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SEPHYRES: A Medical Diagnosis Model based on Semantic Pseudo-Fuzzy Plan and Radar-form Interface

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Abstract
Clinical decision support systems have emerged to help users and patients. Despite the exciting developments, physicians still have not fully accepted and included the decision support systems in daily practice. Some of resistance is related to expressivity and user interface. After publishing SEPHYRES 1, a medical diagnostic assistant focused on only detailed pain descriptors, a more explicit advanced plan has been recommended to relieve above mentioned barriers. Having combined the pseudo-fuzzy and semantic layers could improve expressivity challenge in using diagnostic terms. In addition, applying visual-pain-area module in detailed granularity along with natural language processing module and radar-form interface, a new point of view for the user-interface-related problems has been addressed for future researchers.

Keywords: Clinical information systems; Clinical decision support; Computer assisted decision making; Knowledge modeling and representation; Telemedicine and telehealth; Computer assisted diagnosis

Introduction

The decision support systems have emerged to help users make better decisions and some of them have been presented in the form of recommender systems. Such systems have been directed toward individuals having little experience or skill to evaluate the potential of alternative items or aware of available item ranges [1]. Some recommender approaches turn to predict individual's right items in accordance with his/her requirements and preferences. So far, several kinds of recommender system methods have been introduced: content-based and collaborative. The former, content-based filtering, suggests items that are similar to the user's old related items. In this strategy, the goal is the calculation of similarity between items [2]. In medical diagnostic systems, this similarity should be calculated between patient's profile and pre-defined profile of the disease. The second proeminent type of recommender system is collaborative filtering in which the similarity is calculated among users/patients [3], for example, other patients had already been with a similar profile and right diagnosis.

Using recommender systems, many studies and applications applied the expert system capabilities in their internal engines. It has been done in systems that assist medical diagnosis, such as deDombal's system called AAPHelp [4], INTERNIST I [5], MYCIN [6-7], Dxplain [8], Quick Medical Reference (QMR) [8] and MET1 [9-10].

Moreover, in the last decades, some medical applications have used intelligent techniques borrowed from the semantic web that made it possible to avoid syntax matching between patient's profile and disease profile. Here, the semantic web engineers needed to turn every facet of medical information and knowledge into valid and accurate information artifacts that could bear further reasoning. In addition, the knowledge representation in the form of an ontology translate the information in standardized form to be understandable by machine. Hence, some studies successfully developed medical ontologies, such as HAIKU [11], ACGT-MO [12], DO [13], MedDRA [14], K4Care project [15-17], ODDIN [18], and Ontology Merging [19].

Regarding another intelligent requirement in medical literature, it should be noted that the uncertain nature of medical parameters makes medical decision-making more difficult. Having applied probabilities, Crespo et al. (2010) proposed an uncertain-based ontology [18]. In addition, the recent study of Sanaeifar et al. (2016) focused on inserting the pseudo-fuzzy perception into the medical ontology entitled SEPHYRES 1. However, in that case, they only considered semantic pain descriptors and ignored other signs and symptoms practically [20].

In this paper, a more comprehensive diagnostic model called SEPHYRES (SEPHYRES stands for SEmantic Physician HYbrid Recommender Expert System) is proposed.

Proposed Plan

A multi-layer diagnostic model has been presented in Figure 1 in which semantic technology, fuzziness, image processing and natural language processing have been combined. The relationships among modules have been defined uni- and bi- directionally.

Semantic Infrastructure

The semantic layer, as an infrastructure, can receive the results of the upper layers and enhance recommendation quality. This issue had been implemented in SEPHYRES 1 only on pain descriptors and the comparing test against Isabel symptom checker was satisfactory. Although, SEPHYRES 1 did not tackle all sign and symptoms and all semantic capabilities [20]. Some exciting opportunities are the covering composed terms and terms which include other terms that facilitate the matching process and improve flexibility as well as expressivity. Additionally, this layer embed inherent advantages of semantic technology, and also amplify the upper layer outputs and perform further reasoning.

Pseudo-Fuzzy Engine

This layer has been inserted due to eliminating the uncertainty challenge of medical parameters. Being pseudo-fuzzy has been implemented as no sensitivity to special terms and crisp edges in the matching process, while it has not the fuzzy complexities. Clearly, suppose a disease has pain on *Epigastric* region of abdomen, thus in textual interfaces in absence of fuzziness, user should enter words with the same root until the matching could occur (crisp edges in matching process). However, there are other terms that could be correct with lower confidence level, such as *Abdomen*, *Upper Abdomen*, *Hepatic Area* and so on.

