Application of Fuzzy Ontological Reasoning in an Implementation of Medical Guidelines

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Abstract—**In this paper we address two problems. The first pertains to implementation of medical guidelines in an e-health system supporting self-management of chronic diseases. The system allows patients to enter observed symptoms and measured parameters, then makes assessment of disease state and informs about necessary actions. We propose to formalize guidelines as sets of fuzzy rules. Fuzziness is introduced to cope with uncertainty resulting from self-observations bias, low quality of sensors and limited patients skills. The second problem is more general. It concerns the reuse of knowledge gathered in ontologies and an application of Semantic Web technologies to perform fuzzy inference. We show that, despite the fact that commonly used ontology languages and supporting tools are not intended to handle vagueness and uncertainty, they can be successfully integrated to represent and execute a set of fuzzy rules. The proposed method consists in refactoring a domain ontology, then introducing additional relations expressing fuzzy properties, encoding Mamdani fuzzy rules in SWRL language and executing them with use of Pellet OWL reasoner. We describe a fuzzy reasoning engine applying this approach and discuss translation of fuzzy rules to SWRL constructs taking as example a complete set of rules formalizing a medical guideline for asthma control assessment.**

Index Terms—**ontology, fuzzy reasoning, medical guidelines, e-health systems**

I. Introduction

In this paper we describe an implementation of a fuzzy reasoning engine based on tools and technologies related to ontologies and the Semantic Web. The presented approach consists in refactoring a domain ontology, introducing additional relations expressing fuzzy properties, encoding Mamdani rules in SWRL language and preforming crisp reasoning with use of Pellet OWL reasoner. Fuzzification and aggregation operations indispensable in a complete fuzzy framework are implemented in Java utilizing Jena library for OWL manipulation.

The solution stems from a practical problem of building a component responsible for making assessments and medical decisions in an e-health system supporting chronic care. The main goal of the SWOP system (*SWOP* is an acronym of the Polish name *System Wspomagania Opieki Przewlekłej*) is to help patients in self-management of chronic disease through monitoring of symptoms, self-assessment and informing about necessary actions, when symptoms levels indicate a problem.

This work is supported by the National Centre for Research and Development (NCBiR) under Grant No. NR13-0093-10.

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978-1-4673-5637-4/13/$31.00 ©2013 IEEE

Nowadays, implementation of decision support in health care systems is based on guidelines developed in line with Evidence-Based Medicine (EBM) paradigm. A medical guideline usually gathers knowledge about a single disease and take form of narrative recommendations formulated on the basis of available evidence resulting from clinical trials and observations.

In the last decade many ongoing research projects aiming at formalization of guidelines were initiated. They resulted in proposals of languages for guidelines specification (Formal Guideline Representations – FGRs) that can be processed and validated by software tools. Moreover, in many cases such formal representations were transformed into executable languages that can be interpreted by a computer (Computer Interpretable Guideline – CIG).

We discuss the problem of integrating various Semantic Web tools to perform fuzzy reasoning on an example of management of bronchial asthma, as customization of the developed e-health system to support this disease was selected as one of proof-of-concepts. Presented here fuzzy rules formalize narrative guidelines related to assessment of asthma control, and in that regard can be considered as an executable FGR.

The paper is organized as follows: the next Section II gives motivation for implementing medical guidelines in form of fuzzy rules and discusses works aiming at introduction of fuzziness into ontologies and Description Logics. It is followed by a short introduction to Mamdani inference framework. Section IV gives brief description of SWOP e-health system. A rule based representation of a guideline related to asthma control assessment is described in Section V. Subsequent Section VI discusses main contributions of the work: refactoring of domain model to incorporate fuzziness, architecture of the solution and SWRL based implementation of fuzzy rules. Conclusions and observations are given in Section VII.

II. Discussion and related works

Various competing Formal Guidelines Represenation (FGR) languages were developed over last ten years. Apart from the oldest, ArdenSyntax [11], which is rule based, almost every of them, e.g. GLIF [4], SAGE [24], PROforma [22], Asbru [19] and EON [23] attempts to express guidelines in a process like notation. Basic elements of computer interpretable guidelines were summarized in [17].

Interestingly, the majority of FGRs attempt to include into guideline representations medical terminology, in opposition to process notations, e.g. BPMN, that are agnostic to domain descriptions.

