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Hybrid approach for context-aware service discovery in healthcare domain

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ABSTRACT

Context-awareness computing is a research field which often refers to healthcare as an interesting and rich area of application. Context aware computing attains environments monitoring by means of sensors to provide relevant information or services according to the identified context. In particular, wireless ad hoc sensor networks for medical purposes are playing an increasing role within healthcare. Body Sensor Networks (BSN) are being designed for prophylactic and follow-up monitoring of patients in e.g. their homes, during hospitalization, and in emergencies. This work presents an integrated environment aimed at providing personalized healthcare services which appropriately meet the user's context. Deploying the semantics embedded in web services and context models is a mandatory step in the automation of service discovery, invocation and composition. Nevertheless, in a context aware domain purely logic-based reasoning on respectively context and services may not be enough. The main idea of this work is related to enrich with qualitative representation of context underling data by means of Fuzzy Logic in order to automatically recognize the context and to consequently find the right set of healthcare services among the available ones. Semantic formalisms (e.g., OWL, OWL-S, etc.) enable the context and services modeling in terms of domain ontology concepts. On the other hand, soft computing techniques support activity of unsupervised context analysis and healthcare semantic service discovery. Goal is to define context-aware system whose quality of retrieved services relies on the acquisition of user context by means of a robust theoretical approach. Moreover, this work defines hybrid architecture which attains a synergy between the agent-based paradigm and the fuzzy modeling. Specifically, the system exploits some task oriented agents in order to achieve context recognition, services matchmaking and brokerage activities.

1. Introduction

The rapid worldwide deployment of Internet and web technologies is the enabler of a new generation of healthcare applications, but the provision of systems that can satisfy the needs of healthcare stakeholders is still an open question. One of the main problems in this domain is the healthcare personalization, that is, enabling personalized healthcare services to be delivered to individuals at any place and any time.

With personalized healthcare, we can further achieve "early health" system where disease is addressed at the earliest possible moment, rather than a "late disease" model where the emphasis is mainly on diagnosis and treatment. To achieve healthcare personalization, other than phenotypic and genotypic patient data, factors such as individual's lifestyle,

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surrounding situations, device capabilities, event of happenings, etc., should be taken into account. Such personalization factors are known as context, which is referred to any information that can be used to characterize the situation of an entity (can be person, place or computational objects) and the interaction between them. As the result, personalized healthcare application is context-aware provisioning healthcare information based on user's changing context so that the right information can be delivered to the right person, at the right time, at the right place, using the right way.

On the other hand, the emergence of ubiquitous computing and continuous progress in medical devices and diagnosis methodology, however, is enabling personalized healthcare services to be delivered to individuals. The healthcare domain is one of the most viable and growing application fields for intelligent mobile service coordination, not just for the technical requirements that it imposes, but also for its huge economic and social relevance. For example, a wearable health monitoring device can constantly examine one's blood pressure, body temperature, pulse, etc.; the availability of large display screen, surveillance camera and embedded microphone array at home may support remote medical consultation; web services can tell the consultation hours of a certain doctor.

On the light of described scenario, context-aware computing enhance the capabilities of healthcare applications. Nowadays, the dynamicity of pervasive environments encourages the adoption of a Service Oriented Architecture (SOA). The adoption of SOA in pervasive environments is leading to the development of "context-aware" services. Context-awareness becomes a key feature necessary to provide adaptable services, for instance when selecting the best-suited service according to the relevant context information or when adapting the service during its execution according to context changes. Multiple aspects related to the users (level of expertise, location, etc.) and to the computer resources (on fixed and mobile devices), among others aspects, can be considered in the development of context-aware services. Thus, context-aware services can be defined as services which description is associated with contextual (notably non-functional) properties, i.e., services whose description is enriched with context information indicating the situations to which the service is adapted to. This context information needs to be compared to the real user's or execution context before starting to use the service. However, in ubiquitous environments, context information is naturally dynamic and incomplete. Dynamic context changes and incomplete context information may prevent perfect matches between required and provided properties, which may lead to the non-selection of one (or all) service(s). Service selection mechanisms have to cope with these issues: if some needed context information is missing, service selection still has to proceed and choose a corresponding service that best matches the current situation, even if context information is incomplete.

