A Fuzzy Decision Support Language for Building Mobile DSSs for Healthcare Applications

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Abstract. Recently, Fuzzy Logic has been proposed as the most suitable approach for profitably tackling uncertainty and vagueness in clinical guidelines, and providing a new mobile generation of Decision Support Systems. This paper presents an intuitive XML-based language, named Fuzzy Decision Support Language, for both configuring a fuzzy inference system and encoding fuzzy medical knowledge to be embedded into a mobile DSS. Such a language enables the encoding of: i) fuzzy medical knowledge, in terms of groups of positive evidence rules and fuzzy ELSE rules assembling all the negative evidence for a specific situation; ii) input and output data, respectively elaborated or produced by the fuzzy DSS, in order to provide meaningful and semantically well-defined advices. As a proof of concept, the proposed language has been applied to encode, into a mobile DSS, the medical knowledge required to remotely detect suspicious situations of sleep apnea or heart failure in patients affected by cardiovascular diseases.

Keywords: Decision Support Systems, Fuzzy Logic, Clinical Guidelines, Mobile Computing, XML technologies.

1 Introduction

In the last decade, a new mobile generation of Decision Support Systems (DSSs) for healthcare applications is increasingly appearing on smart phones, aimed at locally reasoning about patient data and providing case-specific advices to health professionals, patients themselves or other concerned about them [1-2]. In particular, recent implementations of DSSs in medicine [3-5] rely on clinical practice guidelines encoded into crisp-based logical formalisms for simulating the process followed by the physicians and improving the efficiency of medical practices. However, they are not able to reproduce the real physician's decision-making process, since clinical practice guidelines are often pervaded by uncertainty and vagueness in both their recommendations and the clinical signs triggering them.

In this respect, Fuzzy Logic [6] has been proposed as the most suitable approach for profitably tackling uncertainty and vagueness in natural (textual) clinical guidelines, and providing enhanced DSSs [7-8]. One prerequisite for the broad usage of fuzzy DSSs in mobile applications and their efficient application to medical

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settings is the guarantee of a high level of upgradability and maintainability in order to: i) change clinical rules according to their evolution in terms of medical progresses in the treatment of individual diseases; ii) adapt generic, site-independent clinical rules to the specific patient to be treated. These issues point out two main needs: first, fuzzy medical knowledge to be embedded in a DSS should be represented by means of a well-defined and machine-readable language to enable both easy of formalization and management; the mobile scenario demands for a technology to share fuzzy data and structure by granting portability, extensibility and re-use.

Several studies [9-11] have analyzed and proposed XML-based solutions to represent the knowledge base embedded into a fuzzy intelligent system in a common and human comprehensible manner, with the aim of supporting the seamless collaboration between developers and final users. Anyway, the existing solutions provide many general-purpose facilities for modeling fuzzy knowledge, without any form of vertical arrangement for the particular domain of interest. Specifically, to the best of our knowledge, so far, none of the existing approaches is specifically tailored to face two main issues regarding the encoding of fuzzy knowledge underpinning clinical practice guidelines: i) each guideline is made of a group of recommendations which contribute as a whole to detect the positive evidence of a single abnormal situation; ii) no recommendation is formulated to encode the negative medical evidence, i.e. when no abnormal situation is happened, and, thus, physicians are forced to write ad-hoc recommendations also for this case.

In this respect, an intuitive XML-based language, named Fuzzy Decision Support Language (in the following, FdsL), has been proposed and implemented for both configuring a Fuzzy Inference System (in the following, FIS) and encoding fuzzy medical knowledge to be embedded into a mobile DSS. In detail, two types of knowledge can be modeled: i) fuzzy terminological knowledge, in terms of both groups of positive evidence rules, which can be customized by means of a peculiar configuration for the inference, and fuzzy ELSE rules assembling all the negative evidence for a specific situation; ii) fuzzy assertional knowledge in terms of input and output data, respectively elaborated or produced by the fuzzy DSS, in order to provide meaningful and semantically well-defined advices and significantly increase the users' confidence in the final system.

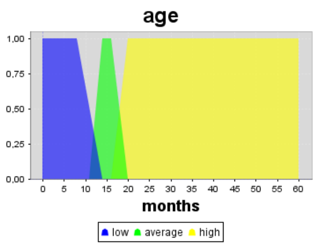
The rest of the paper is organized as follows. Section 2 describes the proposed markup language, whereas, Section 3 depicts a proof of concept regarding a mobile DSS for detecting sleep apnea or heart failure. Finally, Section 4 concludes the work.