There are several factors that limits application of process oriented FGRs for telemonitoring purposes (due to limited capacity we list the most important results of conducted analysis):

- FGRs were developed keeping in mind that primary human interaction will undergo between medical professionals and an IT system, whereas in e-health a patient plays the central role.
- It is difficult or even undesirable to orchestrate actions in the system by a centralized process, as the nature of interactions is event-driven.
- The system should cope with data deviations introduced by patients in subjective self-observations, sensors of lower quality than used in clinical practice and limited patients skills. This can be achieved by externalization and adaptation of guidelines parameters.
- Several constructs appearing in FGRs are superfluous in reference to the system goals and too costly to implement.

The listed above drivers led us to the decision to represent executable guidelines within the SWOP system as a set of fuzzy rules. Such approach satisfies all requirements elicited during the analysis: it is much simpler then process-oriented FGRs, allows adaptation at the level of fuzzy membership functions and is well aligned with the nature of guidelines, which recommend decisions and make assessments based mainly on statistical trials.

There are a few publications on how guidelines were represented in telemonitoring systems. Usually they employ rules [8] or decision trees [16]. Fuzzy based approach seems to be rare in this particular field, although there is a large literature on application of various forms of fuzzy reasoning as a support for diagnosis and making decisions related to therapy plans, e.g. [2], [13], [20]. Such large interest is due to the nature of the medical knowledge collected in guidelines (based on statistically interpreted trials) and the language used to express it (see discussion on decidability and executability in [13]).

In the last decade many researches were attracted by an idea of introducing vagueness and uncertainty into ontologies and Description Logics (DLs), e.g. [6], [14]. Their works aimed at building strong theoretical foundations for fuzzy reasoning by defining both syntax and semantics of Fuzzy Description Logics. This resulted in extending crisp ingredients present in ontology languages by defining fuzzy classes, fuzzy roles (object properties), fuzzy datatype properties and proposals of appropriate OWL extensions.

Advances in theory were followed by emerging software tools allowing to perform reasoning in Fuzzy Description Logics: FiRE reasoning engine [21] and publicly available fuzzyDL [3], which applies tableau algorithm to perform reasoning in a logic covering fuzzy concepts, fuzzy relations and various types of trapezoidal membership functions that can be used to specify a complete set of Mamdani rules. Both implementations, however, do not integrate with widely recognized Semantic Web specifications and technologies, as OWL or SWRL. On the other hand, there are continuous research aiming at extending or integrating existing technologies. Examples are [25], which describe SWRL-F, a fuzzy logic extension to the Semantic Web Rule Language (SWRL), or [5] presenting a system combining fuzzyDL, Drools, Pellet and Jena to perform fuzzy reasoning in order to recommend tourist offers based on clients' profile. Many others are listed in [14].

A deep discussion of theoretical aspects of Fuzzy Description Logics is out of the scope of this paper, however, it should be noticed, that common practice of incorporating into their syntax membership functions goes beyond DLs, which in general are limited to unary and binary predicates. Another remark refers to fuzzification of ontologies. It seems, that building a well founded fuzzy domain model may occur a really hard problem; in particular, to our knowledge, no model described with fuzzy DL is anchored in a foundational ontology like SUMO or Dolce. Actually, the presented ontologies often contain foundations, e.g. [25], but thy are rather metamodels defining fuzzy sets, membership functions and linguistic variables, but not philosophical categories.

III. Fuzzy rules and fuzzy reasoning

Fuzzy rules are proven to be an efficient decision support mechanism in many areas. [18] control, home appliances, cameras, embedded systems, etc. They enable implementing even very sophisticated control mechanism with use of small sets of rules. Rules in the form proposed by Mamdani [15] are simple conditional instructions:

$$\text{IF } var_1 = value_{11} \text{ AND } var_2 = value_{21} \ldots \text{ THEN } var_{out} = out$$

The terms var_x appearing in rules are so called linguistic variables, and $value_x$ and *out* are fuzzy sets. Fuzzy sets are described by a membership function defining the confidence factor belonging to the interval [0,1] that a particular element is a member of the set.

An inference with Mamdani rules encompasses the following stages:

1) Fuzzification: values of the parameters are mapped to the fuzzy sets according to defined membership functions. Then, fuzzy sets are assigned to linguistic variables.
2) Inference: consisting in applying defined rules and assigning values to output variables (results of multiple rules execution are stored in output linguistic variables). Before further processing the contents of output variables is aggregated using different metrics, typically based on maximal on average membership value.
3) The last step consists in defuzzification, i.e. converting fuzzy values to crisp (actual output). Defuzzification is particularly important in control applications that should produce analog output. In the scope of the SWOP system it is rather expected to obtain a single discrete value

on the output of the decision module, e,g, assessment of the patient state or a set of discrete values, e.g. possible decisions with assigned priority based on the membership values.

