A hybrid reasoning system for mobile and intelligent health services

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***Abstract*— Recently, innovative and mobile health services have been developed by embedding knowledge-based systems, with the aim of remotely promoting wellness and healthy lifestyle, monitoring patients' chronic diseases and improving their adherence to therapies. Even if different knowledge-based systems have been proposed for mobile devices, they are typically based on precise production rules built on the top of ontological primitives for describing the domain of interest. Thus, they are not able to handle medical knowledge graded and affected by uncertainty, which often underlies medical decision-making processes. In order to address this topic, this paper presents a hybrid, rule-based reasoning system for mobile devices aimed at enabling the realization of intelligent health services. This system is essentially characterized by two main features: i) a hybrid knowledge representation approach for modelling productions rules involving both precise and vague information by integrating ontological and fuzzy primitives; ii) a lazy reasoning algorithm able to efficiently process this hybrid knowledge and timely produce answers. A case study has been arranged in order to evaluate the effectiveness of the proposed system within a mobile application for detecting heart arrhythmias.**

Keywords—Hybrid reasoning; Rule-based systems; Mobile healthcare applications.

I. Introduction

In the last years, the increase of age-related chronic diseases is translating into tremendous strain on various health-care services [1]. These chronic diseases are the main cause of disease burden and deaths in the developed world [2]. Lifestyles play a central role in the onset and progression of these diseases [3]. Personalized prevention and management strategies are required to handle the mixture of unhealthy lifestyles and comorbidities varying from one individual to another. This need presents a challenge recently faced via the exploitation of information and communication technology.

Recently, wearable and wireless technologies are emerging as a promising solution for large-scale pervasive healthcare service delivery, thanks to their wide penetration in society and their constantly increasing capabilities [4]. Indeed, advances in mobile computing and sensor technologies have facilitated the realization of autonomous, proactive, and intelligent health-care services, by removing locational, time and other constraints, while increasing both their coverage and quality [5].

In particular, today, ubiquitous sensors can be found in the form of commercial devices able to measure vital parameters or count daily steps for medical purposes [6] as well as to acquire biomechanical, physiological, and behavioural parameters for sport purposes [7]. This capability to sense health parameters has enabled the development of a wide range of applications for personalized health monitoring and management [8-10]. In these healthcare applications, a great challenge is to provide them with smartness in terms of automatic reasoning mechanisms able to evaluate huge amounts of monitored data, recognize abnormal situations and/or suspicious changes, and supply warnings or suggestions to enable personalized monitoring and management of health and well-being [11]. The availability of local smartness on mobile devices could reduce the need of continuous network transmissions and, at the same time, the number of potential communication delays or interruptions so to maintain appropriate levels of security and privacy [12].

Despite being a crucial step toward facilitating personalized health care, the realization of reasoning systems able to efficiently deal with as well as reason over different forms of information and knowledge, often graded and affected by uncertainty, directly on the mobile devices represents a critical point, still pending to date. Even if different reasoning systems, and in particular rule-based solutions, specifically devised to mobile devices have been already proposed in the literature [13-18], they are typically based on precise production rules built on the top of ontological primitives for describing the domain of interest. Thus, on the one hand, they are not able to interpret and evaluate rules including uncertainty and vagueness. On the other hand, their performances rapidly worsen when applied on mobile devices under realistic healthcare scenarios. In this respect, the authors in [12] have proposed a light-weight, rule-based, reasoning system, embeddable in mobile devices and purposely designed and optimized to support remote health monitoring applications. Even if such a system offers both an efficient reasoning algorithm and knowledge representation capabilities to manage ontology-models and production rules built on the top of them, it is not able to handle the tolerance for imprecision, uncertainty and partial truth that can arise in medical knowledge as well as in data gathered from sensors.

According to such considerations, this paper proposes a hybrid, rule-based reasoning system for mobile devices aimed at enabling the realization of intelligent health services. This system is essentially characterized by two main features: i) a hybrid knowledge representation approach for modelling productions rules involving both precise and vague information by integrating ontological and fuzzy primitives; ii) a lazy reasoning algorithm able to efficiently process this hybrid knowledge and timely produce answers. The remainder of the paper is structured as follows. Section 2 reviews and compares existing languages and systems for knowledge representation and reasoning. Section 3 presents the architecture of the proposed system, including the knowledge models and reasoning algorithm adopted. Section 4 describes a case study arranged in order to evaluate the effectiveness of the proposed system within a mobile application for detecting heart arrhythmias. Finally, Section 5 concludes the work.