2 Fuzzy Decision Support Language

The approach, presented here, is to create the domain-specific language FdsL that unambiguously specifies all the parameters needed to build the FIS underpinning a DSS for mobile healthcare scenarios without enforcing a particular software framework. In addition, FdsL also enables the encoding of both the input and output data, respectively elaborated or produced by the fuzzy DSS, with the aim of encouraging the rapid development of DSSs for mobile healthcare applications and, contextually, to allow medical experts both i) to communicate domain-specific knowledge clearly when describing their decision-making procedures and ii) to simply understand the DSS's outcome, so that the learning curve is diminished or removed. Therefore, FdsL has been devised as simple as possible, yet as comprehensive as needed to provide general utility in fuzzy modeling with respect to mobile healthcare scenarios. As fundamental step necessary to achieve this objective, XML-derived technologies have been chosen since they allow to create data-oriented markup languages able to describe information in a designed working context. In particular, FdsL has been designed as an XML language in order to exploit its capability of defining a rudimentary syntax for specifying hierarchical data. Indeed, on the one hand, all the parameters needed to build a FIS, and, on the other hand, the input and output data elaborated or produced by the fuzzy DSS, have been arranged in accordance with a tree structure, whose FdsL formalizations is provided hereafter.

FIS. It can be modeled by means of a tag named <fuzzyInferenceSystem>, which represents the root node opening a FdsL markup program. Such a tag has two attributes: *name* and *note*. The *name* attribute permits to specify the name of the FIS, whereas *note* is used to provide a textual description about the final DSS based on it.

Concerning the definition of structural and logical parameters of the FIS, first of all, the set of fuzzy variables composing the knowledge base can be encoded by means of a set of nested tags, namely <fuzzyVariable>, to describe a linguistic concept, and <fuzzySet> to define a linguistic term associated to the concept.




```
<fuzzyInferenceSystem name="Example01" note="">
    <fuzzyVariable lowestx="0.0" highestx="60.0" name="age" range="real" unit="months"
        <fuzzySet name="low" type="Trapezoidal">
            <point x="0.0"/>
            <point x="0.0"/>
            <point x="8.0"/>
            <point x="14.0"/>
        </fuzzySet>
        <fuzzySet name="average" type="Trapezoidal">
            <point x="11.0"/>
            <point x="14.0"/>
            <point x="16.0"/>
            <point x="20.0"/>
        </fuzzySet>
        <fuzzySet name="high" type="Trapezoidal">
            <point x="16.0"/>
            <point x="20.0"/>
            <point x="60.0"/>
            <point x="60.0"/>
        </fuzzySet>
    </fuzzyVariable>
</fuzzyInferenceSystem>
```

Fig. 1. A FdsL fragment modeling a linguistic variable “age”

More in detail, the attributes of the tag <fuzzyVariable > are: *name*, *range*, *unit, lowestx, highestx.* The *name* attribute defines the name of linguistic fuzzy concept; *range* and *unit* are used to define how it is measured; *lowestx, highestx* are used to model its universe of discourse. The tag <fuzzySet>uses two attributes, describing its *name* and the *type* of membership function used. A variety of shapes is supported for the membership functions, each of them customizable via a set of nested tags specifying its operational parameters. In detail, *Trapezoidal*, *Triangular*, *Singleton*, and *Piecewise* are describable by indicating their most significant points of their geometric shape by using the tag <point>. This tag uses one or two attributes, namely *x* and *y,* for defining the coordinates of the single points. In detail, if the attributes *y* are not expressed, the corresponding fuzzy sets are supposed as normal (i.e. for trapezoidal and triangular shapes, if the ordinates of their points are not expressed, they are automatically fixed as [0, 1, 1, 0], and [0, 1, 0], respectively). Other supported membership functions, which are *Bellcurve, Cosine, Gaussian,* and *Sigmoidal*, are not describable point by point but the tag <parameter> and its attributes *name* and *value* are used to define the parameters characterizing a specific function (i.e. for Gaussian shapes, parameters to be specified are mean and variance).

Considering as example, Figure 1 shows the FdsL fragment modeling the fuzzy variable "age" of a monitored patient, in terms of three trapezoidal fuzzy sets.

After defining the knowledge base of the FIS, the rule base can be modeled through a set of nodes named <rulesBlock>, placed under the root note through a father-child relation. This tag has been devised to group a set of fuzzy if-then rules depending on a same linguistic variable used in their consequent parts. Such a way, clinical guidelines, typically composed of isolated care recommendations linked to the same final action [12], can be encoded into the FIS. In this respect, Figure 2 shows an example of clinical guideline made of three recommendations linked to the same action, i.e. the lumbar puncture (LP) in children aged up to 60 months.

