Minnesota Code: Evaluation of Fuzzy Ontology Based Approach

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Abstract—**The Minnesota Code is a hierarchical rule-based system for the evaluation of reference ECG signals. One of its weaknesses is the crisp value based hierarchy system. The proper and effective modeling of the rule hierarchy is the key point of the Minnesota Code. In this paper the authors present a possible method to improve the decision model of the Minnesota Code by applying fuzzy ontology to represent the decision process as a hierarchical description of important classes (concepts) along with the description of the properties (of the instances) of each concept. The paper describes the methods applied and the results of the fuzzy ontology based decision process.**

I. Introduction

In a healthcare diagnostic system the complexity of the reasoning process is also increasing, as the increasing number of measurable factors. The basis for creating modern health diagnostics algorithms and instruments is the general system knowledge and decision making methodology. Medical experts and doctors apply their expertise, experiences, and talent to diagnose a disease. Soft computing based technologies have been used in those systems for more than two decades, because healthcare diagnostics is a complex, multi-criteria decision-making system, full of imprecise, ambiguous primary input information, very often represented in speaking language format. Kerre outlined an expert system for ECG diagnosis using linguistic based fuzzy sets [3], but there are standardized, measurable ECK signals, which can be processed as inputs in a programmed decision making or expert system.

The Minnesota Code (MC) operates with a uniform electrocardiogram (ECG) signal set. This widely used ECG classification system was developed in the middle of the last century by Dr. Henry Blackburn [4] and utilizes a defined set of measurement rules to assign specific numerical codes according to the severity of ECG findings. The diagnostic study and decision making rule set based on MC provides an objective ECG classification system free of impressionist physician bias, by which different studies can have a common standard to compare or pool ECG findings. There are several studies which have tried to determine the effectiveness of the computer based Minnesota Code compared to human usage of the code system. The results have shown that computers are as effective in the evaluation of ECG signal with the Minnesota Code as humans are with visual analysis.

The MC system is sensitive to waveform changes, but is not affected by conduction disturbances and arrhythmic events. An additional downside is that the values predefined in the tree-based rule system are crisp values, which means that any noise or a minor delay can cause the rest of the Minnesota Code to be ignored.

One of the further imperfections of the Minnesota Code is the crisp implementation of the input signals in the decision making system. It means that the system is not sensitive to small differences or inherent imprecision of the measured signals, and can miss some of the relevant information in the reasoning process. The authors applied fuzzy logic [5, 6] to possibly improve the results produced by the Minnesota Code system. The results were promising but the Fuzzy solution has too many inter dependencies between the subsystems and it is hard to extend the fuzzy reasoning method to the whole diagnostic system. Also, the extraction of partial results and handling of missing input values became a problem. To further improve the efficiency of the fuzzy based Minnesota Code solution the authors investigated the advantages of a fuzzy ontology based model for the Minnesota Code. In this paper the authors show the methods applied and describe the fuzzy ontology model based Minnesota Code solution.

II. Fuzzy Ontology

A. Ontology

Ontology is a powerful knowledge representation formalism for modelling realworld concepts, basic mechanism and relationships used in different fields from semantic web modelling to the annotation of life events, goals, sub-goals, services, and other specific concepts from the public administration domain [7].

An ontology[2] (O) organizes domain knowledge in terms of concepts (C), properties (P), relations (R) and axioms (A), and can be formally defined as a 4-tuple $O = (C, P, R, A)$, where:

C is a set of concepts defined for the domain. A concept is often considered as a class in ontology. P is a set of concept properties. A property $p \in P$ is defined as an instance of a ternary relation of the form p(c, v, f), where $c \in C$ is an ontology concept, v is a property value associated with *c* and *f* defines restriction facets on *v*.

R is a set of is a set of binary semantic relations defined between concepts in *C*. R_t = *{one-to-one, one-to-many, many-to-many}* is the set of relation type.

A is a set of axioms. An axiom is a real fact or reasoning rule.

The fuzzy ontology is created as an extension to the standard ontology.

