A knowledge-based framework enabling decision support in RFID solutions for healthcare

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***Abstract*—The benefits of RFID technology in the healthcare sector are widely acknowledged. Nevertheless, the adoption of RFID as a means for pure item identification prevents adequate support to most knowledge-intensive medical tasks. Here an innovative Decision Support System for healthcare applications is presented, based on a semantic enhancement of RFID standard protocols. Semantically annotated descriptions of both medications and patient's case history are stored in RFID tags and used to help doctors in providing the correct therapy. The proposed system allows to discover possible incompatibilities in a therapy suggesting alternative treatments.**

I. Introduction

RFID is an automatic identification technology, relying on storing and remotely retrieving information located on a transponders (named *tags*) exploiting proper interrogator devices (*readers*) [1]. The miniaturization of electronic components and circuits nowadays allows an RFID tag to be applied to or incorporated into objects, animals, or persons for identification and tracking purposes. Some tags can be interrogated at distance and also by-passing possible physical barriers and obstacles. They usually contain a unique code which is read by the interrogator and can be used to identify the associated object via a networked database on a server. Nevertheless, transponders with larger internal memory open new interesting possibilities and enable further applications [1]. Notice that current Radio Frequency (RF) identification methods only enable elementary recognition applications which exploit queries over a database for retrieving object features and properties [2]. If tagged objects, animals or persons expose to a reader not simply a numeric identifier but a compressed semantic annotation, they may describe themselves without referring to a centralized database. This is particularly useful in case: (i) a dependable or networked link toward the fixed information server is unavailable; (ii) the information related to the object/subject has to be always and straightaway available; (iii) an advanced description of object/subject characteristics and capabilities is needed in order to enable complex inference procedures over data stored within the tag.

All the above features have an undoubted interest in the healthcare sector. E-healthcare information systems include applications for tele-medicine, tele-health, and tele-homecare services. RFID technology now has significant impact on healthcare systems, with specific reference to tracking and management of patients and medications within hospitals [3]. Benefits of RF identification in hospitals include error prevention in identifying staff, tracking equipment and access regulation to various divisions for patients and doctors [4]. Although these applications are noteworthy, a more advanced exploitation of RFID technology could further enhance the impact of this technology in e-healthcare. In this paper we present a novel Decision Support System (DSS) for innovative medical applications based on a semantic enhancement of RFID standard protocol. Thanks to semantic annotation of both medications to be administered and patient's case history, the proposed system helps physicians in confirming and then choosing the best therapy based on the medical record of the patient.

By referring to semantic metadata stored within RFID tags attached to pharmaceuticals packaging and patient's RFID wristband, a matchmaking can be performed to discover possible inconsistencies in a therapy, also suggesting further treatment options to the physician. We borrowed ideas and technologies devised for the Semantic Web initiative. We set our stage in an e-healthcare context, where pharmaceuticals and patients equipped with RFID tags are dipped into an enhanced Bluetooth framework. The RFID EPCglobal data exchange protocol [5] and the Bluetooth Service Discovery Protocol [6] have been modified to enable support for advanced inference services, while maintaining legacy RFID applications. Given a previous work that enhanced the basic discovery features of Bluetooth with semantic-based discovery capabilities and on the extension of EPCglobal specifications for RFID tag data standards [7], here we introduce novel semantic-based value-added services for decision support in healthcare.

The remaining of the paper is structured as follows. In the next section relevant related works referred to the exploitation of RFID technology in the medical field are surveyed. Section III outlines the framework, explaining the discovery and matchmaking algorithms devised for the purposes outlined

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above. Section IV illustrates the system architecture and the approach in an example scenario; finally conclusions and future work close the paper.

II. RFID for Healthcare

Hospital activities are characterized by complex workflows requiring the interaction of several different actors and the co-ordination of multiple facilities [4]. Supply chain management has suggested that the identification capability of RFID can be leveraged to improve healthcare services. Patients, equipment and staff can be tagged with RFID transponders and tracked within a hospital by a network of RFID readers deployed in key locations. Actions recognized via RFID can be logged automatically, thus avoiding lengthy and error-prone manual data input by personnel. Research studies and pilot projects have evaluated the impact of such infrastructures in ordinary hospital activities [3], [8] as well as in emergency conditions due to disasters [9] or epidemics [10]. The integration of RFID into a Hospital Information System (HIS) allows to: automate security (authorization enforcement) and safety (prevention of human error) checks during critical processes such as patient admission, checkout and medication administration; reduce response times in emergency situations; improve efficiency of resource allocation. Ultimately, these benefits lead to higher confidence and satisfaction for both patients and personnel [4].