In this work, we present an architecture for context-aware service discovery in the healthcare domain that exploits synergy among intelligent agent technology, semantic web models and computational intelligence techniques. Specifically, the work presents an integrated environment aimed at providing personalized healthcare services which appropriately meet the user's context. Goal is to define context-aware system whose quality of retrieved services relies on the acquisition of user context by means of a robust theoretical approach. This system mainly consists of two steps: context modeling, in order to support recognition of user conditions, and services representation according to the context ontology models. Generally, in a ubiquitous computing environment, a context model should provide application adaptability, resource awareness, mobile service, semantic service discovery. In particular, context modeling should describe the relationship between the domain vocabulary and the concept of the domain knowledge. Several context modeling techniques exist such as key-value modeling, mark-up scheme modeling, graphical modeling, object-oriented modeling, logic based modeling and ontology-based modeling. This architecture emphasizes the need of synergic approach between ontology and Fuzzy Logic to model the user's context. In particular, healthcare context domain ontologies are used to model static (e.g., user profile, preferences, etc.) and dynamic context (e.g., blood pressure, temperature, etc.) data. On the other hand, soft computing techniques are used to enrich ontology context by means of qualitative representation of underling data context. Just to give an example, blood pressure could influence some different contexts but in order to discover the right set of recommendations that may be useful to manage the situation there is a need to be aware about in which range falls parameters values (i.e., high/low blood pressure, etc.).

The overall workflow is composed of two main phases: the *Context Training Phase* and *Context Aware Services Discovery Phase*.

The first phase exploits techniques of soft computing and semantic web in order to acquire and analyze context information and carries out a mathematical models able to process context data. In particular, the system elaborates the input data acquired by the sensors and trains itself according to the collected knowledge. Specifically, on the basis of the processed input users' data, the system performs fuzzy data analysis activity and generates fuzzy classifiers useful to automatically recognize coming users' situations during the next phase (runtime phase). The process of unsupervised fuzzy data analysis enable us to enrich context modeling with qualitative representation of underling data.

The second phase retrieves semantic web services which appropriately meet the user's context. In particular, healthcare context are characterized by means of parameters types and values, for example: patient pressure is low. On the other hand, services which take into account pressure in order to provide assistance should to specify in which range of pressure they may be applied. Specifically, we define a hybrid approach based on soft computing and purely logic matching evaluation in order to evaluate matchmaking among parameters (i.e., pressure, heart beat, etc.) and their values (i.e., low, high, etc.). Task oriented agents perform matchmaking activities in order to elicit highest suitable services among the available ones. Specifically, we stress the situation when no exact match occurs between context and services. So, hybrid approach based on soft computing and purely logic matching evaluation is defined.

In order to support the validity of our approach the healthcare case study outlines that a personalized healthcare system based on context-aware service discovery can improve the quality and efficiency in the user context management.

The chapter is organized as follows: Section 2 presents an overview of works in the literature related to both context-awareness and computational intelligence approaches that deal with healthcare; Section 3 introduces overall architecture which attains the proposed aims and emphasizes the roles played by all the system components; Section 4 describes the complete working flow and details theoretical approach on which relies the work; then, Section 5 describes the process model applied to healthcare case study. Conclusions and future works close the chapter.

2. Related works

In the last years, computational intelligence has been exploited to solve many complex problems in medicine, diagnosis of disease and therapeutic treatments. Furthermore, a number of context aware architecture have been developed to assist patients and medical professionals. On the other hand, medical knowledge on the context environment, patients data are sources of imprecision and vagueness. The nature of these data reveals the requirement of treating the uncertainty by means of robust theoretical modeling. Synergy between fuzzy techniques and semantic formalisms guarantee an appropriate coding of this kind of knowledge.

This approach presents a hybrid system which main aim is related to provide an integrated environment that combines theoretical support and technologies in the Computational Intelligence domain. In this chapter, we focus particularly on this issue: how to identify user context and how to deal with incompleteness of context information when selecting context-aware services. At first instance, we focus on context knowledge extraction issue. Finally, the work proposes an approach to handle incompleteness of context information on service selection by using similarity measures. Indeed, the main idea of this work is related to enrich context awareness by means of ontology concepts and fuzzy data analysis, firstly, in order to characterize better the user's needs, and latter, to find the right set of services among the available ones. From technological point of view semantic formalisms (e.g., OWL, OWL-S, etc.) enable the context and services modeling in terms of domain ontology concepts. Moreover, soft computing techniques support activity of unsupervised context analysis and healthcare service discovery.

In the literature there are many works which separately deal with context aware architecture, healthcare and service discovery aspects. Many approaches have shown their effective in the computational intelligence domain. Specifically, some applications and works in the main sub-domains are described follows.

2.1. Healthcare and context aware architectures

Several service platforms such as OSGi, Web service and .NET have been proposed to manage and provision healthcare services. While web service and .NET are fully distributed service platforms, OSGi provides a centralized and hierarchical architecture for service provisioning and management. In particular, OSGi is designed to link the service providers with smart spaces via wide-area-network. [1] and [2] present an OSGi based service infrastructure for context-aware service in smart homes.

A few projects, including Context Toolkit [3], Semantic Space [4], UC Berkeley's open infrastructure [5], and the European Smart-Its project [6], specifically address the scalability and flexibility of context-aware applications by providing generic architectural supports. These projects generally provide infrastructure support for context aware applications. They are not oriented towards healthcare services, and also lack of personalization support.