IV. SWOP - A TELEMEDICINE SYSTEM SUPPORTING CHRONIC CARE

SWOP is an e-health system dedicated to patients suffering from chronic conditions providing such services, as monitoring of symptoms, informing about disease state, as well as interactions with health care professionals. The operational concept of the system is shown in Fig. 1. On a regular basis patients manually or automatically send results of self-observations or self-measurements specific for their chronic disease. A set of implemented communication modules provide a great flexibility at configuring the parameters, operational modes of sensors and communication channels (WiFi, WAN, GPRS). Entered data are stored in a data base and automatically analyzed to determine patients status, trends in disease course and the risk of symptoms exacerbation. Then, patients are provided with results of the assessment, which may have a form of messages transmitted from the system to a terminal used by specific patient, e.g. personal computer or a smartphone (as SMS notifications). The system offers also capabilities of asynchronous communication between patients and the personnel providing support to them (virtual carers, leading physicians or other health professionals). Moreover, it will offer an option of transferring patients data from an external HL7-compliant health information systems (not marked in the figure).

The decision support component plays a crucial role in the described interaction scenarios. In particular, it is responsible for analysis of new data entered to the system, assessment of the disease state and triggering alarms or notifications. Decision support can be also extended to other users, involving medical team members or informal carers, if needed.

During the system design five goals of guidelines implementation were identified:

1) Assessment of the disease state based on available information (including current values of monitoring parameters, subjective symptoms, historical data and a care plan).

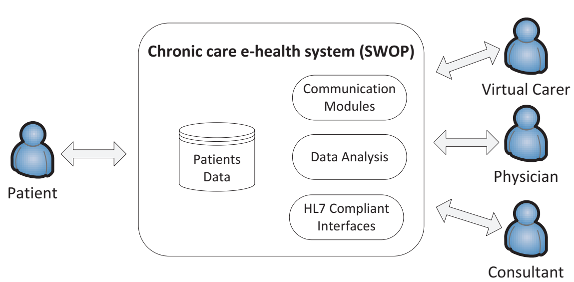

Fig. 1. The operational concept of the SWOP system

2) Assessment of the possibility of exacerbations occurrence.
3) Informing a patient (or patients family) about disease state, including alerting in case of exacerbations. Informing is not visible in traditional guidelines representations, as they assume direct interaction between medical staff and a patient, however, it is an important issue in telemonitoring systems.
4) Recommendations concerning educational materials related to patients disease.
5) Optionally, recommendations concerning changes in patients' care plans (including changes of medications, their dosage and additional examinations). They are visible only for medical staff. Patients can receive information about suggested visit to a doctors office.

V. RULE BASED SPECIFICATION OF ASTHMA CONTROL GUIDELINE

In this section we present a guideline model aimed at assessment of asthma control adopting a fuzzy rules approach. The model is based on Global Initiative for Asthma (GINA) guideline as of 2011 [9]. According to the recommendation, assessments of asthma control should be performed on a weekly basis taking into account the following clinical manifestations: presence of daytime or nocturnal symptoms (including awakening), disruption of daily activities, need for reliever treatment and evaluation of lung function (based on PEV measurement). Asthma is considered controlled if all aforementioned features remain at safe level expressed as a number of occurrences per week or percentage values. If any of the features exceeds its defined level, the disease is considered as partly controlled. In the case, where there are three or more indications of partial control, the asthma is classified as uncontrolled. The same applies, if an exacerbation occur in the analyzed period.

Fuzzy rules expressing the guideline are presented in Fig. 2 a-c. The diagrams can be interpreted as a colored Petri nets [12], where places correspond to linguistic variables, arc expressions to fuzzy sets and transition to rules. A value in the parentheses following a rule name denote its priority. For clarity, we omit elements, which are indispensable in a full specification: definition of membership functions or methods of rules activation and results aggregation. Although rules are here presented in a graphical form, the constructs used to define them can be considered as equivalent to those appearing in textual Fuzzy Control Language (FCL) defined in the norm IEC 61131-7 [10].

Fig. 2.a shows the rule R_1 assessing the *controlled* state that can be expressed in FCL as:

IF DaytimeSymptoms IS rare AND NighttimeSymptoms IS rare AND
ActivityDisruptions IS rare AND UseOfQuickReliefMedication IS rare AND
PEVLevel IS normal THEN AsthmaControl IS controlled

Rules (R_2 – R_6) shown in Fig. 2.b make *partly controlled* assessment based on the presence of an asthma manifestation.