II. Background and Related Work

Generally speaking, in order to realize a proper knowledge-based mobile reasoning system, the employed knowledge representation techniques have to be defined with the goal of optimally representing information in mobile devices, and efficiently reasoning on them without overloading their resources. With respect to the first point, knowledge representation techniques can be chosen taking into account both the domain of interest, and the practical requirements of the final application. In healthcare applications, the form of knowledge representation mostly adopted consists in codifying knowledge in terms of ontological vocabularies and production rules built on the top of them. In detail, on the one hand, ontological vocabularies are used to represent the domain declarative knowledge, namely the structure of the domain of interest. On the other hand, a set of production rules built on the top of ontological vocabularies is used to represent the knowledge about decisional processes, namely the domain procedural knowledge. The standard-oriented language for encoding declarative knowledge in the form of ontologies is OWL (Web Ontology Language) [19], with one of its serializations, such as RDF/XML, most used but characterized by a heavy-weight syntax, or N-Triples, that is light-weight and, thus, easier to parse and process. On the other hand, the most known rule languages for encoding procedural knowledge by extending the semantics of OWL are SWRL (Semantic Web Rule Language) [20], which is characterized by a complex syntax and a reduced set of non-monotonic directives, and the Jena rule language [21], whose syntax relies on a line-based and plain text format and includes a wider set of non-monotonic primitives, such as assertion, retraction and negation-as-failure.

However, the combination of these representation languages is not completely adequate to represent different kinds of uncertainty and vagueness. To address this topic and enable approximate modelling and reasoning, Fuzzy Logic could be used, since it handles approximate information in a systematic way enabling the description of knowledge in terms of soft linguistic variables operating in a continuous range of truth-values. On the other hand, the main drawback of Fuzzy Logic is the lack of a deeper and structured view of the domain of interest, since it is not able to represent and infer more articulated knowledge and relations among the domain objects.

In this respect, different proposals have been presented for hybridizing these formalisms and increasing their overall expressivity, such as Fuzzy OWL [22], fuzzyDL [23], f-SWRL [24]. These methods extend the semantics of OWL, the classical Description Logic and SWRL, respectively, in order to support fuzzy data types, membership functions and fuzzy modifiers. These proposals are mainly characterized by a common disadvantage, the introduction of new and dedicated formalisms for representing fuzzy knowledge within ontological models, making these solutions incompatible with existing ontology-based applications. Moreover, in a preliminary study [25], the authors have proposed an ontology-based approach for formally representing hybrid rules on top of ontology models. However, this approach does not work on the reasoning algorithm. Indeed, the evaluation of hybrid rules has been performed by considering precise and vague knowledge separately. Moreover, no facility has been proposed to operate efficiently on mobile devices. With respect to the issue of efficient reasoning over mobile devices, existing mobile reasoning systems proposed in the literature [13-18] do not support languages for representing both declarative and procedural knowledge, and, contextually handling factors of uncertainty and vagueness. Moreover, they are characterized by very expensive time and space demands for reasoning, since they implement RETE as pattern matching algorithm, which is very efficient on desktop systems, but can result ineffective and wasteful in mobile healthcare applications requiring on board reasoning [12].

Summarizing, all these considerations about knowledge representation and reasoning issues represent the rationale for the hybrid solution proposed in this work.

III. The System Architecture

The proposed hybrid, rule-based reasoning system has been designed to support inferential procedures in mobile healthcare applications. It relies on hybrid production rules as its basic unit of computation and employs the classical recognize-act cycle, made of two main phases, namely *pattern matching* and *rule firing*. In the pattern matching phase, the system looks for the first applicable rule instance, which is matched by the most recent data characterizing the system state. Then, in the rule firing phase, the system executes the matched rule instance, updates its state and cycles back to the pattern matching phase.

The main components of the system are shown in Fig. 1.

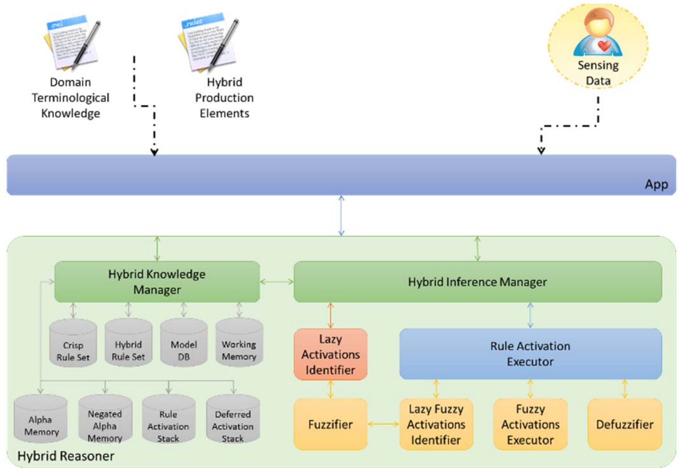

Fig. 1. The main components of the hybrid reasoning system

In detail, the Hybrid Knowledge Manager (HKM) and the Hybrid Inference Manager (HIM) are the main interfaces between the reasoning system and other application layers. The