The integration of RFID with other pervasive computing technologies –such as communications protocols and wireless sensor networks– is leading to further innovative applications in the tele-medicine area, particularly for ubiquitous persistent monitoring of elderly or disabled people [11], [12] as well as for patient follow-up during rehabilitation phase [13]. Context-awareness is the key aspect of such approaches to improve quality of healthcare services. Challenges and benefits were clearly evidenced in a prototype of RFID-enabled smart hospital bed [14], whose architecture resembles our solution. The proposed system, however, provided only basic identification features and lacked more advanced knowledge-based capabilities.

Our proposal takes a step further in this direction, by combining a pervasive and context-aware computing framework with decision support features based on Knowledge Representation (KR) technologies. Decision support to clinical activity is widely acknowledged as one of the most important benefits of medical informatics [15]. Research has also evidenced that artificial intelligence and rule-based systems can be effective in helping clinicians to reduce errors in both diagnosis and treatment. Nevertheless, the first generation of Computerized Physician Order Entry (CPOE) systems was mostly based on manual data entry and a fragmented collection of non-integrated utilities. Experience taught that, in such cases, the improvements in overall quality of patient care are not always clear, since the decrease in some kinds of errors is counteracted by slowdowns in operations and an increased frequency of other types of mistakes. Decision support is highly effective only when it is automatic and seamless [15].

Ontology-based knowledge modeling can ensure that only highly relevant information about a patient's clinical conditions and appropriate treatments are supplied to physicians, thus providing unobtrusive and context-aware decision support services for therapy management. The use of lightweight wireless computing infrastructures and of widely-adopted KR technologies can promote interoperability and integration of solutions designed for hospital centres hosting tele-medicine applications.

Finally, as pointed out in [11], ubiquitous computing technologies allow the capture of health data at an unprecedented scale: knowledge-based approaches can assist in the management, analysis and interpretation of such data for research purposes and/or to improve clinical best practices.

III. Inference Services for Decision Support in Healthcare

In the approach we propose here, non-monotonic inferences presented in [16] are exploited to retrieve suitable treatments for a given disease taking into account the case history of the patient. The system will be able to calculate a score based on the semantic *compatibility* between diseases affecting the patient and characteristics of available medications so allowing to: (i) find possible inconsistencies in a proposed therapy; (ii) arrange best treatment options in relevance order; (iii) explain the matchmaking outcomes in both cases.

In what follows, the Description Logics (DLs) setting we adopt are briefly recalled[1]. We refer to [16], [18] for several examples and wider argumentation. From now on we assume to model ontologies (Terminological Boxes $\mathcal{T}$ in DL-words), patient diseases and pharmaceuticals annotations in a language whose semantics can be mapped to the $\mathcal{ALN}$ DL, for instance (a subset of) OWL-DL [19] or the more compact XML-based DIG [20] language.

DL-based systems provide two basic reasoning services for $\mathcal{T}$, namely (a) Satisfiability and (b) Subsumption in order to check (a) if a formula C is consistent w.r.t. the ontology $-\mathcal{T} \not\models C \sqsubseteq \bot-$ or (b) if a formula C is more specific or equivalent to a formula D $-\mathcal{T} \models C \sqsubseteq D$. It is possible to define at least five different match classes based on subsumption and satisfiability: exact match, subsumption (full) match, plug-in match, intersection (potential) match, disjoint (partial) match.

Both subsumption and satisfiability can be only used to check if there exists an exact correspondence between two formulas. Hence they are not completely adequate in scenarios like the healthcare ones, where simple yes/no answers are insufficient because exact matches are quite rare. In the proposed approach, considering a disease description $\mathcal{S}$ and a medication annotation $\mathcal{D}$, solving the Concept Contraction Problem (CCP) and the Concept Abduction Problem (CAP) [16] (see later on for further details) we are able to provide a support in decision making for doctors determining a therapy.