According to GINA recommendation, asthma is considered as uncontrolled if there are "three or more features of partly controlled asthma”. This statement can be transformed into a set of rules in a fuzzy logic setting either by:

- assigning a dedicated rule to each triple among five input variables or
- defining a second layer of inference, i.e. applying an aggregation function that counts elements and then a membership function yielding the value 1.0 for fuzzy set *uncontrolled*, if number of elements is greater than or equal 3.

As we decided to take the first approach, $\binom{5}{3} = 10$ rules were introduced (see Fig. 2.c. rules R_7 - R_{16}) An additional rule R_{17} is activated in case of exacerbation occurrence.

Rules presented in Fig. 2.d are not a part of a guideline, but are related to its implementation in an execution environment. They select a notification to be send as the result of disease state assessment: *good_state_notification*, *acceptable_state_notification*, *visit_recomendation* and *alert*. These rules are assigned with the priority 2, i.e. they are to be executed after all rules enabled related to assessment are done.

VI. Description of the solution

The presented decision module combining Semantic Web technologies and fuzzy rules approach encompasses three elements:

1) a model of domain knowledge formalized in OWL language supporting extensions required to perform fuzzy reasoning,
2) a set of SWRL rules enabling fuzzy reasoning according to the guideline model described in Section V,
3) a software responsible for fuzzification, aggregation of results and coordination of the whole process.

A. OWL model for fuzzy reasoning

Taking into account assumed application and technologies used we identified three key requirements for the model:

- it should gather a domain knowledge: a disease, its symptoms and assessment; preferably, the model should directly import domain ontologies,
- it should augment it by introducing terms required to implement Mamdani fuzzy rules: linguistic variables, fuzzy sets and membership levels,
- it should be consistent with an intended use of SWRL enabled reasoner.

The first problem to be solved is a possible reuse of existing domain ontologies. Within the SWOP project there were developed several domain ontologies defining concepts related to chronic care, diseases, subjective and objective symptoms, medications, etc. They, however, were not built with an idea to use them as a part of fuzzy reasoning framework. Such application requires extensions to the domain ontology, moreover, it may require some rearrangements.

The problem can be discussed on a small example in Fig. 3 being an excerpt from the project domain ontology. White ovals: *Patient*, *MeasuredPEV* and *PEVLevel* represent concepts (OWL classes) in the domain ontology. Dark gray rectangles constitute a part of the ontology ABox. The patient (individual *John*) has current PEV (individual *pev1*) with the value 0.75; the measurement is classified as having low level (by linking it by object property level with the individual *low* of *PEVLevel* type).

Shapes filled with light blue represent elements introduced to provide support for fuzzy reasoning. The *mambership* datatype property with the range of type *double* is used to express value of fuzzy set membership function. The definition of *FuzzyProperty* class asserts that it has a membership attribute with maximum cardinality equal to 1. This restriction applies to all its subclasses, including *MeasuredPEV*.

Another consequence of fuzzification of domain ontology in the discussed example, is that the patient is linked by *currentPEV* relation with two measurements: *pev1* classified as *low* with membership equal to 0.625 and *pev2* classified as *normal* with membership value 0.375. Presence of such assertion is usually required to perform fuzzy reasoning; however, this can be inconsistent with restrictions defined in ontology TBox. (In the definition of *Patient* class, may appear quite natural restriction that its individual has at most one value of current PEV measure.) This example shows that reusing an ontology in a fuzzy reasoning setting may require several rearrangements, in particular relaxing restrictions that seem to be obvious in a crisp world.

Assumed use of SWRL as a rule language has a large impact on the structure of the model. To make a reasoning process decidable, OWL reasoners, e.g. Pellet are DL-safe. This property is achieved by restricting the possibility of creating individuals during reasoning. In consequence, all individuals, whose properties are to be inferred, must be present in the model before a reasoner is launched. For example, DL-safe reasoner can not create individuals *pev1* and *pev2*, although, it can make inferences about *membership* and *level* relations.

The ontology eventually used for fuzzy reasoning was strongly reduced in rapport to that, which is shown in Fig. 3. As it is not needed to reason simultaneously about a set of patients, the class *Patient* and its individual can be safely removed from the ontology. *MeasuredPEV* is a typical *Role* (in terms of ontological theories) or an associative class (in object oriented modeling). After disappearance of its subject (*Patient*) it become superfluous. The whole model is refactored by removing the *MeasuredPEV* class and asserting *membership* to be a property of *PEVLevel*. A part of the reduced ontology is presented in Fig. 4).