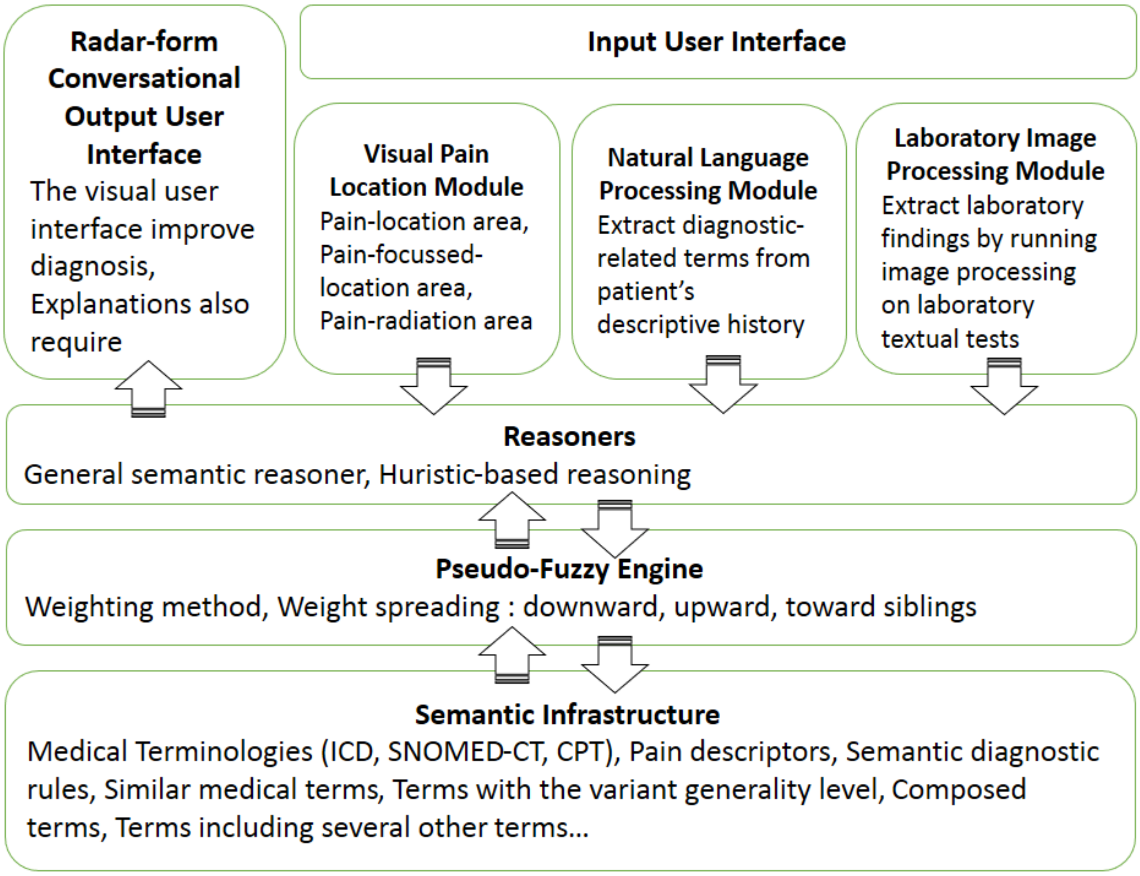

Figure 1. The semantic pseudo-fuzzy model for medical diagnosis

This issue is addressed by pseudo-fuzzy engine in this paper. Consequently, if the user enters the term mistakenly or uses the alternative terms with the different generality level, the SEPHYRES will still perform the matching process with a lower weight. Moreover, this module can be coupled on the one side, with semantic infrastructure and on the other side, with practical upper-layer modules mentioned below. This mechanism was implemented in SEPHYRES 1 on the pain-area-related concepts that were coupled with semantic properties: *hasParent*, *hasHalfParent* and *hasQuarterParent* in order to adapt 9-part terms, 4-part terms and other abdominal pain-area terms [20].