HIM manages the reasoning cycle and it is in charge of invoking other components in order to ensure the correct flow of inference execution, the proper knowledge updating, and the notification of inference outcomes to external components. The HKM is responsible of handling knowledge base repositories and ad-hoc memory structures. Other components can interact with the HKM for visiting or updating the current system knowledge. In this respect, the terminological knowledge describing the domain in terms of classes and properties, is stored into the Model DB (MDB), whereas the assertional knowledge about domain objects of interest, also named facts, is encoded as individuals (instances of concepts) with the corresponding instances of properties, and stored into the Working Memory. All the information stored in MDB and WM is codified in the N-Triples syntax in the form of collections of subject, predicate and object elements. The Crisp Rule Set (CRS) and Hybrid Rule Set (HRS) are repositories where different production rules are stored, namely classic rules operating only on precise information and hybrid rules working with both precise and vague information and eventually grouped when cooperating to generate a shared outcome. Both these typologies of rules are characterized by an antecedent part, namely the rule left-hand side (LHS), containing a conjunction of condition elements (CEs), and a consequent part, namely the rule right-hand side (RHS), containing a set of action elements (AEs). CEs and AEs can be expressed by using the syntax defined and shown in Fig. 2. Three kinds of rule atoms can be used, namely triple pattern (TP), negated triple pattern (nTP) and function to call (FC).

TPs and nTps are N-triple objects which can contain constant values or variable references denoted by prefixing them with a question mark. A TP can be used in a CE for testing the existence of facts in the WM matching it. On the contrary, a TP can be used in an AE for asserting a fact in the WM and, therefore, it can be applied only if its eventual variable references have been properly assigned. nTPs can be used in an CE only, for testing the absence of N-triple facts in the WM matching it.

Rule ::= Name: **if** Antecedents **then** Consequents; Name ::= TextValue; Antecedents ::= ConditionElement [conjunctionOperator ConditionElement]; ConditionElement ::= (N-Triple) | not(N-Triple) | FunctionToCall Antecedents ::= ActionElement [conjunctionOperator ActionElement]; ActionElement ::= N-Triple | NonMonotonicFunction | FuzzyFunction ; conjunctionOperator ::= , | & N-Triple ::= Subject Predicate Object; Subject ::= Term | Variable; Predicate ::= Term | Variable; Object ::= Term | Variable | Value; Term ::= uri-reference (e.g. http://exuri#ex1) | prefix:name (e.g. expre:ex1); Variable ::= ?variableName; Value ::= NumericalValue | BooleanValue | TextValue NumericalValue ::= number (e.g. 10 or 20.5); BooleanValue ::= 'true' | 'false'; TextValue ::= 'a string';	FunctionToCall ::= LogicalFunction | ArithmeticalFunction | NonMonotonicFunction | FuzzyFunction; LogicalFunction ::= equal(fArg, fArg) | notEqual(fArg, fArg) | lessThan(fArg, fArg) | lessEqual(fArg, fArg) | greaterThan(fArg, fArg) | greaterEqual(fArg, fArg); fArg ::= Variable | Value; ArithmeticalFunction ::= sum(fArg, fArg, Variable) | product(fArg, fArg, Variable) | difference(fArg, fArg, Variable) | quotient(fArg, fArg, Variable); NonMonotonicFunction ::= newInstance(Variable, Term) | retract(N-Triple); FuzzyFunction ::= IS(Variable, FuzzyVariableName, FuzzyTermName, FuzzyShape) | ISnot(Variable, FuzzyVariableName, FuzzyTermName, FuzzyShape); FuzzyVariableName ::= TextValue; FuzzyTermName ::= TextValue; FuzzyShape ::= TriangularShape | TrapezoidalShape; TriangularShape ::= NumericalValue, NumericalValue, NumericalValue; TrapezoidalShape ::= NumericalValue, NumericalValue, NumericalValue, NumericalValue

Fig. 2. The syntax of the defined rule language

Function calls (FCs) can be inserted both in the LHS and in the RHS of a rule, and they produce the invocation of specific internal procedures. In the first case, they are usually used for evaluating logical conditions or computing arithmetic expressions. In the second case, they can be used for asserting or retracting facts according to a non-monotonic strategy. In addition, the function call named *FuzzyFunction* (FF) has been defined to enable fuzzy evaluations and operations (such as *fuzzification*, *inference*, *aggregation* and *de-fuzzification*) within the classic inference scheme. A FF can be used in the LHS of a rule in order to associate a fuzzy term to a variable with a smoothed degree of membership, whereas it can be used in the RHS of a rule to perform the fuzzy inference procedure and produce a precise value as output. An example of rule belonging to CRS and stating that *the daily dosage of Aspirin for a patient with a temperature greater than 40°C is equal to 4,* is reported as follows:

```
[R1: if (?y rdf:type Patient), (?y hasTemperature ?x), greaterThan(?x, 40)
          TP1                    TP2                    FC1
     then (?y AspirinDailyDosage '4'^^xsd:int)]
                  TP3
```