Two datatype properties are used to express fuzzy weights. The first one, already mentioned, *membership* relation is intended for making assertions and can be used only in premises of SWRL rules. The second – *imembership* is to be inferred, thus, it appears only in consequents.

The classes *PEVLevel*, *UseOfQuickReliefMedication*, *AsthmaControl* shown in Fig. 4 have a common ancestor: *FuzzySet*, whose specification asserts that it members have at most one *membership* attribute and can have several *imembership* property values. In this model, a linguistic variable as a

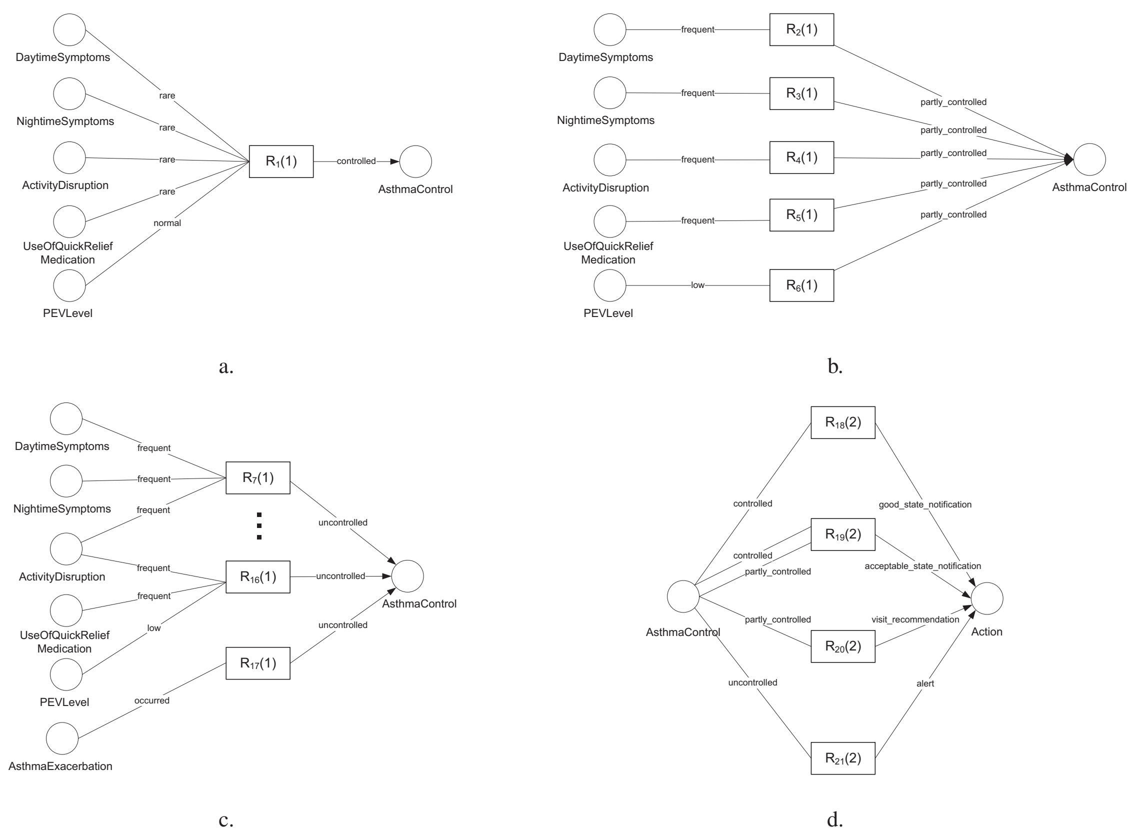

Fig. 2. Rules for asthma assessment yielding: (a) *controlled* (b) *partly_controlled* and (c) *uncontrolled* states; (d) rules inferring actions