Hereafter basics of algorithms to solve abduction and contraction problems are reported:

[1]We assume the reader be familiar with basics of DLs formalisms and reasoning [17].

- given a partial match between $\mathcal{D}$ and $\mathcal{S}$, solving a CCP one can compute what has to be given up G and kept K in $\mathcal{D}$ in order to have a potential match between K (a contracted version of $\mathcal{D}$) and $\mathcal{S}$. Hence, the result of a CCP is a pair $\langle G, K\rangle$ representing respectively elements in $\mathcal{D}$ conflicting with $\mathcal{S}$ and the (best) contracted $\mathcal{D}$ compatible with $\mathcal{S}$;
- given a potential match between $\mathcal{D}$ and $\mathcal{S}$, solving a CAP one can compute what has to be hypothesized in $\mathcal{S}$ in order to have a full match with $\mathcal{D}$ (or its contracted version K). Hence, the result of a CAP is a concept H representing in some way what is *underspecified* in $\mathcal{S}$ in order to completely satisfy a preference $\mathcal{D}$. Please note that we say *underspecified* instead of *missing*. This is because we are under an Open World Assumption.

Of course, for both Concept Contraction and Concept Abduction we have to define some minimality criteria on G (give up as few things as possible) and on H (hypothesize as few things as possible). Algorithms to solve CAPs and CCPs for $\mathcal{ALN}$ have been proposed in [16] (not reported here for brevity) and they have been properly adapted and exploited in our e-healthcare scenario based on RFID.

A. Matchmaking for healthcare

In the application presented here, Concept Contraction and Concept Abduction inference algorithms are used in a slightly different fashion w.r.t. current matchmaking problems. Patient case history and medication annotations have distinct structures and are differently described[2], so inference services outlined above have to be properly used to reach the desired matchmaking objectives.

With reference to classical matchmaking approaches – especially devised for e-commerce [18]– where a demand is compared with a set of supplies, in the proposed approach we have to compare the pharmaceutical annotation stored within the packaging tag with the patient clinical description in her RFID wristband. Notice that the semantic-based matchmaking is a non-symmetric one and the final purpose of the proposed approach is to assess if a given medication encounters patient's diseases. This can be performed enriching the disease semantic annotation with the pharmaceutical classes suitable to cure the disease itself. In this way, Concept Abduction allows to verify if a given treatment is suitable or not. For what concerns contraindications, in the proposed framework treatments and disease descriptions are modeled exploiting disjoint concepts in order to refer to interested organs and bodily systems. In this way, if a given pharmaceutical may present some undesired effects for a specific patient, the abduction check will fail due to the incompatibility between semantic descriptions of medication and disease. So, thanks to Concept Contraction algorithm, the physician can "see" the incompatibilities within a therapy annotation (*i.e.*, the adverse indications for the patient) which will make the part of the therapy to give up. The

[2]The illustrative example presented in Section IV will clarify these aspects.

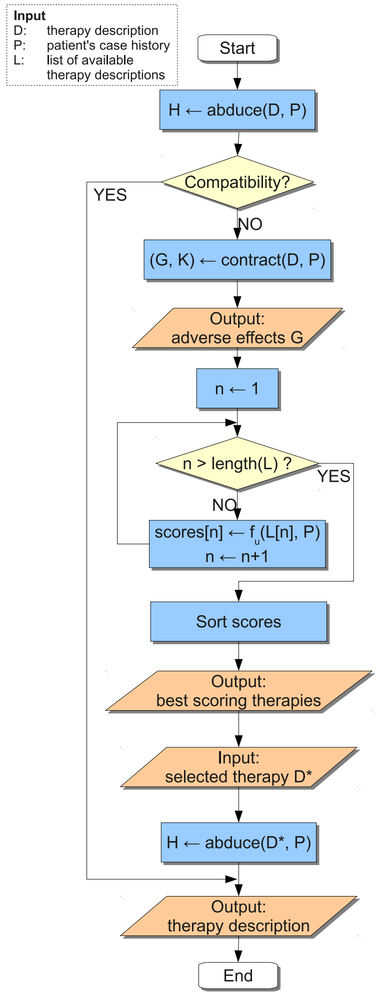

Fig. 1. Flowchart of therapy verification process.

remaining K component will be so used for a new abduction process.