On the other hand, an example of rule belonging to HRS and stating a similar concept, i.e. that *the daily dosage of Aspirin for a patient with a high temperature is high,* is shown as follows:

```
[R2: if (?y rdf:type Patient), (?y hasTemperature?x), IS(?x, Temp, High, 35, 38, 42, 42)
          TP1                    TP2                    FF1
     then IS(?z, AspirinDailyDosage, High, 3, 4, 6, 6), (?y AspirinDailyDosage?z)]
                  FF2                                     TP3
```

In particular, in this rule, FF1 and FF2 allow determining the daily dosage of Aspirin when the patient's temperature is high. Starting from the value of the input variable *?x*, FF1 associates the fuzzy term *High* to the fuzzy variable *Temperature* with a degree of membership to a trapezoidal fuzzy shape, classically represented by means of four points (*35, 38, 42, 42*). Instead, FF2 reproduces the fuzzy inference scheme by operating on this degree of membership and, successively, generates a precise value for the variable *?z,* starting from the fuzzy term *High* assumed by the fuzzy variable *AspirinDailyDosage* and characterized by a trapezoidal fuzzy shape, expressed via four points (*3, 4, 6, 6*). The difference between rules R1 and R2 relies on their behaviour around values of temperature that are close but placed around 40°C. In the first rule, patients with a temperature equal to 39.9°C will not be administered with a daily dosage of Aspirin equal to 4 tablets. On the contrary, in the second rule, the same patients will be administered with a dosage not equal to 4 tablets but very close to that value.

Rules belonging to HRS are eventually grouped depending on the fuzzy variable used in their AE. In particular, rules with the same fuzzy variable in their AE must be processed together since all of them contribute to produce a new assertion about that variable, in accordance with the dictates of Fuzzy Logic in case of multiple levels of inference. Therefore, an assertion about a fuzzy variable can be used by rules belonging to other groups only after all the rules of the same group have been considered and integrated for producing that assertion. Furthermore, the Hybrid Reasoner (HR) is based on a forward chaining scheme, where available data are supplied as facts in order to evaluate eligible rules and draw all possible new inferred facts. The reasoning scheme adopted by this component extends the lazy evaluation approach proposed by the authors in [12], with the final aim of supporting both crisp and hybrid rules and, contextually, granting an efficient handling of memory and computational resources.

In detail, Fig. 3 describes the whole reasoning procedure as follows. At each recognize-act cycle, the HIM invokes the *Lazy Activations Identifier* (LAI) in order to determine the first rule instance to execute. The LAI processes WM elements (WMEs) and evaluates if they satisfy TPs or nTPs contained in the LHSs of rules stored in both CRS and HRS by means of the so-called *intra-condition tests.* The results of these tests are WMEs matching TPs or nTPs. They are stored into ad-hoc memory structures, named *Alpha-Memories* and *Negated Alpha-Memory,* respectively. Such memories are arranged coherently with the order of the matching WMEs, since *intra-condition tests* are computed by moving tidily on the WM. After filling these memories, the LAI processes the rules and labels them as active if all the *Alpha-Memories* linked to their TPs contain at least a matching WME. In case of group of hybrid rules, it labels the group as active if at least one of its rules is active.

Successively, all the active crisp and hybrid rules are processed in order to determine the first eligible rule instance to execute, also named *rule activation*. Each rule activation is essentially computed as the set of available WMEs satisfying it. A rule admits one activation in case when its CEs do not contain variable references, and more activations in case when its CEs contain a variable reference, i.e. one activation for each value assigned to the variable reference. In the case when the CEs of a rule contain more than one variable reference, the activation is constituted by the set of WMEs matching the CEs where no variable is present plus a finite set of couples (*variable*, *value*) where for each *variable* contained in one (more) CE(s), a *value* is chosen among the WMEs matching such CE(s). In order to determine these couples (*variable*, *value*), the LAI performs *inter-condition joins*, i.e. visits the space of all possible variable bindings and chooses the ones that do not violate any other CEs.