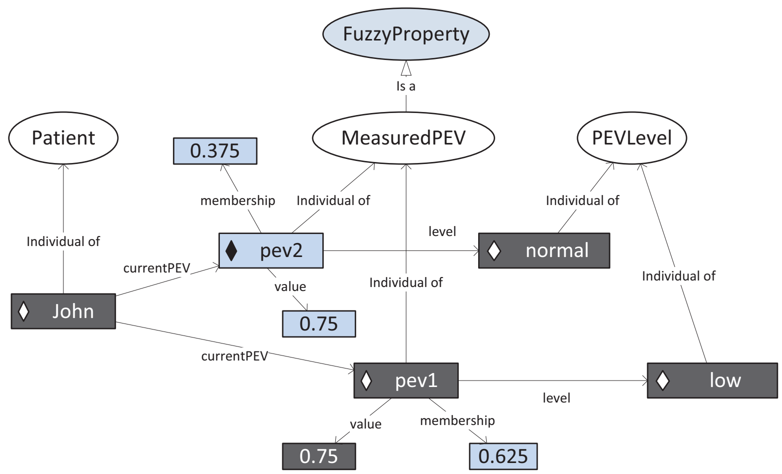

Fig. 3. Full OWL model supporting fuzzy reasoning

collection of fuzzy sets corresponds to a subclass of *FuzzySet*. In fact, while writing rules references to a linguistic variable are omitted.

B. Architecture of the reasoning engine

Architecture of the reasoning engine is presented in Fig. 5. The system is written in Java and uses Jena [1] library to access OWL models and Pellet [7] to perform reasoning. Its main functional blocks are *Fuzzifier*, *Reasoner*, *Aggregator* and *DataCollector*.

Fuzzifier converts input data into values in the range $[0, 1.0]$ using ramp shaped functions or a mapping from a finite set of values. Results are asserted in *OWL model* using the

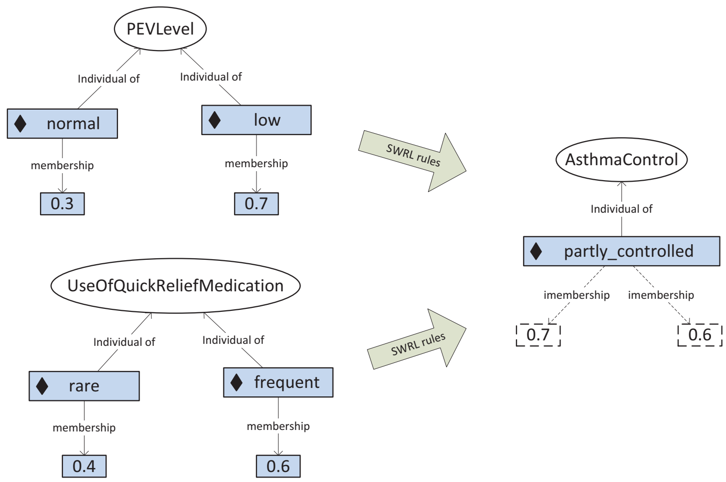

Fig. 4. Reduced OWL model for fuzzy reasoning

membership datatype property. It should be mentioned, that patient questionnaires aimed at collecting subjective observations, even querying for numerical data, e.g. a number of daily activity limitations, provide also such answers, as: "*Not sure*", "*Probably one*" or "*I have observed limitations, however, I am not sure if they are related to asthma*". Such answers are also mapped to membership values.

Reasoner is provided by the Pellet library. It executes SWRL rules to process assertions defined in input model and stores inferences (values assigned to fuzzy sets through *imembership* property) in *Inferred OWL model*. Fig. 4 shows sample reasoning results: inferred relations for the individual *partly_controlled* marked with dashed line.

Aggregator collects arguments of *imembership* statements for an individual and calculates an aggregated value: maximum, minimum or a mean. (We decided to apply an aggregation based on maximum values, although, other approaches are possible). Then, it asserts it back as membership property in the OWL model. The reasoning and aggregation steps can repeat a number of times. The model stores also the current iteration number, after each cycle it is incremented. The number is used in premises of rules to control the order of their execution.

Finally at the end of reasoning, *DataCollector* is responsible for reading the values asserted by *Aggregator* and setting output variables.

In the production environment the presented components are wrapped by a simple synchronous web service that accepts and returns a list of key–value pairs. Keys, and in many cases values, are defined in the domain ontologies.

C. SWRL based implementation of fuzzy rules

The crucial part of the guideline representation is the set of rules encoded in SWRL language and stored as a separate OWL module importing the basic model. Table I presents

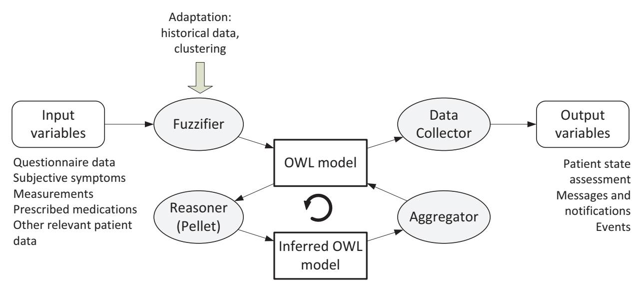

Fig. 5. Architecture of the reasoning engine

sample rules responsible for assessment of asthma control and producing notifications. Each rule is constructed in a similar manner:

- the premise *hasValue(Step.current, number)* activates a rule at a certain iteration,
- binary predicates *membership* map property values to variables,
- multiple *lessThanOrEqual* predicates referencing built-in SWRL function are used to calculate a rule activation level,
- conclusions assign *imembership* values to target individuals.

