medical entities from CN-DBpedia to build a test set in which entities already have "owl:sameAs" links with DBpedia. Fig 4 shows the test set consists of three categories that are medical tests (150), treatments (100) and surgeries (50).

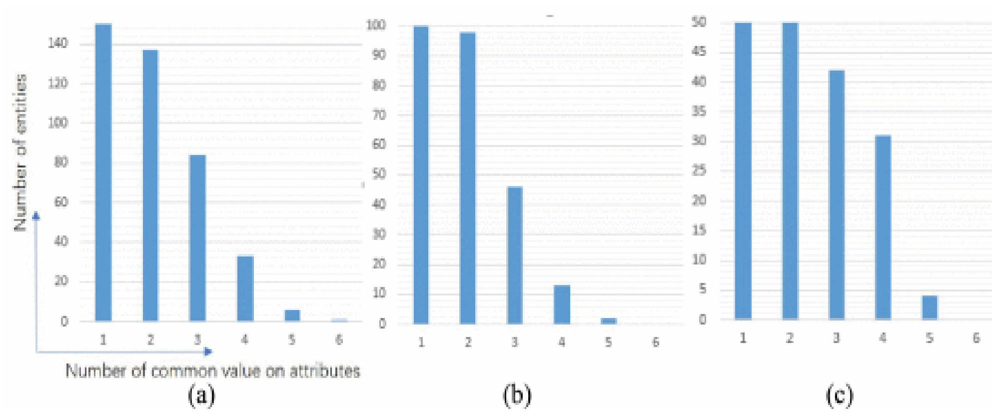

Fig 4. Test Set

It is observed; cross-lingual medical entities share common values in different sources.

The probability of being equivalent between entities is proportional to the number of common values. We mark this feature as Common Value (CV).

According to the observations that the probability of being equivalent between entities is proportional to the number of common values. CV could be imported into a probability function,

The range of PE is started from 0.0, while there are no common values between entities, to 1.0, while two entities share infinitely many common values.

Further, since various common values provide different contributions to the equality of two entities, the equality of two entities. In detail, 100 drug entities are randomly selected from the dataset. Then, manual works are applied on these drugs to connecting with entities in Drugbank by "owl: sameAs" link. Finally, a contribution analysis of common values is conducted on these entities, are shown in fig 5 below.

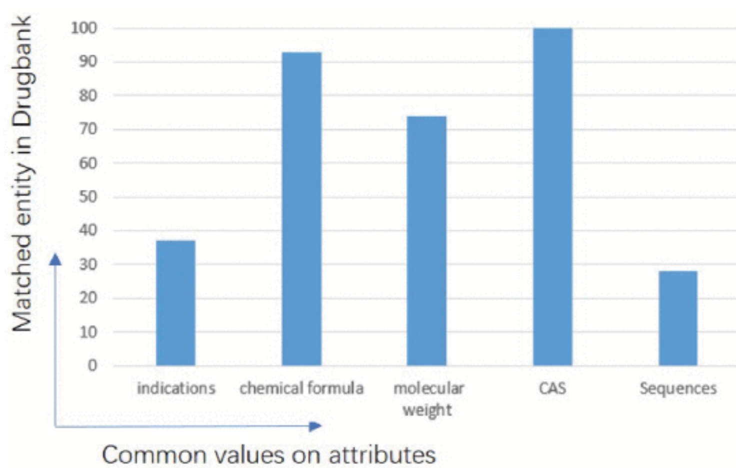

Fig 5. Matched entity in Drugbank

In the fig 5, attribute "indications" means two entities share the same values on "indications" have 0.37 probabilities to being equivalent "indications" value. Particularly, entities share the same value on "CAS" achieves 1.0 probability to being equivalent. It is because CAS number is a unique identifier (or say defining attribute) that can address distinct drugs.

II. CASE STUDY

In the section, step by step, a real-world case is provided with the proposed method applied on the case.

2.1 Dataset

2.1.1 Medical Set

Fig 6 Shows the Medical Set which is extracted from the HIS system. It consists of three relational tables that are Patient, Diagnosis and Medical Record related to intestinal cancer from Dec 12th, 2012 to May 5th, 2016. It contains 699 patients with intestinal cancer, 3600 diagnoses, and 89082 medical records. Further, six sub tables in Medical Recordare Treatment (14311), Drug (36919) Transfusion (658) Test (33203), Surgery (489) and others (3502).