Each activation determined by the LAI is characterized by a degree, which is equal to 1 for crisp rules and can vary from 0 to 1 for hybrid rules, depending on the fuzzy aggregation of the FFs contained in their LHSs. In this second case, after calculating the *inter-condition joins* for TP and nTPs, the LAI invokes the *Fuzzifier*, which calculates the degree of each FF occurring in the LHSs of the considered rule and, then, chooses their minimum as final output. Obviously, in case of final degree equal to 0, the activation is discarded since ineligible.

For each active rule, the LAI visits the space of all possible variable bindings for determining the unique activation to fire at each recognize-act cycle, in accordance with the lazy evaluation approach. To this aim, it makes use of a *Rule Activation Stack* (RAS), whose elements enable to enumerate a subset of potential rule activations by combining the facts stored into *Non-Negated Alpha Memories*. As soon as an eligible activation is found, the research of other possible ones is paused by storing a reference to the interruption point into the RAS, and, then, it is timely executed by the *Rule Activations Executor* (RAE).

In case of eligible activations associated to crisp rules containing only precise information, their AEs are executed and possible updates to the WM are timely produced. On the other hand, in case of eligible activations associated to hybrid rules, a different procedure is applied. In particular, when the activation of a hybrid rule, also referred as *main activation*, is identified as eligible in a group, the RAE repeatedly invokes another component named *Lazy Fuzzy Activations Identifier* (LFAI), which is responsible of searching for activations, related to other hybrid rules but belonging to the same group, that are able to contribute to the same outcome with a coherent binding space.

To this aim, the RAS has been enhanced in order to efficiently manage *contributing activations* of hybrid rules belonging to a same group and, contextually, avoid repeatedly examining the same binding space of hybrid rules when other contributing rules exist. In particular, in case when a potential contributing activation of another hybrid rule belonging to the same group is detected as ineligible, its reference is removed from the RAS. In case when it is detected as eligible, it is collected by the LFAI only if it is coherent with respect to the current main activation. In case of eligibility and independently from the coherency with respect to the current main activation, the reference to the contributing activation is however preserved into the RAS. Indeed, the activation of another hybrid rule can be considered as eligible also successively, when that rule is considered for searching the main activation. This management of the RAS assures that time and space resources are saved by avoiding evaluating more than one time the same potential activation. As soon as all the existing *contributing activations* have been collected, the final execution is demanded to the *Fuzzy Activations Executor* (FAE), which processes FFs occurring in their AEs and in the AE of the main activation in accordance with the classical fuzzy inference scheme. Successively, it cooperates with the *Defuzzifier* to calculate and bind a precise numerical value to the TP also present in the AE of the main activation, and finally, execute this TP. After a rule execution, the RAE modifies the rules' binding spaces according to the inferred WM updates. In detail, in the case when the WM has not be updated, the research of eligible activations can be resumed from the last interruption point, i.e. by removing the next element from the top of the RAS. On the contrary, in the case when some updates have been generated, the HIM recognizes the rules involved by these changes and updates the *Alpha-Memories* associated to their CEs and the related RASs. As final step of this process, the HIM restarts the research of activations by selecting one active rule from the ones having non-empty stack.

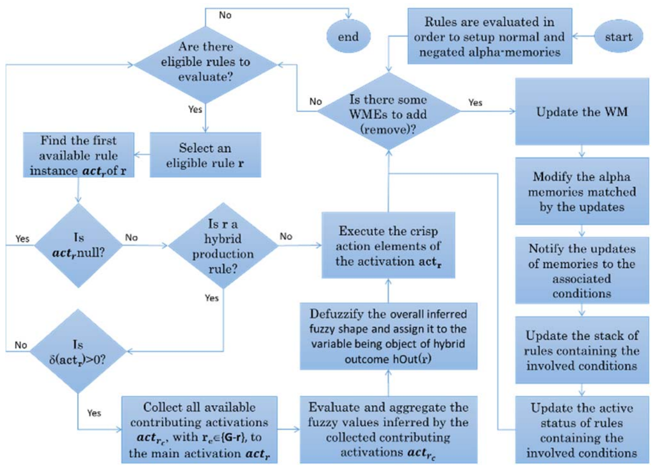

Fig. 3. The whole hybrid lazy matching procedure.

IV. Case Study

As a proof of concept, the presented reasoning system has been implemented for resource-limited mobile devices equipped with the Android platform and embedded within a mobile application aimed at monitoring and managing cardiac arrhythmias, such as bradycardia and tachycardia. The mobile application has been built by using a bracelet equipped with multiple sensors, i.e. a 3-axis accelerometer, a temperature sensor and a reflectance-based pulse oximeter, in order to acquire, via the Bluetooth Low Energy protocol, different vital parameters, such as heart rate, temperature and spO_2, as well as other derived parameters pertaining the physical activity, such as step count. It is aimed at detecting a set of anomalies involving the subject wearing the bracelet by correlating all the parameters directly acquired or indirectly calculated, together with other anthropometric information manually inserted by means of the GUI of the application itself. Each anomaly is labeled with a color expressing its severity. In particular, the color "yellow" is associated to an anomaly occurred once, whereas the color "red" is associated to an anomaly happened more than once. In order to describe all the above mentioned parameters and information necessary to the reasoning system for detecting possible anomalies and associating them a severity, the ontology model reported in Fig. 4 has been arranged.