The main limit of SWRL language is that it does not provide appropriate built-in functions to calculate minimum, maximum or a product of values stored in a list. To set appropriate values of rules' activation levels, we were obliged to rewrite some rules to cover all the cases, where a given variable, e.g $?m_i$ is a lower bound of a set of all variables $\{?m_1,\ldots,?m_n\}$. Therefore, the rule $R_1(1)$ was encoded as 5 SWRL rules, 10 rules $R_7(1)$ – R_{16} yielded 30 SWRL rules and the rule R_{19} was encoded as two rules in SWRL.

The described multiplication of rules does not introduce errors into inference results. Event if five variations of the rule R_1 are fired for equal values of variables $?m1 = ?m2 = ?m3 = ?m4 = ?m5 = a$, the reasoner infers only one value a for the *imembership* property assigned to $AsthmaControl.controlled$ individual.

Rules for asthma controlled	
Rule $\mathbf{R_1(1)[a-e]}$	hasValue(Step.current, 1), membership(DaytimeAsthmaSymptom.rare, ?m1), membership(NightimeAsthmaSymptom.rare, ?m2), membership(ActivityDisruption.rare, ?m3), membership(UseOfQuickReliefMedication.rare, ?m4), membership(PEVLevel.normal, ?m5), *lessThanOrEqual(?m1, ?m2), lessThanOrEqual(?m1, ?m3), lessThanOrEqual(?m1, ?m4), lessThanOrEqual(?m1, ?m5)* → imembership(AsthmaControl.controlled, ?m1)
Rules for asthma partly controlled	
Rule $\mathbf{R_2(1)}$	hasValue(Step.current, 1), membership(DaytimeAsthmaSymptom.frequent, ?m) → imembership(AsthmaControl.partly_controlled, ?m)
Rule $\mathbf{R_4(1)}$	hasValue(Step.current, 1), membership(ActivityDisruption.frequent, ?m) → imembership(AsthmaControl.partly_controlled, ?m)
Rule $\mathbf{R_6(1)}$	hasValue(Step.current, 1), membership(PEVLevel.low, ?m) → imembership(AsthmaControl.partly_controlled, ?m)
Rules for asthma uncontrolled	
Rule $\mathbf{R_7(1)[a-c]}$	hasValue(Step.current, 1), membership(DaytimeAsthmaSymptom.frequent, ?m1), membership(NightimeAsthmaSymptom.frequent,?m2), membership (ActivityDisruption.frequent, ?m3), lessThanOrEqual(?m1, ?m2), lessThanOrEqual(?m1, ?m3) → imembership(AsthmaControl.uncontrolled, ?m1)
Rule $\mathbf{R_{17}(1)}$	hasValue(Step.current, 1), membership(AsthmaExacerbation.occurred, ?m) → imembership(AsthmaControl.uncontrolled, ?m)
Rules for actions	
Rule $\mathbf{R_{18}(2)}$	hasValue(Step.current, 2), membership(AsthmaControl.controlled, ?m) → imembership(Action.good_state_notification, ?m)
Rule $\mathbf{R_{19}(2)[a-b]}$	hasValue(Step.current, 2), membership(AsthmaControl.controlled, ?m1), membership(AsthmaControl.partly_controlled, ?m2), lessThanOrEqual(?m2, ?m1) → imembership(Action.acceptable_state_notification, ?m2)
Rule $\mathbf{R_{20}(2)}$	hasValue(Step.current, 2), membership(AsthmaControl.partly_controlled, ?m) → imembership(Action.visit_recommendation, ?m)
Rule $\mathbf{R_{21}(2)}$	hasValue(Step.current, 2), membership(AsthmaControl.uncontrolled, ?m) → imembership(Action.alert, ?m)

TABLE I
SELECTED SWRL RULES FOR ASSESSMENT OF ASTHMA CONTROL AND SELECTING ACTIONS. RANGES IN SQUARE BRACKETS FOLLOWING A RULE NAME, E.G. $\mathbf{R_7(1)[a-c]}$, INDICATE, THAT THE RULE IS REPEATED A NUMBER OF TIMES WITH ALTERING *lessThanOrEqual* EXPRESSIONS.