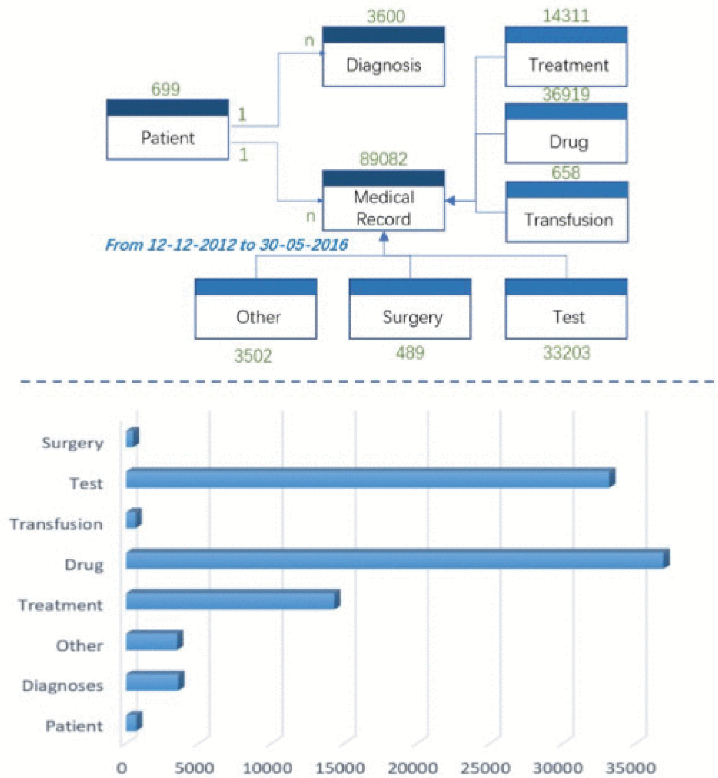

Fig 6. Medical Set

2.1.2 Open Knowledge Base

Fig 7. Shows the MCN-DBpedia Knowledge.**CN-DBpedia**Baseis an LOD knowledge base encyclopedia sites, such as Baidu Baike, and make this information available on the Web. It contains 9 million entities, 67 million RDF triples, 4 million abstracts, 19.8 million labels and 41 million info boxes. **DBpedia** is the core knowledge base of LOD. DBpedia allows users to semantically query relationships and properties of Wikipedia resources, including links to other related datasets. It describes 4.58 million entities with 583 million RDF triples, including persons, places, drugs, disease, etc. **Drugbank** is a LOD knowledge base. It is a unique bioinformatics and cheminformatics resource that combines detailed drug data with comprehensive drug target information. It contains 10,922 drug entries including 2,357 approved small molecule drugs, 926 approved biotech (protein/peptide) drugs, 108 nutraceuticals, and over 5,070 experimental drugs.

CN-DBpedia is mainly used to annotate or extract medical entities (drugs, treatments, surgeries, test, etc.) from Chinese records. DBpedia is used to linking knowledge to treatments, surgeries, and tests in the records. Drugbank is used to enriching the knowledge for drugs in the records.

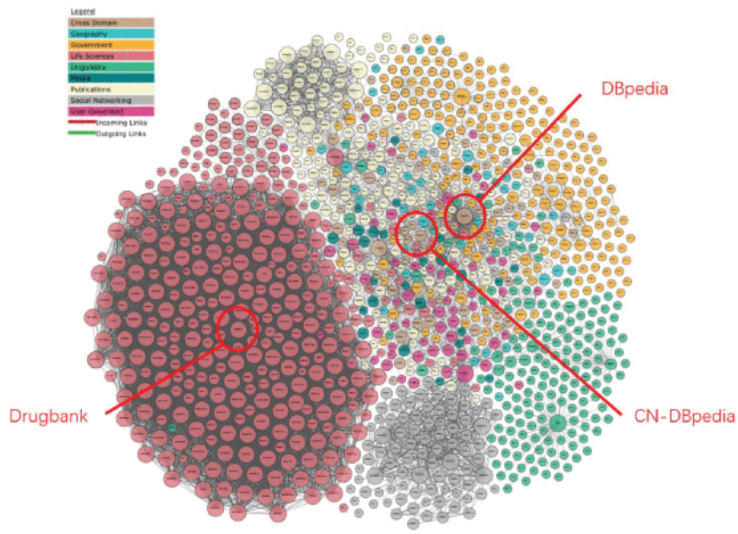

Fig 7. MCN-DBpedia Knowledge Base

2.2. RDB to LOD Transforming

Fig. 8 shows the RDB to LOD Transforming. Since the technology of transformation from RDB into LOD is mature, state-of-arts tools could be used. D2RQ mapping platform is applied to transform dataset (RDB format) into LOD (RDF format). D2RQ has implemented standard mapping language that enables customized transformation.