Most of the existing approaches for context-aware service discovery and selection rely on a key-value pair [11,12] or keyword-based [8] service matching process. Context information is also represented by key-value pairs and may be supplemented by simple if–then-rules. An exception is the COSS approach [7] that utilizes an extensible set of ontologies for context and service description and therefore provides a common understanding of the represented information in contrast to the other solutions. The CAPEUS architecture of [14] also represents context information by key-value pairs, but allows to describe entities and simple relations between these. Instead of integrating context data into service offers the systems of [8,11,12] separately add them to the offers. Consequently the context-based matching process in these architectures (except for the CAPEUS architecture) occurs subsequently to the ordinary service matching. Thus the potential for service selection provided by context information isn't used to full capacity.

Besides [12] none of the matching algorithms takes user preferences into account. The approach of [7] also allows to integrate user-defined attributes like 'nearby' into a service request. Advanced concepts for context-aware request modification come from the field of database systems [9], but aren't directly adaptable to service oriented architectures. Some approaches allow dynamic attributes within service offers. The process of updating their values takes place either by permanent monitoring [10–12] or on inquiry [13], but isn't coupled to the matching process, where we actually need it. Merely [11,12] utilize dynamic service attributes within the matching process.

2.2. Healthcare and personalization

Personalization is about building customer loyalty by building a meaningful one-to-one relationship; by understanding the needs of each individual and helping satisfy a goal that efficiently and knowledgeably addresses each individual's need in a given context [15]. Personalization mainly consists of two steps: user modeling/profiling and content/service recommendation according to user profile. The recommendation techniques can be generally classified into rule-based, classifiers, clustering, and filtering-based methods.

The filtering-based personalization systems provide recommendations based on user preference, which can be classified into content-based [16], collaborative [17], and hybrid methods [18].

There has been some work done in the area of personalized healthcare. Koutkias et al. [19] propose a system delivering personalized healthcare according to every patient's special requirements using Wireless Application Protocol (WAP). This system involves monitoring and education services, designed specifically for people suffering from chronic diseases. It also applies data mining techniques to extract clinical patterns. Abidi et al. [20] introduce an intelligent Personalized Healthcare Information Delivery Systems that aims at enhancing patient empowerment by pro-actively pushing customised, based on one's Electronic Medical Record and health maintenance information via the WWW. This system dynamically authors an HTML-based personalized health information package on the basis of an individual's current health profile. Takeshi et al. [21] developed health check-up services using mobile phones managing personal healthcare data in accordance with one's health awareness and lifestyle. While few papers have addressed the infrastructure support for personalized healthcare in ubiquitous computing environment, this work attempts to identify the key components and enabling technologies for such an infrastructure. It is expected that personalized healthcare services can be provisioned at anytime, anywhere with the support of the infrastructure.

2.3. Healthcare and computational intelligence

Advances in computer and information technology and the amount of data these new technologies generate have created challenging opportunities for the Computational Intelligence (CI) community. This is particularly true in healthcare where computers play an active role in all realms from capturing, storing and processing patient data in all formats at all times. This bears tremendous opportunities for developing effective computational solutions to improve the overall quality of healthcare.

In the literature there are many approaches to healthcare applications that combines three core Computational Intelligence techniques: Neural Networks [22], Genetic Algorithms and Fuzzy Logic. In particular, several Fuzzy Logic applications have been developed in the field of anesthesia. Anesthesiology requires monitoring of patient vital signs during the controlled administration of drug infusion to maintain the anesthetic level constant. Examples of applications (extracted from [23]) include depth of anesthesia [24], muscle relaxation [25,26], hypertension during anesthesia [27], arterial pressure control [28], mechanical ventilation during anesthesia [29] and post-operative control of blood pressure [30]. Fuzzy Logic has been applied to computerized clinical guidelines [31], as well as in risk assessment in a healthcare institution [32]. Similarly, knowledge management techniques have been applied to structuring clinical and patient information [33,34].

3. Architectural overview

Our approach for healthcare context-aware service discovery, selection and usage is based on a hybrid integrated environment based on the synergic application of semantic technologies and soft computing techniques.

In particular, Fig. 1 presents an architectural overview of all system's component aimed at providing personalized healthcare services according to the user context. More specifically, as highlighted in Fig. 1, our approach is essentially based on a distributed service oriented architecture based on multi-agent paradigm.

There are three main tiers that we distinguish in the architecture:

- *Context sensing user domain* – it includes body sensor network, wearable devices, user profile and mobile devices that gathers the information and interacts with the backend of the architecture (*Context aware brokerage domain*);
- *Semantic provider domain* – it includes semantic enhanced services provider that offer typical services in healthcare domain;
- *Context aware brokerage domain* – it is composed of some task oriented agents that offer the behaviors of mediation, brokerage and matchmaking. In particular, it also includes knowledge component, like as: *Context Domain Ontologies*, *Context Training Data Set*, *Context Fuzzy Rule Base* and OWL-S *Healthcare Services*. So, this domain represents the backbone of the overall architecture.