IF the child age is low,
then LP is *strongly considered*

IF the child age is average,
then LP is *considered*

IF the child age is high,
then LP is *not routinely warranted*

Fig. 2. Clinical guidelines involved in the decision to perform the lumbar puncture

Since each rule block can be characterized by peculiar logical parameters, the tag <rulesBlock> uses the set of attributes described in the following. The *name* attribute uniquely identifies the rule block, *outputVar* attribute permits to specify the linguistic variable common to all the rules belonging to the block at issue. The *implicationMethod, aggregationMethod* and *defuzzificationMethod* attributes define the methods used to implication, aggregation ant defuzzification processes, respectively. The *andMethod* and *orMethod* attributes define, respectively, the fuzzy *And* and *Or* operators to connect the different clauses in antecedent parts of the rules belonging to the block. Such a way, the fuzzy inference is configurable with respect the single block of rules to best fit the peculiarities of the guideline evaluated.

In order to define the single implication rule within a block, the tag <rule> is used, which contemplates two attributes, namely *name,* to identify the rule, and *weight*, to encode the rule relevance to be considered during the inference process.

Each implication rule is characterized by two nodes, the <if> node containing the antecedent part of the rule, and the <then> node containing the consequent part of the rule. They can be used to model pieces of positive evidence, i.e. looking for those manifestations sufficient to establish a positive conclusion.

For what concerns the <if> node, rule antecedents can assume the form of: (i) a simple expression of only one clause (e.g., A is large); (ii) two clauses (e.g., A is large AND B is small), or (iii) composite expressions (e.g., A is large AND (B is small OR C is high)), where priorities have to be also managed. A simple expression of only one clause can be modeled by means of the <ruleClause> tag, directly nested under the <if> node. This tag uses four attributes, namely *variable* and *set* to indicate the fuzzy linguistic concept and term involved, *connector,* which can be either *is* or *isNot,* to relate the variable to a set or its complement, and *modifier* to associate a modification to the fuzzy set.

A rule antecedent of two clauses can be modeled by using the <ruleExpression> tag, directly nested under the <if> node, and a couple of <ruleClause> tags to express the clauses involved. The <ruleExpression> tag uses two attributes, namely *connection,* to express the logical connection between the clauses involved, and *isnegated,* to model the logical complement of the whole expression. Finally, composite expressions can be encoded by means of a set of nested <ruleExpression> tags, where the order of evaluation goes from the most internal rule expression to the most external one. As a result, a <ruleExpression> tag can contain two or more nested nodes, where each node can be either a <ruleClause> term or a <ruleExpression> one.

For what concerns the <then> node, the <ruleClause> tag is used to define the rule's conclusion about the linguistic variable associated to the rule block.

Finally, a <rulesBlock> can also contain one <elseRule> tag to model a rule for the negative evidence that is activated when the other rules of the block are weakly satisfied or not satisfied at all. Similarly to the <then> node, <ruleClause> tag is admitted to formalize the conclusion of the ELSE rule [13] about the linguistic variable associated to the rule block and, thus, to face the lack of exclusionary clinical recommendations in clinical guidelines. Figure 3 depicts the detailed structure of the whole FdsL model, designed for representing the FIS underpinning a DSS.

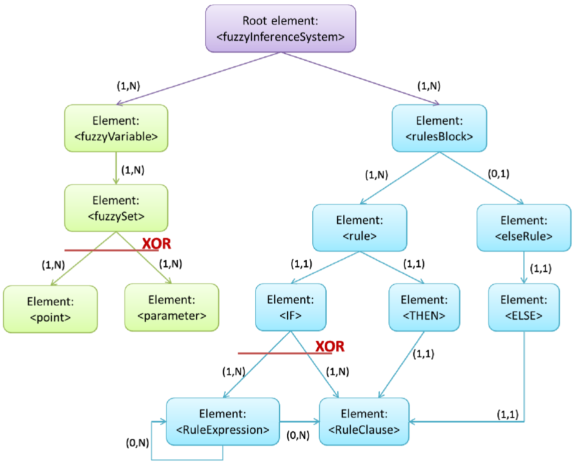


Fig. 3. The FdsL model for representing a FIS

Input and output data. The input and output data, respectively elaborated or produced by the fuzzy DSS, can be codified through two different FdsL descriptions, starting with the root tags named <reasoningInput> and <reasoningOutput>, respectively. Such tags have an attribute *name* which permits to specify the name of the input/output dataset. They admit the nested tags <fuzzyInferenceSystem>, to specify the system to be referred to, and <dataset>, which defines the collection of input data to be evaluated or output data inferred. Each element in this collection is referred by means of the <item>

tag. This tag uses the attribute *id* to specify a univocal identification number with respect to the dataset. Each <item> tag can contain two child tags, namely <input> and <output>, where the latter one is always omitted in the FdsL description of an input dataset.