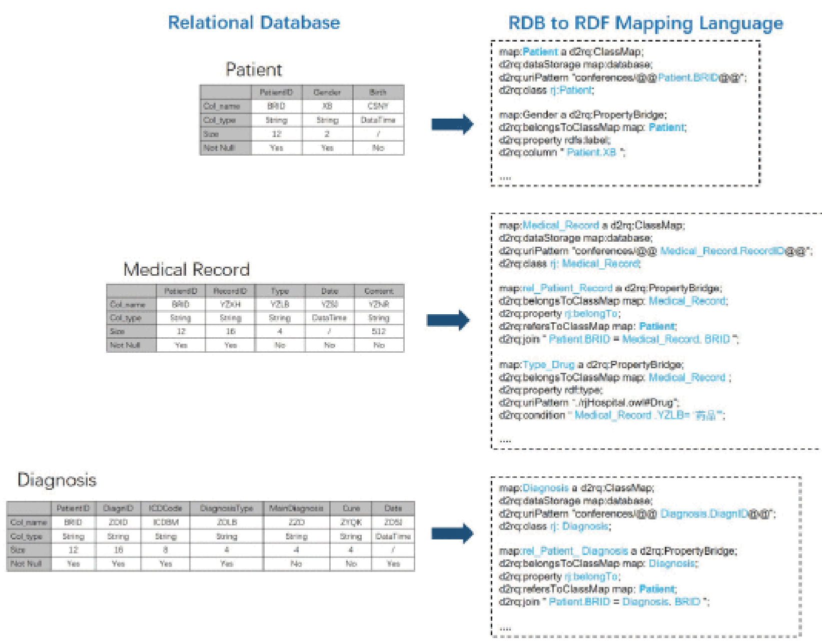

Fig 8. RDB to LOD Transforming

After transformation, a table-based dataset becomes graph-based LOD dataset. The table becomes RDF node in LOD graph. Further, each node has been identified by a unique URI that could be referred by other nodes or other data sources among LOD environment. Fig 9 shows the Graph based LOD Dataset.

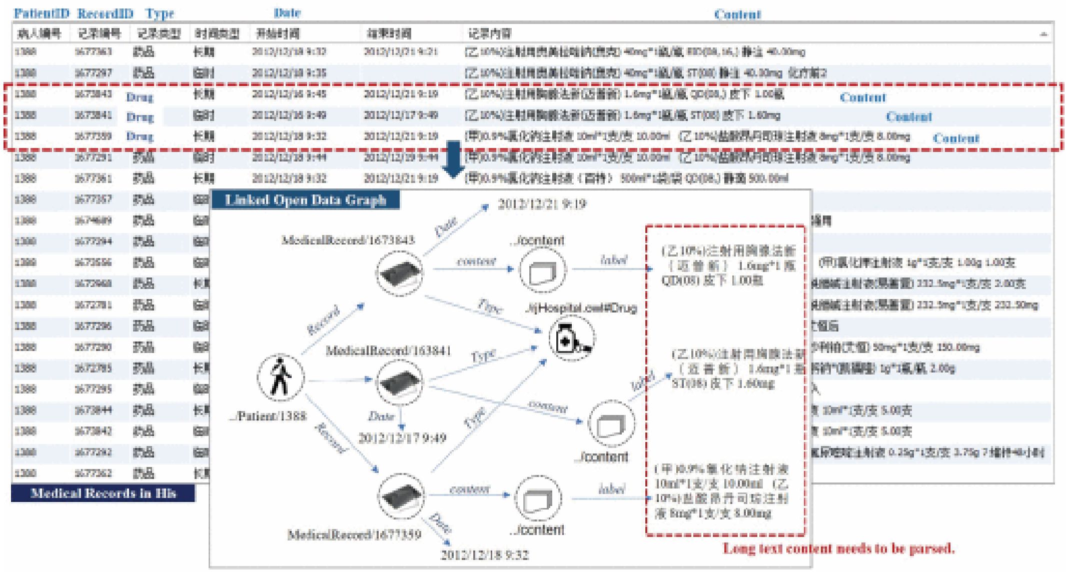

Fig 9. Graph based LOD Dataset

2.3. Medical Entiry Extracting

In this step, medical entities contained in the long text content of RDF triple are extracted and then linked as new RDF triples.