The steps for therapy verification are reported in Figure 1 as a flowchart and are summarized hereafter:

1) the system performs a Concept Abduction between therapy description $\mathcal{D}$ and patient's case history $\mathcal{S}$;
2) if $\mathcal{D} \sqcap \mathcal{S}$ are satisfiable w.r.t. $\mathcal{T}$, the proposed therapy is verified by the system;
3) if $\mathcal{D} \sqcap \mathcal{S}$ are incompatible, Concept Contraction algorithm allows to extract the contraindications of the treatment for building a new compatible request to be submitted against the pharmaceuticals in the hospital Knowledge Base (KB), in order to find a new pharmaceutical $\mathcal{D}*$;
4) the system performs a new Concept Abduction between $\mathcal{D}*$ and $\mathcal{S}$ to verify the new therapy.

Note that step 3 returns a list of further options in a relevance order. By means of *rankPartial* and *rankPotential* algorithms [16], the system measures the semantic distance (hence the affinity level) between each treatment annotation and the description of the patient case history. In order to

Anatomy
- $Immune\_System \sqsubseteq Anatomic\_Part$
- $Adverse\_Immune\_System \sqsubseteq Anatomic\_Part \sqcap \neg Immune\_System$
- $Circulatory\_System \sqsubseteq Anatomic\_Part$
- $Adverse\_Circulatory\_System \sqsubseteq Anatomic\_Part \sqcap \neg Circulatory\_System$
- $Skeletal\_System \sqsubseteq Anatomic\_Part$
- $Muscular\_System \sqsubseteq Anatomic\_Part$
- $Adverse\_Skeletal\_System \sqsubseteq Anatomic\_Part \sqcap \neg Skeletal\_System$
- $Adverse\_Muscular\_System \sqsubseteq Anatomic\_Part \sqcap \neg Muscular\_System$
- $Bone \sqsubseteq Skeletal\_System$
- $Adverse\_Bone \sqsubseteq \neg Bone \sqcap Adverse\_Skeletal\_System$
- $Visual\_System \sqsubseteq Anatomic\_Part$
- $Adverse\_Visual\_System \sqsubseteq Anatomic\_Part \sqcap \neg Visual\_System$
- $Eye \sqsubseteq Visual\_System$
- $Adverse\_Eye \sqsubseteq Adverse\_Visual\_System \sqcap \neg Eye$

Diseases
- $Disease \sqsubseteq \exists affects$
- $Musculoskeletal\_System\_Disease \sqsubseteq Disease \sqcap \forall affects.(Adverse\_Skeletal\_Sys$ $Adverse\_Muscular\_System)$
- $Immune\_System\_Disease \sqsubseteq Disease \sqcap \forall affects.Adverse\_Immune\_System$
- $Autoimmune\_Disease \sqsubseteq Immune\_System\_Disease$
- $Connective\_Tissue\_Disease \sqsubseteq Autoimmune\_Disease$
- $Systemic\_Lupus\_Erythematosus \sqsubseteq Connective\_Tissue\_Disease \sqcap \forall affects.(Adverse\_Integumentary\_System \sqcap Adverse\_Hematopoietic\_System \sqcap Adverse\_Joint \sqcap Adverse\_Kidney \sqcap Adverse\_Nervous\_System \sqcap Adverse\_Lung \sqcap Adverse\_Muscle \sqcap Adverse\_Gastrointestinal\_Tract \sqcap Adverse\_Circulatory\_System)$
- $Severe\_SLE \sqsubseteq Systemic\_Lupus\_Erythematosus \sqcap \forall therapy.(NSAID \sqcap Plasmapheresis \sqcap Corticosteroid \sqcap Immunomodulator\_Immunosuppressant)$
- $Mild\_SLE \sqsubseteq Systemic\_Lupus\_Erythematosus \sqcap \forall therapy.(NSAID \sqcap Corticosteroid \sqcap Immunomodulator\_Immunosuppressant)$