The following sections give major details about the roles played by all the system components.

3.1. Context sensing user domain

In a healthcare system the user play a central role and he/she is the main information source. This architectural domain focus on the user context data acquisition. Context data consists of two kind of information static (e.g., user profile, preferences, etc.) and dynamic (e.g., blood pressure, temperature, etc.) data. Context Domain Ontologies are used to model acquired data.

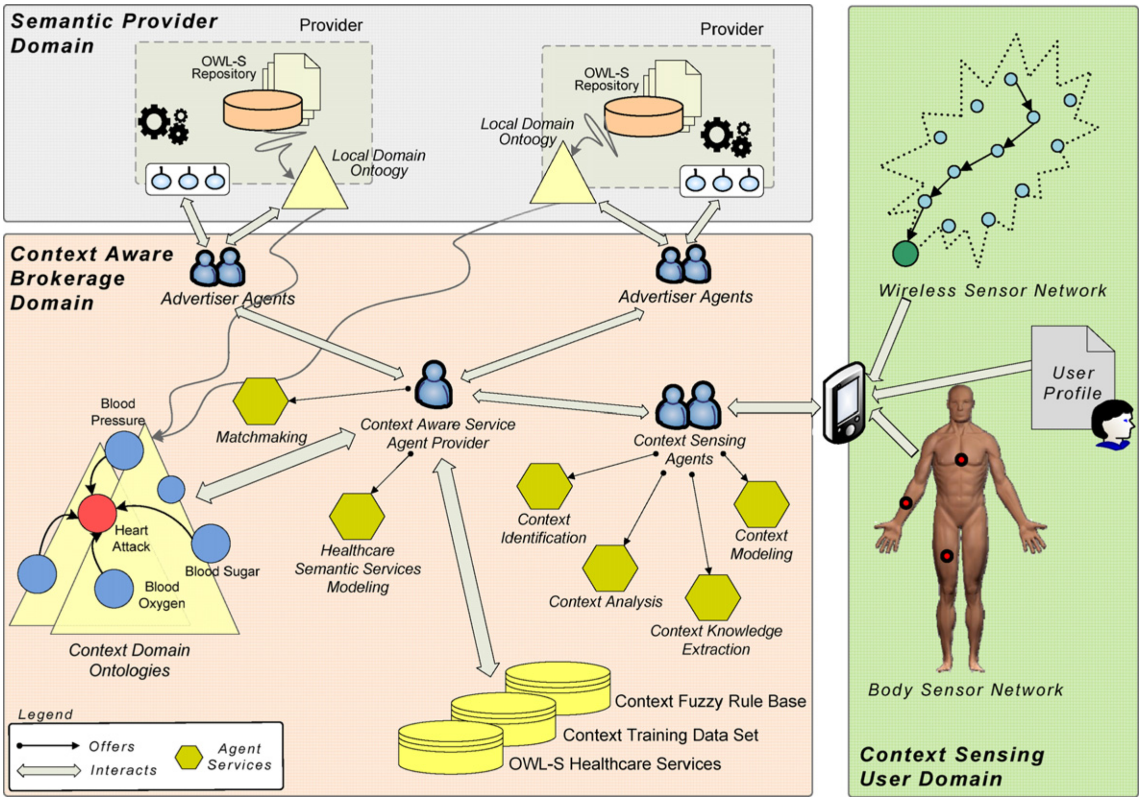

Fig. 1. Architectural overview.

In particular, Zigbee compliant Wireless Body Sensor Network (BSN) is used in the architecture for healthcare monitoring to connect sensors that are placed on the human body and measure physical parameters of a person. Sensors commonly used in BSNs are pulse monitors for heart rate, accelerometers and gyroscopes for movements, pulse oxymeters for blood oxygen level, spirometers for the amount of air inspired and expired by the lungs. BSN architectures are usually composed of a coordinator node and sensor nodes connected in a star topology. Sensor nodes transmit raw or interpreted data to the coordinator node, which may further analyze it. In remote monitoring applications the BSN is connected through a gateway and a wide area network to remote locations. A common application of BSNs is the recognition of physical activities or health conditions. In order to support the architecture design this work use a recent platform software framework for the design of Body Sensor Network (BSN) applications, i.e. SPINE (Signal Processing in Node Environment).[1]

Furthermore, Wireless Sensor Networks are used to acquire also environmental data (e.g., temperature, etc.) and profile information that is stored in order to manage user preferences.