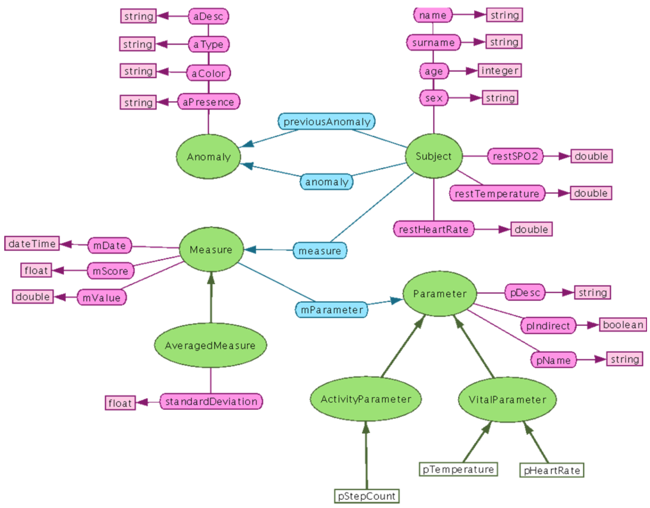

Fig. 4. The ontology model arranged for the reported case of study.

In detail, the main concepts are the following: Subject, Measure, Parameter and Anomaly. Subject models all the anthropometric information characterizing an individual, such as name, surname, age, sex, rest heart rate, rest temperature and rest spO_2. Measure represents all the measurements that can be accomplished by means of the bracelet, and is characterized by a value, a reliability score and an acquisition time. Parameter indicates all the typologies of measurable parameters, either directly or indirectly, and is further classified into two sub-concepts, namely ActivityParameter and VitalParameter. Anomaly describes all the recognizable abnormal situations and is characterized by a color indicating the severity, as introduced above, and a typology, such as cardiac or respiratory.

After introducing these concepts, more instances of Parameter have been defined in order to specify the different parameters that can be detected by the bracelet, such as pTemperature, pHeartRate or pStepCount. On the top of such concepts and instances, a group of crisp and hybrid rules has been defined. For the sake of brevity, only an example of hybrid rule has been here reported and, for the sake of clarity, both informal and formal syntaxes have been used. If (*Measure* of *VitalParameter pHeartRate* is greater than 40% of *RestHeartRate* of *Subject*) and (*Measure* of *VitalParameter pTemperature* is between 35°C and 37°C) and (*Measure* of *ActivityParameter pPhysicalActivity* is Low) then (Subject has *Anomaly* of typology *Tachycardia* and color *Yellow*)

```
[R3: if (?y base:restHeartRate ?rhr), product(0.40, ?rhr, ?rhr_040)
        (?y base:measure ?m1), (?m1 base:mParameter base:pHeartRate),
        (?m1 base:value ?v1), greaterThan(?v1, ?rhr_040), (?y base:haMisura ?m2),
        (?m2 base:mParameter base:pTemperature), (?m2 base:value ?v2),
        ge(?v2, 35), le(?v2, 37), (?y base:haMisura ?m3),
        (?m3 base:mParameter base:pPhysicalActivity), (?m3 base:mValue ?v3),
        IS(?v3, PhysicalActivity, Low, 0, 0, 30, 70), (?y base:anomaly ?a),
        (?a base:aType 'Tachycardia'^^xsd:string)
    then (?z, AnomalyColor, Yellow, 30), (?a base:aColor ?z) ]
```

For the described case study, the mobile application has been deployed and executed on a smartphone with the following characteristics: Samsung Galaxy S5, Android 4.4.2, 2 GB RAM, CPU Quad-Core Snapdragon-801 2.5 GHz. In detail, a tachycardic subject has been monitored during his daily activities in order to detect abnormal situations and potentially cardiac arrhythmias. This preliminary study has highlighted that the proposed system is effectively able to correlate precise and vague knowledge about the monitored subject. Moreover, as shown in Fig. 5, since both vital and physical parameters are contextually examined, the proposed system is able, on the one hand, to not classify normal situations as anomalies and, on the other hand, to signal potentially abnormal events only when they persist over time, and, thus, their presence is confirmed.