Treatments
- $Pharmaceutical \sqsubseteq Treatment$
- $Physiotherapy \sqsubseteq Treatment$
- $Plasmapheresis \sqsubseteq Treatment$
- $NSAID \sqsubseteq Pharmaceutical$
- $Corticosteroid \sqsubseteq Pharmaceutical$
- $Immunomodulator\_Immunosuppressant \sqsubseteq Pharmaceutical$
- $Anti\_TNFalpha \sqsubseteq Immunomodulator\_Immunosuppressant$

Fig. 2. Excerpt of the ontology engineered for the case study.

improve flexibility of decision support, the semantic distance is combined with context-specific variables by means of a *utility function* f_u, whose details are provided in Section IV. Results are arranged according to the overall correspondence with the disease.

IV. Case Study

The proposed approach was tested in a case study for a hospital rheumatology unit. The general ontology structure outlined in Section III was specialized for *connective tissue diseases*, an important class of autoimmune rheumatic diseases. Figure 2 shows a relevant excerpt of the ontology, reported in classical DL notation for the sake of legibility.

The prototypical system simulates rheumatology ward room containing a number of "smart beds". Each smart bed integrates a tablet computer with touchscreen and an RFID reader (see Figure 3 for details). The device connects to the HIS through semantic-enhanced Bluetooth Service Discovery Protocol, via a hotspot placed in the ward within radio range of beds. Each resource (patient, staff member and pharmaceutical) is identified by means of an RFID tag with unique EPC code, unique identifier of the reference ontology (OUUID), semantic-based annotation in compressed DIG format and data-oriented resource attributes [7]. The HIS is based on SQLite[3], a lightweight serverless transactional RDBMS (Relational Data Base Management System).

The key system capabilities are control of medication submission procedures and decision support to the physician for therapy management. Let us consider a small example to better explain how everything works. *A smart bed hosts a patient with a mild form of Systemic Lupus Erithematosus (SLE) and a generic disease of the muscular and skeletal system.* This

[3]SQLite project: http://www.sqlite.org/

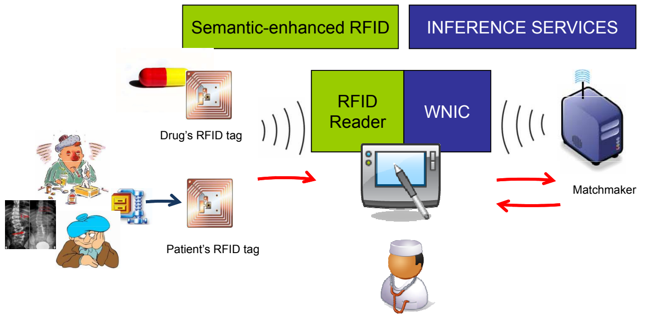

Fig. 3. System architecture

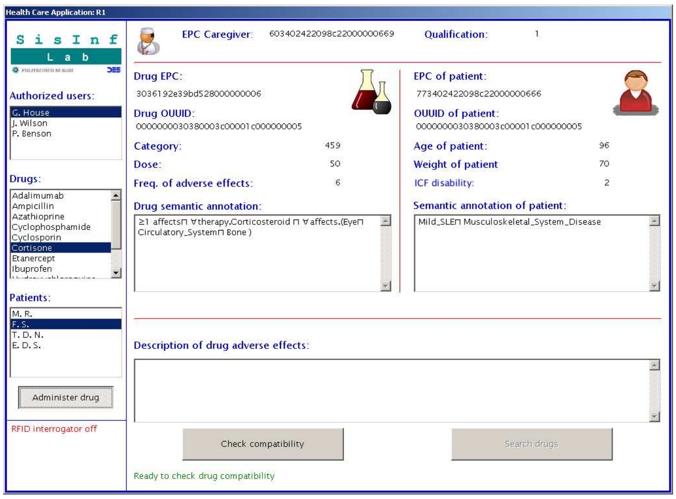

Fig. 4. Prototype display: access granted.

is expressed w.r.t. the reference ontology with the following $\mathcal{ALN}$ formula:

P: $Mild\_SLE \sqcap Musculoskeletal\_System\_Disease$

A rheumatologist approaches the bed to give cortisone to the patient. The RFID reader detects the triple {patient,staff member,pharmaceutical} so that the display is activated: relevant information extracted from tags is shown and the authorized operation is recorded into the HIS. It is important to note that real implementations should properly take into account the possibility of spurious readings from an interrogator placed on another smart bed. Several strategies during RFID equipment deployment can be adopted to minimize interference, including proper calibraton of reader signal power and selection of tag model and reader antenna type [21]. Figure 4 shows the output in our current prototype (the panel on the left hand side allows to simulate tag reading events with manual input). If an unauthorized staff member –*e.g.*, a janitor or a physician from another ward– approached the bed with a medication, then the system would provide a warning as shown in Figure 5 and log the event into the database of the HIS.

Cortisone is described in the KB as:

D: $\exists affects \sqcap \forall therapy.Corticosteroid \sqcap \forall affects.Eye \sqcap Circulatory\_System \sqcap Bone$

so it has potential adverse effects towards eyes, bones and

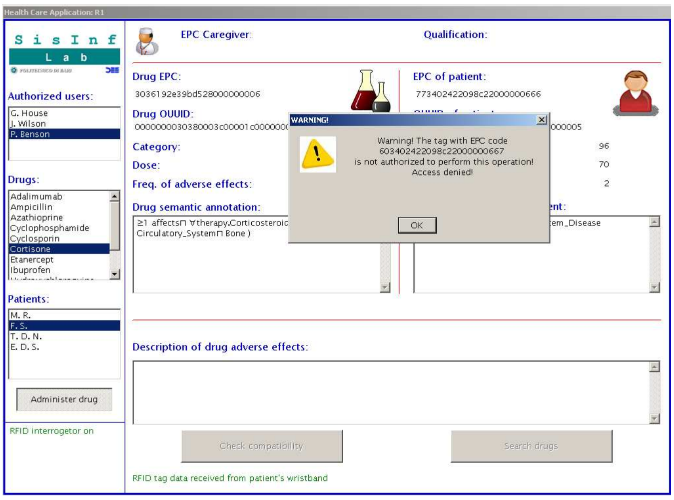

Fig. 5. Unauthorized access is detected.

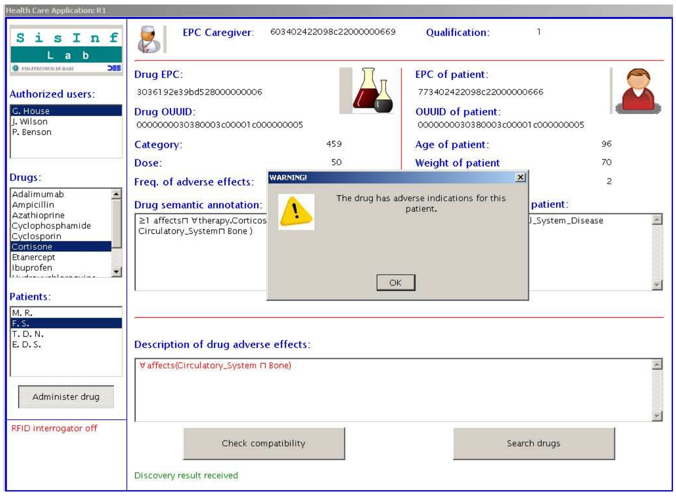

Fig. 6. Physician is alerted of potential adverse effects.

circulatory system. Our patient has no eye problems, but a skeletal disease, while SLE can affect the circulatory system. *Special care must be taken for this patient during treatment of SLE with cortisone. The system is capable to perform this inference automatically and issue a warning to the doctor.* Figure 6 shows the warning, with an alert and the description of the conflicting characteristics in a box in the lower part of the display. Further decisions are then left to the judgment of the human expert. Steps 1 and 2 of the algorithm in Section III-A produce the following outcome:

Give up: $\forall affects.Circulatory\_System \sqcap \; Bone$

Keep: $\forall therapy.Corticosteroid \sqcap \; \forall affects.Eye$

The physician can now query the system for other therapy options. The smart bed computer sends via Bluetooth a request to the ward hotspot. For each pharmaceutical in the hospital KB, *rankPotential* is computed w.r.t. the patient's description. If compatibility arises, *rankPartial* is computed to extract and evaluate the incompatible part of the demand, then *rankPotential* is computed again for the Keep part.