B. Fuzzy Domain Ontology

Fuzzy domain ontology is used to model domain expert knowledge, it can be defined as a 4-tuple $O_F = (C, P_F, R_F, A_F)$, where:

C is a set of concepts. Differing from the original ontology definition, every concept here has some properties whose value is a fuzzy concept or fuzzy set. P_F is a set of properties. A property $pF \in PF$ is defined as a 5-tuple of the from pF(c, vF, qF, f, U), where $c \in C$ is an ontology concept, v_F represents property values, q_F models linguistic qualifiers, which can alter or control the strength of a property value v_F. *f* is the restriction facets of v_F and *U* is the universe of discourses. Both v_F and q_F are fuzzy concepts at U, but q_F changes the fuzzy degree of v_F. For example, *"price"* is a property of concept *"fruit"*. The value of *"price"* may be either fuzzy concept *"cheap"* or fuzzy number *"around 50"*, and the linguistic qualifiers may be *"very"*, *"little"*, *"close to"* etc. Therefore, the final value of *"price"* may be *"very cheap"* or *"little expensive"*.

R_F is a set of inter-concept relations between concepts Like fuzzy concept properties $rF \in RF$ is defined as a 5-tuple of the form rF(c1, c2, t, sF, U), where $c1, c2 \in C$ are ontology concepts, t represents relation type, U is the universe of discourse and sF models relation strength and is a fuzzy concept at U, which can represent the strength of association between concept-pairs <c1 ,c2>.

A_F is a set of fuzzy rules. In a fuzzy system the set of fuzzy rules is used as a knowledge base.

Combining fuzzy domain ontology with fuzzy linguistic variable ontology, we obtain the three-layered ontology structure shown in Figure 1, which could represent fuzzy knowledge more effectively [1].

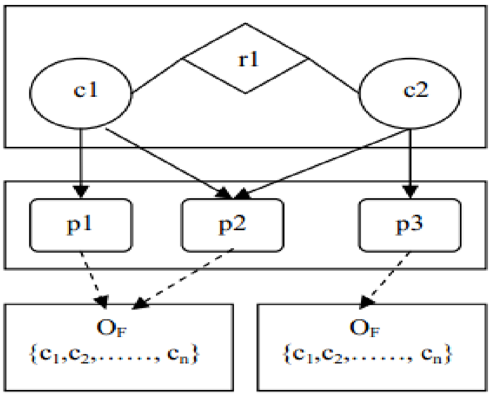

Figure 1. Three-layered ontology structure

III. MINNESOTA CODE ONTOLOGY MODEL

Ontologies are used to capture knowledge about some domain of interest. Ontology describes the concepts in the domain and also the relationships that hold between those concepts. Different ontology languages provide different facilities. The most recent development in standard ontology languages is OWL from the World Wide Web Consortium (W3C).

Minnesota Code rules are ordered into 9 major groups. Each group consists of a number of ECG waveforms and corresponding ECG leads. Groups are identified by a number, ranging from 1 to 9. Major groups can have subgroups containing rules. For example, a rule belonging to the first major group, with the subgroup of 2 and rule number of 8 would be called 1-2-8. Major groups are mapped to wave patterns. The Minnesota Code also specifies a table representing incompatible codes which was used as a starting point for creating a hierarchical structure for representing a fuzzy logic based solution based on the groups and exclusion rules [5, 6]. Figure 2. shows the result which is an overview of the dependencies between different groups. Because of the original rule definitions, hierarchical structure based representation of the Minnesota Code has its own issues. It can be seen that based on this approach there is no clear hierarchy between groups. The problem with the approach shown on Figure 2. is that the exclusion rules are not consistent with the diagnostic rule definitions. Exclusion rules are defined for individual diagnostic rules and not diagnostic groups. This solution is not ideal for an ontology based representation. In ontology solution the exclusion rules are defined as additional non-taxonomic relations representing the diagnostic rule, which is a similar solution used by the Minnesota Code definition, where exclusions are defined for rules.

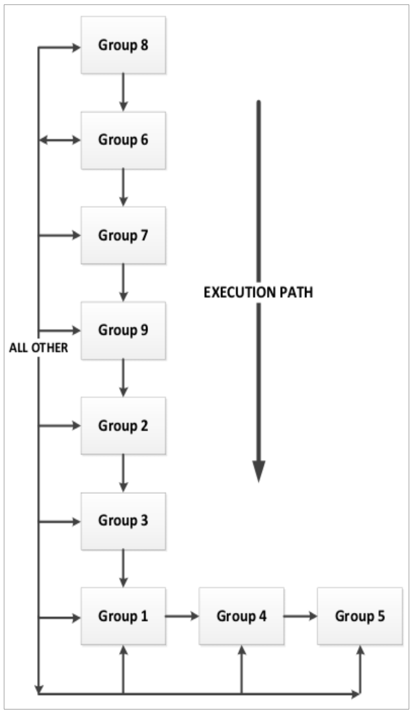

Figure 2. Overview of fuzzy logic approach (based on ECG waveform groups)