3.2. Semantic provider domain

Web services interoperability aims at supporting the interpretation of heterogeneous information, in order to automate the discovering of suitable services in open environment applications. Syntactical limitations of languages, such as WSDL, often hinder the elicitation of service description and semantics. Through a proper "abstraction" of web services, a well-formed, semantic request finds the eligible service among all the available ones.

In order to enable automation of the discovery, manipulation and composition of services, it is necessary to add a layer of semantics to the contents description through reasoning-based approaches and formal specification languages. Several studies and projects aim at adding semantics to Web service infrastructures, [62–64]. This work assumes that there exist semantic web services providers. So, in the architecture *Semantic Provider Domain* as shown in Fig. 1 promises a new level of interoperability, by providing semantic annotations to specific functionality, in order to facilitate the interpretation and the representation of non-trivial statements (input, output, constraints, etc.). In the next future, with the maturity of Semantic Web service technologies, a lot of public and private registries will request and provide semantic web services, but the sharing of knowledge, integrating the Semantic Web design principles as well as design principles for distributed, service-orientated Web computing, will be necessarily based on ontologies.

[1] http://spine.tilab.com/.

3.3. Context aware brokerage domain

In this architectural domain brokerage, mediation and matchmaking activities take place. In particular, as shown in Fig. 1 this domain include knowledge component (ontologies and databases) on which elaboration and updating depend quality of system feedbacks.

This architectural tier is built on the agent-based platform Jade[2] and specifically we distinguish the following task-oriented agents: *Context Sensing Agents, Context Aware Service Agent Provider* and *Advertiser Agents*. The agents communication is FIPA[3] compliant according to the brokerage interaction protocol. The agents perform some tasks during the system workflow. In particular, agents tasks involve the manipulation of ontologies and reasoning about them. In this work, the management and reasoning about ontologies by agents will be achieved through SPARQL[4] queries and description logic reasoner. Next subsections details the agents' individual goals.

3.3.1. Context sensing agents

The monitoring and detection of the activities and conditions of patients normally requires the use of imaging or external sensors around the body. This imposes a significant burden on the overall requirements of the system. The suitable sampling rates for different types of sensor can be significantly different. This, along with the large amount of sensor data due to real-time continuous sampling, has raised the need for appropriate multi-sensory data fusion techniques, such as application-specific classifiers, feature selection and data synchronization.

Healthcare applications makes large use of body sensor networks and other sensors rely on wireless technology which can be affected by noise and wrong sampling of data.

The current prototypes of motion sensors that are worn at different places on the body, while the wearer performs certain activities of interest (such as walking, sitting down, running, climbing stairs, cycling, etc.).

Since sensors affects the training activity, it is necessary to calibrate them in order to obtain more precise measuring. In our experimentation, we have applied the familiar offset, gain, and linearization corrections. Furthermore, whereas the results might not be in the most useful form, a follow-up step has been applied too, that is, unit scaling. Thanks to this step, it was possible to convert the results to a common and useful representation. On the other hand, the management of large amount of sensor data in real time is another not trivial problem we have faced in this work. In particular, our approach has provided the clustering of sensor data and the subsequent extraction of fuzzy control rules from clustering. Thanks to this approach the clustering can be once carried out and enable us to properly add new sensor data to clusters with no excessive time consuming and performance degradation for real-time reasoning.

In particular, the task of Context Sensing Agents is to provide the services of *Context Modeling*, *Context Analysis*, *Context Knowledge Extraction*, *Context Identification*. More specifically, the *Context Modeling* service refers to the acquisition of multi-sensory row data from context, its semantic definition by care givers contribute and the extraction of relevant features to store in a *Context Training Data Set* database; the *Context Analysis* service provides a method of context categorization based on a clustering algorithm, whereas the *Context Knowledge Extraction* service concerns if/then rules extraction starting from clustering. Finally, the *Context Identification* service refers to the correct allocation of users to the suitable context by the rules extracted from *Context Knowledge Extraction* service. All the theoretical techniques implied in the above services will be detail in the following sections of the paper.

3.3.2. Context aware service agent provider

The role of the *Context Aware Service Agent Provider* is crucial for the operation of the whole healthcare system. In particular, its task includes the services of *Healthcare Services Modeling and Matchmaking*.

Healthcare Services Modeling refer to healthcare services semantic characterization based on pre- and post-conditions of services, whereas Matchmaking refer to optimized selection of healthcare services based on a similarity between user context and services. The Matchmaking approach proposed in this work takes advantage both semantic and rule based similarity and represent the strong point of the whole system. As well as Context Sensing Agents, Context Aware Sensor Agent Provider also use semantic ontologies for the modeling of healthcare services and a database to registry them.