The <input> tag contains one or more nested <fuzzyVariable> tags which specify the linguistic variables involved. Each <fuzzyVariable> tag can contain either a <fuzzySet> tag or a <crispValue> tag to express respectively its fuzzy or crisp input value. The attributes of the <fuzzySet> tag have been already described above, whereas <crispValue> tag uses the attribute *value* to indicate its input value.

The <output> tag contains one or more nested <fuzzyVariable> tags which specify the inferred fuzzy values for each linguistic variable involved in every single rule block of the FIS. In this context, the <fuzzyVariable> tag includes a nested <fuzzySet> tag to specify the inferred fuzzy value, a nested <defuzzifiedValue> tag to indicate the corresponding crisp value defuzzified according to the method set in the rule block, and, finally a set of <rulesActivationDegrees> tags to report the activation degree of each rule contained into the block. The attributes of the <fuzzySet> tag have been already described above, even if it is important to note that, in this situation, the only value admitted for the attribute *type* is Piecewise, since the shape of the inferred fuzzy set does not match with one of the predefined ones but it has to be specified point by point. The <defuzzifiedValue > tag uses the attribute *value* to indicate its output value. The <rulesActivationDegrees> tag uses the attribute <rulesBlock> to specify the block to be referred to, and includes a set of nested tags, namely <rule> and <else>. Both these tags use the attributes *name* and *degree* to describe the name of the rule and its activation degree, respectively.

3 A Mobile DSS for Detecting Sleep Apnea or Heart Failure

As a proof of concept, the proposed language has been applied to encode the medical knowledge required to remotely detect suspicious situations of sleep apnea or heart failure in patients affected by cardiovascular diseases. A smart phone, equipped with a mobile fuzzy DSS, has been supplied to the patient and wirelessly connected to some wearable sensors for gathering significant parameters, such as the respiratory rate (RR), the heart rate value (HR) and its percentage deviation (HR_Δ), the percentage deviation of the heart rate from respiratory rate ($RRHR_\Delta$), the hemoglobin oxygen saturation (SpO_2), and an estimation of the current physical activity.

Starting from such parameters, two guidelines, each of them made of four clinical recommendations, has been considered for determining situations of sleep apnea or heart failure, as shown in Figure 4. Each guideline has been modeled as a block of rules, where the first three ones enable to identify the positive evidence of the suspicious situations, whereas the last ones are ELSE rules, used when the other ones are weakly satisfied or not satisfied at all, to model the negative evidence.

Afterwards, the knowledge base of fuzzy linguistic variables has been constructed based on the ranges of the measured parameters. Finally, the rule base, the knowledge base and the whole set of parameters needed to configure the fuzzy inference engine underpinning the mobile DSS have been codified in FdsL as reported in the Figure 5. Such a FdsL program has been used to configure the fuzzy DSS deployed on the smart phone of the patient. Considering as a proof of the effectiveness of the proposed

r1:	IF $\lvert RRHR_\Delta \rvert$ is Negligible, THEN Apnea is Present	r5:	IF HR is High AND Activity is Resting, THEN Heart-Failure is Present
r2:	IF $\lvert HR_\Delta \rvert$ is Great, THEN Apnea is Present	r6:	IF HR is Low AND (Activity is Walking OR Activity is Running), THEN Heart-Failure is Present
r3:	IF SpO_2 is Low, THEN Apnea is Present	r7:	IF HR is VeryHigh OR HR is VeryLow, THEN Heart-Failure is Present
r4:	ELSE Apnea is Absent	r8:	ELSE Heart-Failure is Absent