A typical Minnesota Code rule has the following structure: *Q/R amplitude ratio ≥ 1/3, plus Q duration ≥ 0.02 sec and < 0.03 sec in lead I or V6*. This rule falls into the Q and QS Patterns category, under the Anterolateral site subgroup, and has the name 1-1-1. This sub categorization can be modeled with ontology. As shown on Figure 3. The rule is a sub concept, with the necessary properties. All Minnesota Code rules are concepts in ontology under different grouping concepts.

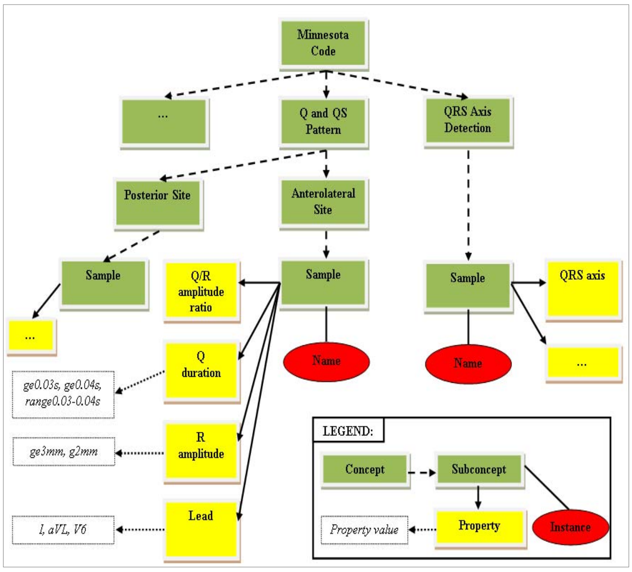

Figure 3. Minnesota Code ontology model

OWL ontology consists of individuals, properties, and classes (concept), where we use classes to model the identified domain concepts of the Minnesota Code, where individuals represent the objects we are interested in such as ECG leads and properties describe the relations and links between different individuals or classes, such as restricting a specific rule to concrete ECG leads.

The definition of the Minnesota Code ontology starts with the *Thing* class. OWL classes are interpreted as sets of individuals (or sets of objects). The class *Thing* is the class that represents the set containing all individuals. Because of this all classes are subclasses of *Thing (*part of the OWL vocabulary). The top level domain concepts are the leads, waveforms and rule groups.

The *Lead* class represents a specific ECG lead used in the diagnostic logic. This is the top level domain concept representing the ECG leads. Lead class has corresponding subclasses that model all ECG lead groups, such as *AnteriorSite, PosteriorSite* and *AntelorateralSite.* Since the ECG leads are constant factors in the diagnostic rule descriptions, they are modeled as such in the ontology of the Minnesota Code. A single instance is created for every ECG lead type as an instance of the class representing the group the lead belongs to. It would be incorrect to have a class V6 (ECG lead), as its members would be deemed to be "things that are instance of V6", whereas ECG leads are thought of as individuals.

The distinction for lead groups would not be mandatory, but by specifying this taxonomy, it is possible to enforce the model/logic of the ontology by defining the relationships and properties between classes.

OWL Classes are assumed to "overlap". We therefore cannot assume that an individual is not a member of a particular class simply because it has not been asserted to be a member of that class. In order to "separate" a group of classes we must make them disjoint from one another. This ensures that an individual has been asserted to be a member of one of the classes in the group cannot be a member of any other classes in that group. In case of the Minnesota Code it would not make sense for an individual lead to be an instance of more than one ECG group class (*AnteriorSite, PosteriorSite* and *AntelorateralSite).* To achieve this result, we specify that the classes AnteriorSite*, PosteriorSite* and *AntelorateralSite* are disjoint classes. This taxonomy provides the possibility to enforce the logic of the model, by specifying relationships between ECG leads and diagnostic rules.

Ontologies are based on crisp logic and do not provide well defined means for expressing and representing fuzzy values and logic. Fuzzy concepts and roles are considered as fuzzy sets. Thus an instance does not fully belong to a given fuzzy concept but has a membership degree being an instance of that concept.