Visual Pain Location Module

So far, limited standard terms or visual segments have defined the pain location with low flexibility. In some symptom checkers, it is typed by textual terms such as Patient.info [21], and in others with visual pain location interfaces, it is selected by only some limited visual segments such as a segment for *Upper Abdomen* and another segment for *Lower Abdomen* so that it is not possible to select *Epigastric* or *Umbilical* regions in abdomen, as is in WebMD [22]. On the one hand, the visual selection of more detailed segments could be required, but on the other hand, there is no detailed information in the evidence-based scientific literature due to equipping a knowledge base with detailed pain location. As a result, the pseudo-fuzzy-enabled visual interface is suggested, and thus the user could select pain-location-related information, including *Pain Location*, *Pain Focused Location* and *Pain Radiation* in a more detailed visual manner. A sample interface has been shown in Figure 2 with which the mentioned possibility has been provided by three colors. After selection of pain areas, the pseudo-fuzzy engine transforms them to semantic pain-related triples based on standard terms and some heuristic rules. As above-mentioned, these semantic triples are delivered to the semantic infrastructure for further reasoning.

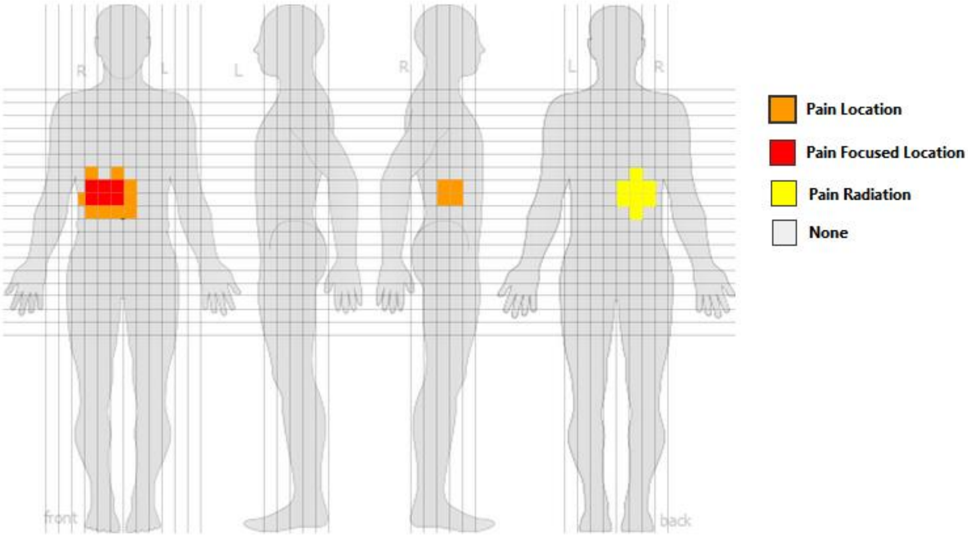

Figure 2. The pseudo-fuzzy visual pain location interface

Laboratory Image Processing Module

For the laboratory findings to be attached, this module can perform image-processing techniques on the laboratory tests and deliver laboratory findings to the lower layers including pseudo-fuzzy module and semantic infrastructure layer for fuzzy and semantic analysis. Even though the best performance is achieved on textual-typed test results, other visual test results should not go unnoticed. For example, as soon as a novice general practitioner takes a mobile photo from patient's laboratory test, the inferred triples could be added to the diagnostic query on his/her mobile health application.

Natural Language Processing Module (NLP)

The evaluation process of SEPHYRES 1 was implemented based on manual extracting of pain-related terms from the descriptive medical history of evidence-based test cases published in MEDSCAPE and PubMed [20]. The manual extracting could be done automatically by an NLP-based module. Like other upper modules, the outputs are inserted to the diagnostic query.

Reasoners

The reasoners could extract new facts based on knowledge base and some standard criteria. For example, in SEPHYRES 1, the primary knowledge base was developed about 15 times by semantic reasoners (Pellet, Jena rule reasoner) [20]. In spite of applying semantic reasoners in the previous semantic medical applications and studies [11-19], the general semantic reasoners can only infer some standard-defined relations seamlessly and can not bear domain-heuristic inferences. One of the pseudo-fuzzy solutions is the weight spreading method in the graph performed in forms of downward, upward and toward siblings [23-25]. However, to achieve the best performance and tackle domain heuristics, several types of complement reasoners should be applied.