TIME	HR	SPO2	TEMP.	Steps	Physical Activity	Anomaly		
						Presence	Color	Type
17:00	81	99.8%	35.4	11	Low	Absent	-	
17:10	80	99.6%	35.5	10	Low	Absent	-	
17:20	75	99.8%	35.7	12	Low	Absent	-	
17:30	82	99.6%	35.7	10	Low	Absent	-	
17:40	80	99.8%	36.0	12	Low	Absent	-	
17:50	110	99.8%	36.6	40	High	Absent	-	
18:00	118	99.6%	36.5	45	High	Absent	-	
18:10	91	99.8%	36.2	21	Medium	Absent	-	
18:20	110	99.7%	36.0	10	Low	Present	Yellow	Tachycardia
18:30	120	99.3%	36.2	11	Low	Present	Red	Tachycardia

Fig. 5. The case study results.

Finally, the reasoning system has been efficiently ran on the abovementioned smartphone, providing timely responses with no need for extra computational resources. In particular, the overall reasoning time has been, on average, roughly equal to 200 ms, whereas the system response time has been more or less equal to 60 ms, i.e. the time required for recognizing and firing the first rule instance, and its existing contributing activations. So, the response time has resulted significantly less than the overall reasoning time, in accordance with the response time of common non-lazy evaluation approaches, since they typically produce outcomes only at the end of the whole reasoning process time.

V. Conclusions and Future Work

In this paper, a rule-based reasoning system for mobile devices has been proposed with the aim of enabling the realization of intelligent health services based on two main features: i) a hybrid knowledge representation approach for modelling productions rules involving both precise and vague information by integrating ontological and fuzzy primitives; ii) a lazy reasoning algorithm able to efficiently process this hybrid knowledge and timely produce answers.

Different from existing solutions, and also from our previous work, the great novelty of the proposed system is the ability to properly represent both precise and vague knowledge on mobile devices, via a set of efficient reasoning mechanisms able to handle and interpret such a hybrid knowledge without overloading their resources. To the best of our knowledge, this is the first proposal of a lazy-based reasoning system specifically designed for efficiently reasoning on top of ontology models enriched with fuzzy primitives. Moreover, even if some existing wearable sensors are able to address, more or less, the need of mobile smartness, a further novelty aspect of the proposed hybrid reasoning system is the ability to handle and reason on knowledge acquired from different sources, enabling the composition and evaluation of more structured and enriched descriptions of individuals' health status, with the final goal of assisting them anywhere they need.

As a proof of concept, the proposed reasoning system has been implemented for mobile devices equipped with the Android platform and embedded within a mobile application aimed at monitoring and managing cardiac arrhythmias, such as bradycardia and tachycardia. The preliminary results of the performed experiments have shown that the proposed system is able, on the one hand, to efficiently evaluate and correlate hybrid knowledge about the contextual information of the monitored subject. Such a way, it is also able to reduce the number of false positive alarms generated.

Next step of the research activities will be, on the one hand, to define a more formal and mathematical background to describe the designed hybrid knowledge framework and, on the other hand, to minutely evaluate the performance of the proposed reasoning system in terms of computation and memory resources required when executed in several scenarios and subjected to different load situations.

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REFERENCES

[1] P. J. Soh, G. A. Vandenbosch, M. Mercuri, D. M. P. Schreurs, "Wearable Wireless Health Monitoring: Current Developments, Challenges, and Future Trends", in Microwave Magazine, vol. 16, no. 4, pp. 55–70, 2015.

[2] Gaining health, "The European Strategy for the Prevention and Control of Noncommunicable Diseases", WHO, Regional Office for Europe, Copenhagen, Denmark, 2006.

[3] E. Mattila, I. Korhonen, J. H. Salminen, A. Ahtinen, E. Koskinen, A. Särelä, J. Pärkkä, R. Lappalainen, "Empowering citizens for well-being and chronic disease management with wellness diary", in IEEE Transactions on Information Technology in Biomedicine, vol. 14, no. 2, pp. 456–463, 2010.

[4] A. Triantafyllidis, C. Velardo, D. Salvi, S. A. Shah, V. Koutkias, L. Tarassenko, "A Survey of Mobile Phone Sensing, Self-reporting and Social Sharing for Pervasive Healthcare," in IEEE Journal of Biomedical and Health Informatics , 2015.

[5] U. Varshney, "Pervasive healthcare," Computer (Long. Beach. Calif)., vol. 36, no. 12, pp. 138–140, 2003.

[6] S. Adibi, A. Mobasher, T. Tofigh, "LTE networking: extending the reach for sensors in mHealth applications", in Transactions on Emerging Telecommunications Technologies, vol. 25, no. 7, pp. 692–706, 2014

[7] A. Baca, P. Dabnichki, M. Heller, P. Kornfeind, "Ubiquitous computing in sports: A review and analysis", in Journal of Sports Sciences vol. 27, pp. 1335–1346, 2009.