The CN-DBpedia-based extraction system is applied on entities extraction from records of drugs, treatments, surgeries, and test. The result is provided in Table 2.

Table 2. CN-DBpedia-based extracted data

	Records	Extracted	Distinct	Entities/Record
Drugs	36919	78268	627	2.12
Treatments	14311	16171	116	1.13
Surgeries	489	431	24	0.88
Tests	33203	32873	1542	0.99

To evaluate the effectiveness of entity extraction, we select 100 records as a test set for each category with at least 100 distinct drugs, treatment, test and 20 distinct surgeries. Entities in the test set are annotated by human efforts as the ground truth.

Table 3. Effectiveness of entity extraction

	Records	Ground	Extracted	Correct	F1
Drugs	100	187	182	178	0.964
Treatments	100	133	108	97	0.806
Surgeries	100	100	119	34	0.310
Tests	100	104	95	89	0.895

In Table 3, Ground means the ground truth of the test set. F1 is F1-measure calculated by precision (Correct/Extracted) and recall (Correct/Ground). From the evaluation, it is observed that entity extractions in drugs, surgeries, and tests records achieve relatively high scores in F1-measure. Most of the medical entities are correctly extracted. But, only about 30% entities of surgery are correctly extracted. It is because the expressions of surgeries in HIS database are input mainly based on physician's practice. The same surgery usually is typed in different expressions by different physicians. It leads deep semantic heterogeneities in surgery records that hard to be extracted by the system.

After extraction, medical entities hidden in long text records are extracted. Then, these entities are becoming new RDF triples link to original graph by the link "rj:entity." is shown in fig 10.

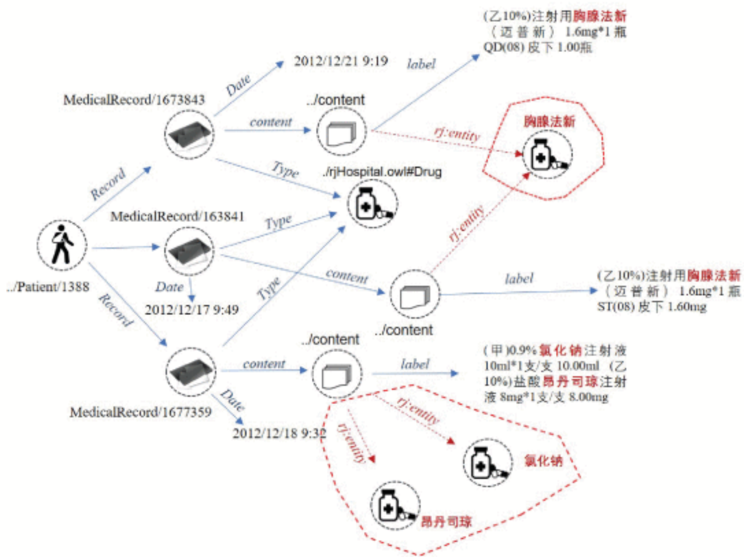

Fig 10. ***Link "rj:entity."***

After entity extraction, CN-DBpedia knowledge has also been linked to the entities. Thus, the isolated entities existing in the medical records become linked entities (linked with CN-DBpedia) represented as RDF graph is shown in fig 11.