3.3.3. Advertiser agents

The advertiser agents wrap the interaction with services provider, elicits new services and indexes them. When an advertiser agent discovers a web service, it translates the relative OWL-S service specifications into a concept based representation. The advertiser agent analyzes the OWL-S Profile and elicits the ontology terms, used in the ontologies (reached by the namespaces declared in the OWLS file). In our approach, the agents refers only the OWLS Profiles (as said, no assumptions have been taken into account on the other OWLS modules) has highlighted in the next sections. Let us assume each service provider is monitored by an advertiser at least.

[2] JADE, Java Agent Development Framework, URL: http://jade.tilab.com/.
[3] FIPA, Foundation for intelligent physical agents, URL: http://www.fipa.org/.
[4] SPARQL, RDF query language, URL: http://www.w3.org/TR/rdf-sparql-query/.

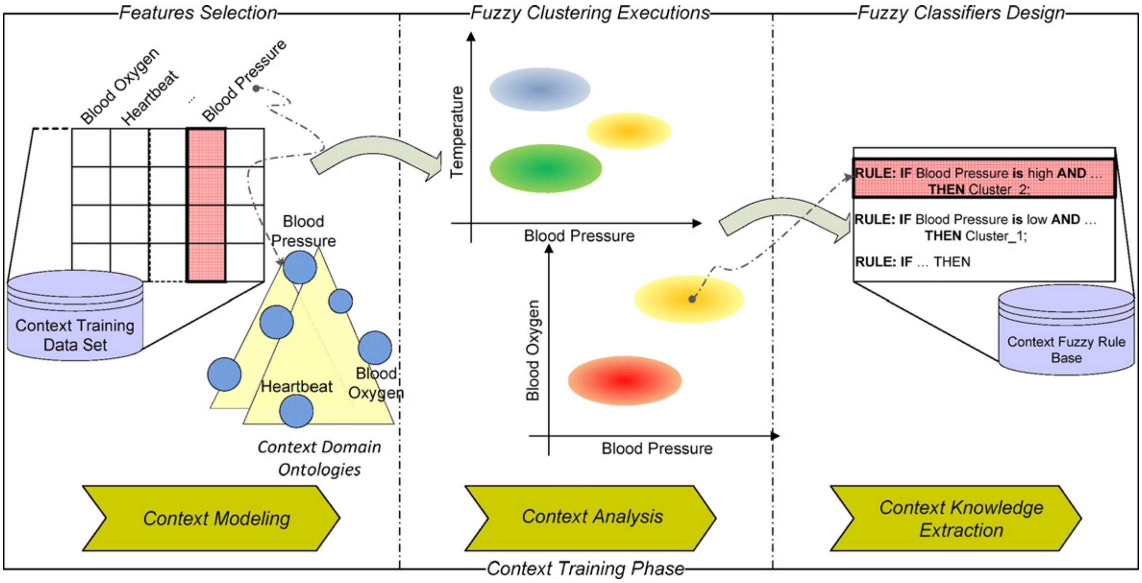

Fig. 2. Main phases of the workflow during Context Training Phase.

4. Workflow

In this section the main aim is to present the workflow phases in the proposed healthcare system. The whole workflow can be split into two main phases:

- *Context Training Phase*;
- *Context Aware Services Discovery Phase*.

The first phase of the workflow refers to the context modeling, context analysis and context knowledge extraction activities; on the other hand, the second phase of the workflow is focused on context identification, healthcare services modeling and matchmaking. Through the section we stress the activity embedded in this two phases of the workflow and we will try to simplify the interpretation of our model by using illustrative images of the main components.

4.1. Context Training Phase

The main goal here is to propose a systematic approach to analyze and train context by means of simple workflow and robust mathematical models.

Fig. 2 shows a sketched view which leads to design a straightforward context-aware healthcare system.

The working flow proceeds from one phase to another one in a purely sequential manner, with possible feedbacks when further specifications and requirements force to revise and/or readapt one or more phases in cascade. The output of each phase becomes the input of the successive one in order to incrementally reach the final system prototype. In fact, the final result is the development of the system architecture, which closely satisfies the requirements in the healthcare service-discovery process.

As shown in Fig. 2, our approach is essentially based on three main general activities: Context Modeling, Context Analysis and Context Knowledge Extraction.

Next subsections introduce each activity: for each one, the main inherent problems and the individual goals are presented; then associated theoretical and methodological approaches are introduced.

4.1.1. Context Modeling

This phase consists of activities that enable the retrieval of all the information useful for a complete and correct context analysis. More specifically, once the context is modeled, the real world is translated in a corresponding mathematical model, in order to manage and process the intrinsic knowledge. This activity foresees a meticulous study of the user context data, the interpretation of them by care givers with the resulting semantic modeling by the use of context domain ontologies and the actual mapping to a suitable model, based on a well-defined mathematical formalism. Homogeneous data representation is often required to guarantee a right data processing.