[8] S.P. Rajan, S. Rajamony, "Viable investigations and real-time recitation of enhanced ECG-based cardiac telemonitoring system for homecare applications: a systematic evaluation", in Telemed J E Health, vol. 19, no. 4, pp. 278–286, 2013.

[9] A.G. Logan, "Transforming hypertension management using mobile health technology for telemonitoring and self-care support", in Canadian Journal of Cardiology, vol. 29, no. 5, pp. 579–585, 2013.

[10] B. Martínez-Pérez, I. de la Torre-Díez, M. López-Coronado, J. Herreros-González, "Mobile apps in cardiology: review", in JMIR Mhealth Uhealth vol. 1, no. 2, e15, 2013.

[11] B. Martínez-Pérez, I. de la Torre-Díez, M. López-Coronado, B. Sainz-de-Abajo, M. Robles, J.M. García-Gómez, "Mobile clinical decision support systems and applications: a literature and commercial review", in Journal of Medical Systems, vol. 38, no. 1, pp. 1–10, 2014.

[12] A. Minutolo, M. Esposito, G. De Pietro, " Design and validation of a light-weight reasoning system to support remote health monitoring applications", in Engineering Applications of Artificial Intelligence, vol. 41, pp. 232–248, 2015.

[13] S. Ali, S. Kiefer, "μOR – A micro OWL DL reasoner for ambient intelligent devices", in Proceedings of the 4th International Conference on Advances in Grid and Pervasive Computing, 2009.

[14] T. Gu, Z. Kwok, K.K. Koh, H.K. Pung, "A mobile framework supporting ontology processing and reasoning", in Proceedings of the 2nd Workshop on Requirements and Solutions for Pervasive Software Infrastructures (RSPSI' 07), in Conjunction with the 9th International Conference on Ubiquitous Computing (Ubicomp' 07), Innsbruck, Austria, 2007

[15] T. Kim, I. Park, S.J. Hyun, D. Lee, "MiRE4OWL: mobile Rule engine for OWL", in Proceedings of the IEEE International Workshop on Middleware Engineering, 2010.

[16] Lorecarra, "Androjena: Jena android porting", ⟨http://www.code.google.com/p/androjena/⟩, 2009.

[17] W. Tai, J. Keeney, D. O'Sullivan, "COROR: a composable ruleentailment owl reasoner for resource-constrained devices", in Rule-Based Reasoning, Programming, and Applications. Springer, Berlin, Heidelberg, pp. 212–226, 2011.

[18] B. Motik, I. Horrocks, S. M. Kim, "Delta-reasoner: a semantic web reasoner for an intelligent mobile platform", in Proceedings of the 21st International Conference Companion on World Wide Web, ACM, 2012.

[19] P. Patel-Schneider, P. Hayes, I. Horrocks, "OWL web ontology language semantics and abstract syntax", W3C Recommendation 10, 2004 ⟨http://www.w3.org/ TR/owl-semantics/⟩.

[20] I. Horrocks, P.F. Patel-Schneider, H. Boley, S. Tabet, B. Grosof, M. Dean, " SWRL: A Semantic Web Rule Language Combining OWL and RuleML", W3C Member Submission, W3C, 2004 ⟨http://www.w3.org/Submission/2004/SUBM-SWRL-20040521/⟩.

[21] J.J. Carroll, I. Dickinson, C. Dollin, D. Reynolds, A. Seaborne, K. Wilkinson, "Jena: implementing the semantic web recommendations", in Proceedings of the 13th International World Wide Web Conference on Alternate Track, New York, USA, pp. 74–83, 2004.

[22] G. Stoilos, G. Stamou, V. Tzouvaras, J. Z. Pan, I. Horrocks, "Fuzzy OWL: Uncertainty and the Semantic Web", in OWL:Experiences and Directions (OWL-ED 2005), 2005.

[23] F. Bobillo, U. Straccia, "fuzzyDL: an expressive fuzzy description logic reasoner", in Proceedings of the 17th IEEE International Conference on Fuzzy Systems (FUZZ-IEEE 2008), pp. 923–930, 2008.

[24] J Z Pan, G Stoilos, G Stamou, V Tzouvaras, and I Horrocks. "f-SWRL: a fuzzy extension of SWRL", J. of Data Semantics VI, pp. 28–46, 2006.

[25] A. Minutolo, M. Esposito, and G. De Pietro. "An ontology-based fuzzy approach for encoding cognitive processes in medical decision making", in proceedings of the 5th IEEE Conference on Cognitive Infocommunications (CogInfoCom 2014), pp. 397-402, 2014.