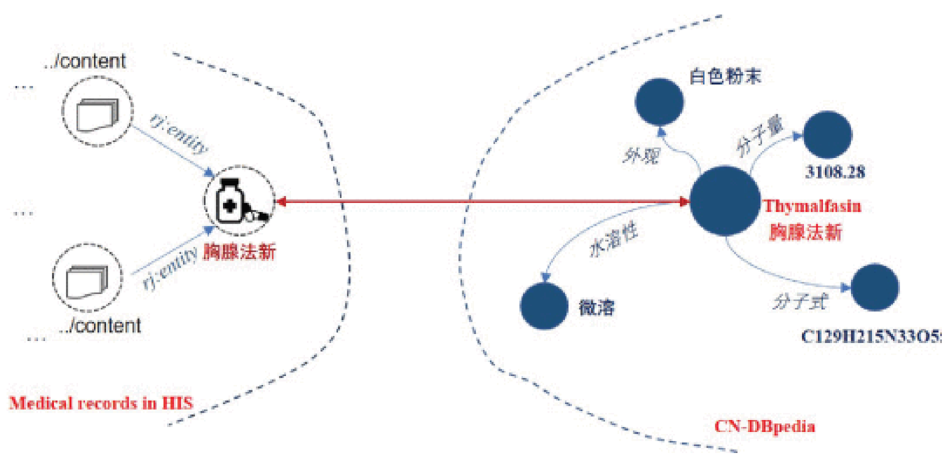

Fig 11. RDF Graph

2.4. Open Knowledge Accessing

The purpose of graph matching is to discover corresponding knowledge from open knowledge graph. Particularly, the open knowledge graphs selected in this work are Drugbank and

DBpedia. First, drug, treatments, surgeries and test records have been transformed into RDF graph. Then, drugs graph is matched to Drugbank graph as well as treatments, surgeries and test are matched to DBpedia graph is shown in Table 4.

Table 4. DBpedia Graph

Medical Records	Distinct Entities	Matched Entities	Knowledge Base	Added Knowledge (RDF triples)
Drugs	627	615	Drugbank	52,894 triples
Treatments	116	97	DBpedia	2,622 triples
Surgeries	24	18	DBpedia	344 triples
Tests	1542	863	DBpedia	18,126 triples

It is observed that knowledge extracted for drugs (52,894) are much more than knowledge for treatments (2,622), surgeries (344) and tests (18,126). This is because Drugbank is a domain-specific knowledge base contains richer medical related information than DBpedia which is a cross-domain knowledge base. Even so, from the result, knowledge extracted from DBpedia could significantly enrich the local database of HIS.

After graph matching which is shown in fig 12, knowledge (RDF triples) in Drugbank and DBpedia are accessed with medical entities in HIS database. Noting that these RDF triples are the level-1 triples based on the matched entities. I.E., the triples start (end) from the matched entity with one depth to other nodes in the knowledge graphs (Drugbank or DBpedia).

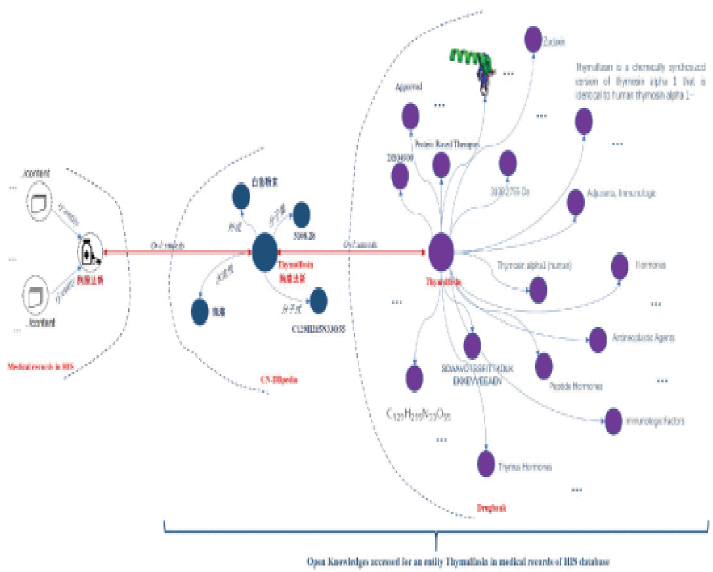

Fig 12. Matched Graph

It is feasible to evaluate the correctness of knowledge accessing since the database selected for the work is rather small. There are 2309 matched entities (distinct) that could be checked by human efforts. Four matching experts are asked to cross check these 2309 entities and annotate the correct matching entities in knowledge as ground truth. Based on the ground truth, F1-measure criterion is applied is shown in Table 5.