Radar-form Conversational user Interface

Most recommender systems in all domains get the user requirements in their one-step user interface. However, in most cases, this model is not effective because of the lack of user information. In addition, the first recommendations may be mistaken and the user wants to refine the query. Of course, there is a problem about how the design conversation in optimized steps [1]. Hence, an interactive user interface should be investigated.

Moreover, there are two metadata that have been frequently used in differential diagnostic results: *Weight or Rank* and *Urgent Level*, as they are in Patient.info symptom checker powered by

Isabel [21]. It is observed that the ranked flat list of differential diagnoses along with an urgent flag (0 or 1) could not be practically effective, instead, the visual radar-based interface is recommended. A sample of such interface has been shown if Figure 3 that presents the results of a query with some symptoms in a pregnant female.

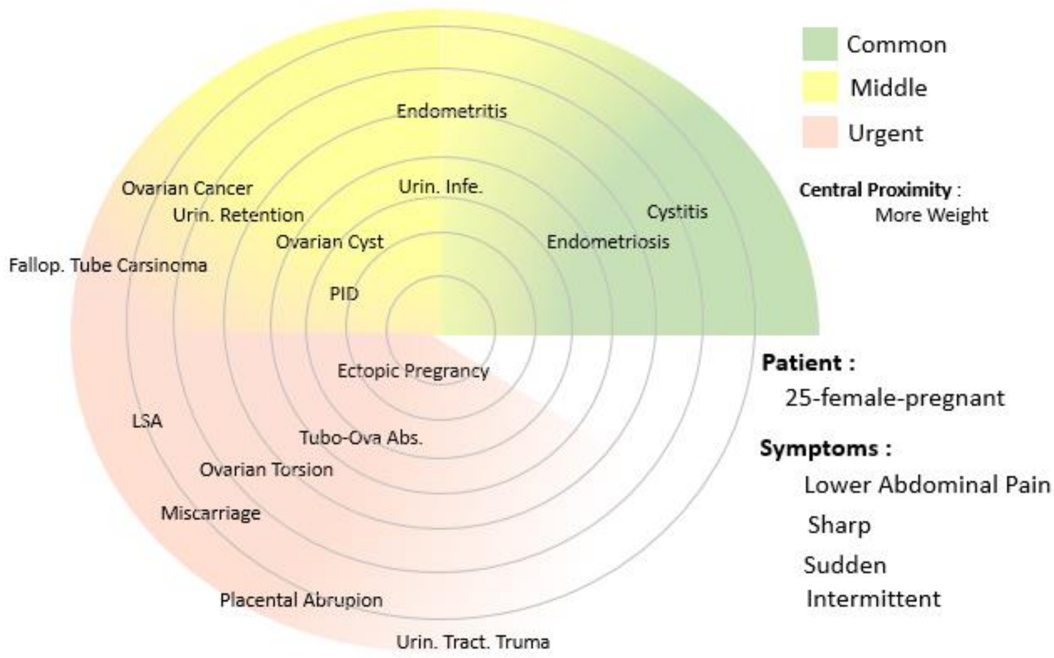

Figure 3. The radar-form interface for results

In this interface, points (diseases) closer to the center have more weight/rank. Furthermore, the entire radar-form screen has been divided into three distinct colors: green for common diseases, red for emergency diseases and yellow for middle urgent. In other words, a ranked-flat list of diseases has been transformed to a visual interface in which a physician could focus on either urgent diseases or more weight diseases at a glance. In addition, the urgent level transformed from the Boolean values to a weighted-pseudo-fuzzy parameter.

Concluding Remarks

Even though the proposed combined plan is flexible and expressive enough with the enriched, exciting user interface, there are several concerns about different medical terminology standards (eg. ICD, SNOMED-CT, CPT) as well as scalability issues. Of course, the integration challenge of diverse medical terminologies is an old problem in medical diagnostic systems. However, this variety could be intelligently resolved by semantic infrastructure in the form of ontology. Clearly, a sophisticated semantic engineer could tackle with this problem by several methods of ontology matching [26] as well as embedded pseudo-fuzzy engine. Furthermore, considering scalability, SEPHYRES 1 was developed the knowledge base about 15 times by reasoning strategies, thus, the scalability concern is really reasonable so that a more comprehensive study should be done, as has been noted in SEPHYRES 1 [20].

Declaration of interest

The authors report no conflict of interest.

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