In our case study, this phase is accomplished by the semantic characterization of concepts involved in the user context and the resulting extraction of data matrix representing users with features opportunely defined thanks to care givers' contribute. More specifically, the main task foreseen in this phase is the selection and representation of context data. Sample data are taken into account in order to extract features that characterize the context of a user that could be at heart attack risk or at fainting risk. Then, this collection of data enables the building of a relative context store. Additional factors such as user profile data and further medical evaluations could be considered in the mapping of the contextual model, according to the studied case.

Generally, the context is any information that can be used to characterize the situation of an entity. And context aware computing is the use of context to provide relevant information and/or services to the user, where relevancy depends on the particular task of the user [35]. A context-aware system should automatically recognize the situation which is based on various sensors.

Several context modeling techniques exist such as key-value modeling, mark-up scheme modeling, graphical modeling, object-oriented modeling, logic based modeling and ontology-based modeling.

According to Thomas [36], the ontology-based approach is very powerful and applicable in the ubiquitous environment. Ontology is a formal, explicit specification of a shared conceptualization of a domain [37]. Ontology includes the machine-interpretable definition of basic concepts in the domain and relationships among taxonomies. Ontology shares a common understanding of the structure of descriptive information and enables reuse of domain knowledge [38]. By mapping concepts in different ontologies, structured information can be shared. Hence, ontology is a good candidate for expressing context and domain knowledge.

In this phase one of the key points is the description of relationships between the domain vocabulary and the concepts of the domain knowledge by the use of context domain ontologies.

Many ontology languages exist including Resource Description Framework Schema (RDFS) [39], DAML + OIL [40], and OWL [41]. OWL is a key to the Semantic Web and was proposed by the Web Ontology Working Group of W3C. OWL is based on the Resource Description Framework (RDF) [42].

The overview of Context Modeling is shown in Fig. 2. Specifically, the ontological representation in the reference domain exploits relationships between context and sensing concepts and context where the user is included in. For example some of sensing concepts could be the following: heartbeat, blood pressure, blood sugar, blood oxygen, height, weight, age, temperature etc.; whereas, context concepts could be fainting, heart attack, etc. Therefore, the ontologies become a valid tool to navigate through the semantic relationships and discover interesting correlations between sensing and context concepts loosely correlated. Finally, this process of context semantic modeling results in the creation of a matrix whereas rows represent the users and columns refers to context concepts in the domain ontologies; this matrix becomes the input for the next phase of context analysis.

4.1.2. Context analysis

This phase exploits techniques to collect and arrange the context data according to similar characteristics, such as emergency situations for the patient's health. In medical diagnosis and healthcare approaches, several methodologies are exploited in the Computational Intelligence domain for the analysis and the elicitation of knowledge: genetic algorithms enable the extraction of relevant features [43,44] and clustering techniques [45,46] are widely employed in the extraction of knowledge automatically from the clinical data. Moreover, combined approaches between fuzzy clustering and GA-optimization [47], fuzzy mining medical rules [48] are demonstrated the responsiveness at this kind of activity.

In our case study, this phase is accomplished by fuzzy clustering approach. More specifically, the main tasks foreseen in this phase are listed as follows:

- Data pre-processing: collected data are processed through filtering and normalization procedures, in order to get an accurate and homogeneous representation of the information. Critical task in this step is the individuation of the values range associated to each characteristic and the relative mapping in the modeling. Let us note the pre-processing task is often strictly related to the technique of knowledge extraction exploited, because it has to be tailored according to the input specification, required for the appointed technique. For instance, in our case study, a data matrix is required as input to the fuzzy clustering. Specifically a matrix with users as rows and value of context concepts as columns is built.
- (Fuzzy) Clustering procedure: once the context data are collected and arranged adequately, they are often processed by means of clustering techniques. The Fuzzy C-Means [49] (briefly FCM) algorithm represents a suitable way to partition the initial data collection. In fact, the generated clusters arrange data, according to similar symptoms or data characteristics. FCM is an unsupervised clustering algorithm, which considers a prior fixed number of clusters. In order to give more accurate partitions of data, many researchers have studied the cluster validity criteria [50–53]. Advanced approaches to (fuzzy) clustering methods could be exploited, in accord with the nature of the data space and the inherent relationships.

The context of our case study regards a generic user; in particular, the initial analysis converges to a selection of some specific characteristics that are representative for the study of the user context. For example, eight characteristics can be identified in order to characterize the user context: heartbeat, blood pressure, blood sugar, blood oxygen, height, weight, age, temperature. They are the candidates for being the features of our clustering. In fact, the data matrix to input to the fuzzy clustering is composed of a set of rows, which represents the users and a set of columns, which are the our selected features.

Let us note the values of the features did not required to be normalized, because the reference range of them exhibits values in comparable intervals and thus the preprocessing of data was not accomplished.