Table 5 F1-measure Graph

Medical Records	Ground Truth	Matched Entities	Correct Matchings	F1-measure
Drugs	627	615	615	0.990
Treatments	116	97	42	0.395
Surgeries	24	18	15	0.713
Tests	1542	863	812	0.675

From the result, knowledge accessing for drugs achieves 100% precision and 98% recall. It means most of all drug entities in the local database could efficiently be linked with an open knowledge base. It is because the drugs in both local dataset and open knowledge base share the same naming standard. Physicians in the hospital input the drugs by selecting the drug from a dictionary instead of typing the drug names. It significantly reduces the semantic heterogeneity among the drug names. Test entities matching achieve 94% precision and 53% recall. It means most of all test entities match the correct entities in open knowledge base if the matching pairs could be found in the knowledge base. 47 % of test items cannot find a matching pair from the knowledge base. This is because these test items are the local test item, i.e., the name of the tests usually appears only in this hospital. It cannot find a match from the open environment. The same circumstances happen in treatment and surgeries records.

III. LESSONS LEARNED

From the real-world case study, we learned that open knowledge base and automated accessing method could significantly enrich the data environment of local hospital database, especially for the database of HIS system. The proposed method is a novel, effective and feasible way for hospital integration and medical data analysis. On the other hand, three major problems also learned from the case study:

3.1. Knowledge Base Selection

The quality and quantity of knowledge accessing are mainly depended on the selected knowledge base. There is neither standard nor criteria to guide us to select a proper knowledge base. With the rapid development of Linked Open Data, more and more open knowledge bases are accessible in a unified way (RDF triples). There is an urgent need for the criteria of knowledge base evaluation.

3.2. Cross-Lingual Knowledge Base

CN-DBpedia is selected as middleware to bridge Chinese medical records with English knowledge in DBpedia and Drugbank. Most of the items (entities) in Chinese knowledge base have no “sameAs” link to other knowledge bases. It significantly reduces the interoperability of open knowledge base.

3.3. Meta-Data of Knowledge Base

RDF graph based matching method for accessing knowledge from different knowledge bases. It is affected by the meta-data of the knowledge bases. If two Knowledge Bases share the same or similar meta-data, it will be much easier and more efficient to match knowledge between knowledge bases. Thus, meta-data or schema mappings between knowledge bases are the essential in open knowledge inter-operation.

CONCLUSION

In this paper, we presented a Link Open Data based knowledge accessing method for IoT-based HIS system. In our approach, initially the state-of art LOD technologies are used to transform local data model into LOD compatible model. Then, the medical entities are obtained from the target medical records by applying an entity extraction approach. Finally, a cross-lingual entity matching approach is proposed to access medical knowledge from LOD based graph. In the real-world case study, our approach clearly demonstrates a valuable application of enriching IoT-based HIS system with medical knowledge from LOD. In the future, beyond specific knowledge bases such as DBpedia and Drugbank, a more compatible knowledge accessing method will be studied for the complete knowledge bases in LOD cloud.

REFERENCES

1. H. E. Zouka, An Authentication Scheme for Wireless Healthcare Monitoring Sensor Network, in:14th International Conference on Smart Cities: Improving Quality of Life Using ICT &IoT (HONETICT), Jordon, Irbid, 2017.
2. M. H. alieragh, A. Page, T. Soyata, G. Sharma, M. Aktas, G. Mateos, Health monitoring andmanagement usinginternet-of-things (IoT) sensing with cloud-based processing: Opportunities andchallengesin Services Computing (SCC), IEEE International Conference on, pp. 285–292, 2015.
3. A. J. Jara, M. A. Zamora-Izquierdo, A. F. Skarmeta, Interconnection Framework for m Health andRemote Monitoring Based on the Internet of Things, in IEEE Journal on Selected Areas inCommunications, Vol. 31, pp. 47–65, 2013.
4. R. Wijaya, Heart rate data collecting using smart watch,IEEE 4th International Conference on SystemEngineering and Technology (ICSET), 2014.
5. P. D. M. Koshti, Sanjay Ganorkar, “IoT Based Health Monitoring System by Using Raspberry Pi and ECGSignal,” International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering Vol. 5, 2016.
6. Z. Yang, Q. Zhou, L. Lei, K. Zheng, W. Xiang, An IoT Based Wearable ECG Monitoring System forSmart Healthcare, Journal of medical systems Vol. 40, 2016.
7. R.AnariToninelli, A. Corradi, Enabling secure service discovery in mobile health care enterprise networks, IEEE Wireless Communications, Vol 16, pp. 24–32, 2009.
8. H. E. Zouka, Challenges in Securing Wireless Sensor Networks, in: The Seventh International Conference on Sensor Technologies and Applications, Barcelona, Spain, pp. 145–150, 2013.

Conflict of Interest

None of the authors have any conflicts of interest to declare.

About the License