Fig. 4. The fuzzy clinical guidelines of the considered case of study

```
<?xml version="1.0" encoding="UTF-8"?>
<fuzzyInferenceSystem name="FIS" note="">
    <fuzzyVariable lowestx="0.0" highestx="10.0" name="abs(RR_HR_delta)" range="real" unit="$">
        <fuzzySet name="Negligible" type="Triangular">
            <point x="0.0"/>  <point x="0.0"/>  <point x="10.0"/> </fuzzySet>
    </fuzzyVariable>
    <fuzzyVariable lowestx="10.0" highestx="30.0" name="abs(HR_delta)" range="real" unit="$">
        <fuzzySet name="Great" type="Trapezoidal">
            <point x="10.0"/> <point x="20.0"/> <point x="30.0"/> <point x="30.0"/> </fuzzySet>
    </fuzzyVariable>
    ...
    <rulesBlock aggregationMethod="max" andMethod="min" defuzzificationMethod="centerOfGravity"
            implicationMethod="min" name="Apnea" orMethod="max" outputVar="Apnea">
        <rule name="Rule1" note="" weight="1.0">
            <if> <ruleClause connector="is" set="Negligible" variable="abs(RR_HR_delta)"/> </if>
            <then> <ruleClause connector="is" set="Present" variable="Apnea"/> </then> </rule>
        ...
        <elseRule name="Rule4" weight="1.0" note="otherwise Apnea is Absent">
            <else> <ruleClause connector="is" set="Absent" variable="Apnea"/> </else> </elseRule>
    </rulesBlock>
    ...
</fuzzyInferenceSystem>
```

Fig. 5. The medical knowledge of the considered case of study codified in FdsL language

approach, some experimental tests have been produced and the corresponding outputs have been formalized according to the FdsL language. Figure 6 depicts a FdsL fragment of the encoded outcome for a single item of the input dataset used.

```
<?xml version="1.0" encoding="UTF-8"?>
<reasoningOutput name="FIS_reasoningOutput_test">
    <fuzzyInferenceSystem name="FIS"/>
    <dataset>
        <item id="1">
            <input>
                <fuzzyVariable name="abs(RR_HR_delta)"> <crispValue value="20.0"/> </fuzzyVariable>
                <fuzzyVariable name="abs(HR_delta)"> <crispValue value="5.0"/> </fuzzyVariable>
                <fuzzyVariable name="SpO2"> <crispValue value="98.0"/> </fuzzyVariable>
                <fuzzyVariable name="Activity"> <crispValue value="30.0"/> </fuzzyVariable>
                <fuzzyVariable name="HR"> <crispValue value="100.0"/> </fuzzyVariable> </input>
            <output>
                <fuzzyVariable highestx="100.0" lowestx="0.0" name="Apnea" range="real" unit="$">
                    <fuzzySet name="Apnea" type="Piecewise">
                        <point x="0.0" y="1.0"/> <point x="15.0" y="1.0"/> <point x="60.0" y="0.0"/> </fuzzySet>
                    <defuzzifiedValue value="20.972"/>
                    <rulesActivationDegrees rulesBlock="Apnea">
                        <rule degree="0.0" name="Rule1"/>
                        <rule degree="0.0" name="Rule2"/>
                        <rule degree="0.0" name="Rule3"/>
                        <else degree="1.0" name="Rule4"/> </rulesActivationDegrees> </fuzzyVariable>
                <fuzzyVariable highestx="100.0" lowestx="0.0" name="HFailure" range="real" unit="$">
                    <fuzzySet name="HFailure" type="Piecewise">
                        <point x="0.0" y="1.0"/> <point x="15.0" y="1.0"/> <point x="60.0" y="0.0"/> </fuzzySet>
                    <defuzzifiedValue value="20.972"/>
                    <rulesActivationDegrees rulesBlock="HFailure">
                        <rule degree="0.0" name="Rule5"/>
                        <rule degree="0.0" name="Rule6"/>
                        <rule degree="0.0" name="Rule7"/>
                        <else degree="1.0" name="Rule8"/> </rulesActivationDegrees> </fuzzyVariable> </output>
        </item>
        ...
    </dataset>
</reasoningOutput>
```

Fig. 6. FdsL fragment of the encoded outcome for a single item of the input dataset used

4 Conclusions

In this paper, the XML-based FdsL language has been proposed for defining all the parameters needed to build a FIS underpinning a DSS for mobile healthcare scenarios.

Differently from existing solutions, which provide general-purpose facilities for modeling fuzzy knowledge, without any form of vertical arrangement for the particular domain of interest, the FdsL language enables the encoding of: i) fuzzy medical knowledge, in terms of both groups of positive evidence rules and fuzzy ELSE rules assembling all the negative evidence for a specific situation; ii) input and output data, respectively elaborated or produced by the fuzzy DSS, in order to provide meaningful and semantically well-defined advices and significantly increase the users' confidence in the final system. As a proof of concept, a case study has been arranged, where the proposed language has been applied to encode into a mobile DSS the medical knowledge required to remotely detect suspicious situations of sleep apnea or heart failure in patients affected by cardiovascular diseases. Next step of the research activities will regard the design and development of an editing and visualization framework supporting the proposed knowledge formalization language, for enabling physicians to update and handle the fuzzy medical knowledge embedded into the clinical decision support components deployed on mobile devices while they are running by avoiding any service interrupt.

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