Waveforms represent the inputs of the decision logic which are identifiable from the rule definitions, as described in [6]. In the diagnostic rules of Minnesota Code, the same waveform types are examined for different ECG leads. To model this in the ontology based representation, waveforms are represented as ontology classes sub classing the *Waveform* class. Different waveform classes are specified as disjoint classes, since an ECG waveform cannot classified into multiple waveform groups.

Waveform values fall into categories [6], which are modeled as sub classes of a specific waveform. For example Q/R amplitude ratio input is modeled as a class *Q/RAmplitudeRatio,* which has two subclasses, *Q/RAmplitudeRatioLow* and *Q/RAmplitudeRatioNormal*. These subclasses are not disjoints because waveform value categories can overlap. They can be viewed as membership functions representing fuzzy values. Figure 4. Shows the ontology model of *Waveform* classes. This is a fine-grained system model solution compared to the original fuzzy logic blocked based approach shown on Figure 2.

As mentioned earlier, ontologies are based on crisp values, to support fuzzification of these crisp value representations waveform value category modeling classes have a data property defined (*hasSomeCrispValue),* which assigns a specific crisp value to an instance. This crisp value is used in the fuzzy inference to calculate the degree of membership. Fuzzy logic specific information of the waveform classes is stored as ontology class meta-data and/or OWL annotation properties [8]. This information is used by the fuzzy inference engine.

Diagnostic rules are modeled with the *Rule* class. For each defined diagnostic rule of the Minnesota Code there is an ontology class representing the diagnostic rule. Additionally, we can use relationships and properties to enforce the correctness of the diagnostic model. Properties may have a domain and a range specified. We use properties, to link individuals from the domain (rule) to individuals from the range (waveform) by specifying the exact type (category) of the input waveform. The ontology definition of the rule *"Q/R amplitude ratio ≥ 1/3, plus Q duration ≥ 0.03 sec in lead I or V6"* is defined as a class, which *hasWaveform* of some *RAmplitudeRatioNormal* and *hasWaveform* of some *QdurationShort.* Additionally we define a restriction for ECG leads as well by specifying the properties hasLead for the ECG lead instances representing I and V6. Since ontologies have no support for fuzzy inference, the required information to execute the fuzzy inference is declared as annotation properties on the rule class [8]. Fuzzy reasoners use this information to get the result of the implication. The result of a *Rule* is an instance of the *RuleResult* class, specified by the property *hasResult.* Rule classes also have a property *hasExclusionRule* which refers to classes representing the exclusive diagnostic rules defined by the diagnostic code system.

The OWL model is the declaration of the ontology based setup of the Minnesota Code diagnostic system. By itself

Figure 4. Overview of input waveforms ontology (defined ECG groups)

it cannot be used to infer diagnostic decisions. It only models the decision logic and the constraints behind it. An inference of a decision would involve the following steps:

- Create an instance of a *Waveform* class for an ECG lead with the specified crisp value.
- Create an instance of a *Rule* class with the specified waveform instances
- The inference engine uses the *Rule* instance to execute the fuzzy decision steps.
- Using the annotation properties of the *Waveform* instance the inference engine extracts the membership function type corresponding to the *Waveform* class.
- Using the extracted membership type, fuzzification of the crisp value is done.
- Using the annotation properties of the *Rule* instance the inference engine extracts the rule criteria
- The inference engine executes the fuzzy reasoning and stores the result in an instance of *RuleResult*

IV. Advantages of the Fuzzy Ontology Approrach

The ontology based model of the Minnesota Code is simpler and easier to manage and extend then the previous approaches [5, 6]. Ontology allows to model the hierarchical dependency based setup of the Minnesota Code without explicitly specifying the execution order. The rule explosion problem of the original fuzzy approach is also solved and easier to manage. The Minnesota Codes are mapped as the appropriate non-taxonomic relations. The original fuzzy version required all inputs to be specified, it was not possible to execute a part of the decision tree. The ontology model allows the execution of single rules with the ability of querying partial diagnostic results as well.

V. Conclusion

As it can be seen, the fuzzy logic based approach shown on Figure 2. Is a rigid approach compared to the fuzzy ontology based solution shown on Figure 4. Fuzzy ontology is a viable solution for representing complex hierarchical knowledge models. It provides a model which is easier to extend and manage and also opens up the possibility to fine tune complex decision trees with minimal or no side effects at all. Future plans include medical case studies on datasets which failed on the fuzzy based solution due to missing or corrupt samples. These case studies will reveal further possibilities to optimize and improve the knowledge base by identifying relationships between different ontology concepts.

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