An overall *utility function* combines results of the matchmaking framework explained in Section III with context-specific variables. The following parameters are taken into account: (1) age of patient; (2) estimated frequency of pharmaceutical adverse effects; (3) severity of patient's condition, expressed in a numeric scale from 0 to 4 according to guidelines of the *International Classification of Functioning, Disability and Health* framework issued by World Health Organization [22]. The utility function has the following formula:

$$f_u = \frac{r_{par}+r_{pot}}{max_{r_{pot}}} \cdot tanh\frac{age}{\alpha} \cdot severity \cdot tanh\frac{adv\_frequency}{\beta}$$

The function was modeled as a distance measure, hence a lower value means a better overall match. The first factor allows different medications to be ranked according to their compatibility w.r.t. patient's conditions: r_{par} and r_{pot} are the *rankPartial* and *rankPotential* values between the medication and the patient, while $max_{r_{pot}}$ is the highest (worst) *rankPotential* among all medications (*i.e.*, the less effective treatment). The next factors take patient's age and severity into account: a younger patient or with a lower impairment level will tolerate therapy better in general (the model is not defined for pediatric patients). The last factor models pharmaceutical contraindications, where $adv\_frequency$ is the statistical frequency of the main adverse effects, expressed in number of occurrences per 100 patients. Empirical evaluation has suggested values for the two tunable weights $\alpha = 50$ and $\beta = 10$ respectively.

The patient is 96 years old and has an overall impairment degree of 2. Cortisone has a 6% frequency of adverse effects. With respect to the patient, cortisone has a Rank Partial value of 4 and its compatible part has a Rank Potential of 7, whereas the maximum Rank Potential among all medications in the KB is 9. Hence the final outcome is:

$f_u = \frac{4+7}{9} \cdot tanh\frac{96}{50} \cdot 3 \cdot tanh\frac{6}{10} = 1.2575$

Iteration of the procedure over each pharmaceutical in the KB produces the ranking depicted in Figure 7, which is shown to the physician. We notice that prednisone is quite similar to cortisone (both are corticosteroids), having the same risks toward the particular patient; however, its estimated frequency of adverse effects is lower (5% vs 6%), hence it is preferable.

The physician selects an appropriate therapy and leaves. The administration is timestamped and recorded into the HIS database. RFID reader detects the leaving event and the application screen is closed. Even though expressiveness of the logic language is limited by the need to provide acceptable reasoning performance, the example showed that careful modeling of the domain can provide useful knowledge-based decision support. Our prototypical DSS system helps the domain expert in an unobtrusive way, by automatically invoking inference procedures upon relevant fragments of knowledge extracted directly from RFIDs.

V. Conclusion and Future Work

We have presented an novel DSS for healthcare purposes based on a semantic enhancement of RFID standard protocol.

Fig. 7. Suggested medications for the patient, in ranking order.

The proposed system exploits semantically annotated descriptions of medications to be administered as well as annotations of patient's case history to help medical personnel in providing the correct therapy. Thanks to the semantic metadata accompanying the description of both pharmaceuticals (stored on RFID tags attached to packaging) and diseases (saved on patient's RFID wristband), it is possible to discover possible inconsistencies in a therapy and to suggest alternative care options. The RFID data exchange protocol and the Bluetooth Service Discovery Protocol have been modified and enhanced, to support the required inferences preserving legacy applications.

Current solution has now two kind of limitations. First of all, in the prototype the RFID infrastructure is simulated, therefore a significant assessment cannot be provided yet for performance in the field (RFID reading accuracy, range, speed; possible tag placement issues). A full implementation of the proposed system is ongoing in a testbed with real RFID tags and readers. Secondly, the knowledge base is currently focused on a narrow set of diseases. Since the approach has been validated through the case study, it is possible to expand the scope of modeled medical knowledge. Furthermore, in order to improve decision support, interactions should be considered between the different medications that the patient is on. Future work includes also: wider tests on the proposed methods; extension of the prototype to support multiple hospital rooms and beds; improvement of the user interface, possibly with guidance by medical personnel.

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