D. Discussion

1) Aggregation issues: In the literature on application of fuzzy rules, there can be found several aggregation or defuzzification functions that consist in calculating mean values over a set o weights. Such functions are not compatible with the presented solution. To give an example: if nine rules yield 0 and one 1.0, its mean is 0.1. However, in OWL it is not possible to assign 0 value to a datatype property multiple times. The inference would produce just two results 0 and 1.0 giving the mean value 0.5. Theoretically, a reasoner may give nine explanations to obtained 0 result, but the whole process of calculating explanations seems to be too time-consuming to be applied in production environment.

A question that can be posed is, whether it is possible to perform aggregation at the level of SWRL rules. The SWRL language is open and it is possible to extend it with user defined built-ins. The following example can be a justification for rejecting such approach. Let us analyze the rule:

imembership(AsthmaControl.partly_controlled, ?m1),
imembership(AsthmaControl.partly_controlled, ?m2),
maxOfTwo(?max,?m1,?m2) → membership(AsthmaControl.partly_controlled,?max)

It uses a hypothetic built-in predicate $maxOfTwo(?max, ?m1, ?m2)$ that would return *true* value, if the following conditions were satisfied: $?max \geq ?m1$ and $?max \geq ?m2$. For a model presented in Fig. 4 the rule would have been executed for four bindings $(?m1/0.7, ?m2/0.7)$, $(?m1/0.7, ?m2/0.6)$, $(?m1/0.7, ?m2/0.6)$ and $(m1?/0.6, ?m2/0.6)$ giving two *membership* values and violating the consistence of the model.

2) Special case – negation: The definition of Fuzzy Control Language [10] allows to use negation in premises of rules. There are at least two approaches (both based on Łukasiewicz negation) to express such kind of rules in SWRL. Let us take as an example the following rule: *IF A IS NOT a AND B IS b THEN C is c*. It can be rewritten in SWRL using *substract* built-in as:

membership(a, ?p),subtract(?m1, 1.0,?p),
membership(b, ?m2), lessThanOrEqual(?m1,?m2) → imembership(c, ?m1)

Another approach may consist in defining a complement property *not_membership*, that is to be asserted by a fuzzifier or an aggregator with a value $1 - m$ simultaneously with making *membership* assertion of m, allowing the following rule specification:

not_membership(a, ?m1),
membership(b, ?m2), lessThanOrEqual(?m1,?m2) → imembership(c, ?m1)

VII. CONCLUSIONS

The main contribution of this paper is the description fully functional executable implementation of a medical guideline for an e-health system based on contemporary Semantic Web technologies: OWL, Jena, Pellet and SWRL.

Although still not deployed in a production environment, the system was thoroughly tested for various combination of input parameters. It should be mentioned, that with assumed granularity of inputs, there are over million test cases. As an average time to perform reasoning is about 300 ms, we preferred to run random tests consisting of 2000 test cases, then manually analyze the correctness of results gathered in a spreadsheet, introduce required changes (corrections in rules, shapes of fuzzification functions) and rerun tests. This process has been continued until no anomaly was detected.

An important reason to focus on technologies related to the Semantic Web was the need to share and reuse a domain knowledge. The general medical knowledge and information related to patients are expressed with a medical terminology, which can be ambiguous and may contain many implicit assumptions. On the other hand, medical information to be processed by IT systems must refer to terminology gathered in vocabularies, preferably ontologies. The SWOP project included tasks aiming at development of domain ontologies covering such topics, as diseases, their subjective and objective symptoms, measured parameters and medications. Hence, an idea to use already gathered and formalized knowledge in guidelines implementation.

The decision to represent medical guidelines in SWOP e-health system in the form of fuzzy rules was preceded by an analysis of formal guidelines representation languages, e.g. GLIF and PROforma. Long lasting discussions between the medical professionals and representatives of the IT world indicated, that there is a substantial gap between, how guidelines are perceived by both parties. IT people expect, that a knowledge collected in guidelines can be easy transformed into algorithms or strict rules, whereas the other party emphasizes the fact that recommendations collected on guidelines are often very general, present several alternatives, and dependent on many vague factors. An approach based on fuzzy rules seems to be a rational compromise in this area. Moreover, it provides a framework allowing personalized adaptation that can be done independently based on statistical analysis of collected data without changes in the structure of rules.

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