As said, we exploit the well-know FCM algorithm, particularly useful for flexible data organizationally. It takes as input a data matrix representing the given context parameters measures and it tries to get an "optimal" partitioning of the feature space (composed by the data matrix). FCM aims at maximizing the homogeneity, grouping into the same cluster the patterns which are closer. Herein, each pattern is a row of matrix, i.e. some context parameters measures. FCM recognizes spherical "clouds of points" (clusters of patients' exams) in a multi dimensional data space (i.e. data matrix) and each cluster is represented by its center point (prototype or centroid). The function minimizes the weighted sum of the distances between data points x and the centroid v, according to this formula:

$$V(U)=\sum_{i=1}^{c}\sum_{j=1}^{n}u_{ij}^{m}\|\underline{x}_j-\underline{v}_i\|^2 \tag{1}$$

where $c \geqslant 2$ is the number of clusters, $u_{ij} \in [0,1]$ is the membership degree of x_j in the i-th cluster and $m > 1$ controls the quantity of fuzziness in the classification process (usually in our application $m = 2$).

In this approach, each row of data matrix is a vector representing the context parameters measures (viz. eight characteristics identified before) of each user $x = (x1, x2, x3, x4, x5, x6, x7, x8)$. After the FCM execution, data partitions are returned, in a prior fixed number c of clusters.

In order to give an intuitive idea of the clustering approach, let us set $c = 3$; applying the clustering algorithm, the final partition matrix shows three clusters.

Let it emerge that a cluster is composed of all the users, whose parameters blood pressure, weight/height and blood sugar are quite high and blood oxygen is low; thus the presumable context could be at heart attack risk; another cluster presents normal values for almost all the eighth features: this cluster could be considered those one of the healthy users.

The last cluster contains the following parameters out of the range of normality: blood pressure, temperature, hearth beat. This cluster could identify users whose context is at fainting risk.

In the next subsection will be showed as it is possible to take advantage of the context analysis discussed here.

4.1.3. Context knowledge extraction

This phase carries out a further processing on data, by means of intelligent reasoning and inference engine, aimed at producing possible user contexts. In computational intelligence literature, fuzzy rules have been often exploited in different approaches for decoding the knowledge in a way closer to the human understanding. In neural network [54] approach, if–then fuzzy rules enable the emulation of the decisions or reasoning of a human expert, whereas fuzzy number and compositional rules of inference have been employed for fuzzy decision making in medical diagnosis and healthcare [55,56].

The fuzzy if–then rules provide an interpretation of the clusters, closer to the human understanding and easier to evaluate, with respect to the values range of each feature.

Outputs of previous phase are prototypes and a partitioning matrix of the data patterns. This matrix contains the memberships of the elements of the given data set in each of the c clusters.

Generally, the linear interpolation of memberships is computed; in order to easily assign linguistic label, the membership function is computed by linear interpolation of the projected membership to each axis (according to the n-dimension space), for each cluster.

More specifically, exploiting the cylindrical extension technique [57] (a projection-based method of n-dimensional argument vector), the generic i-th fuzzy cluster can be described by a fuzzy rule, where each features is described through a fuzzy set. Each fuzzy cluster K_i with $i = 1, \ldots, c$ can be represented through n functions $A_{i1}, A_{i2}, \ldots, A_{in}$, obtained by the projected and interpolated memberships.

These data are interpretable easily, because are described through linguistic (fuzzy) tools that make them more comfortable to human interpretation and understanding.

Last result of this phase is the serialization of the rules exploiting standard representations that enable the flexible translation and use of the interpreted data. In fact, these fuzzy rules are serialized by means of known languages, such as FIS employed by Matlab Simulink or FCL (Fuzzy Control Language).

In particular, as shown in Fig. 3, in our case study we foresee a mapping between sensing and context concepts of domain ontologies and a FCL/FIS file input and output parameters respectively. FCL/FIS file describes a fuzzy controller, with the specific rules and declarations. In particular, the controller contains a knowledge base, composed of fuzzy concepts (specifically sensing and context concepts) and terms (defined through fuzzy sets) and a fuzzy rules base.

Due to the flexibility of this model, possible modifications of the knowledge base in the fuzzy controls correspond to a change of FIS/FCL files.

Let us note the use of fuzzy control in the design of the architectural model satisfies the requirements of a technical interoperability.

Just to provide an example, a fuzzy rule, supposed to be in the form of Takagi–Sugeno model [58] is described as follows:

$$R_i\text{:}\quad \text{If } x_1 \text{ is } A_{i1} \quad \text{and} \quad x_2 \text{ is } A_{i2} \quad \text{and} \quad \ldots \quad \text{and} \quad x_n \text{ is } A_{in} \quad \text{then}$$

$$y_i = a_{i1}x_1 + a_{i2}x_2 + \cdots + a_{in}x_n + b_i, \quad \text{with weight } [w_i],\ i = 1, \ldots, c$$

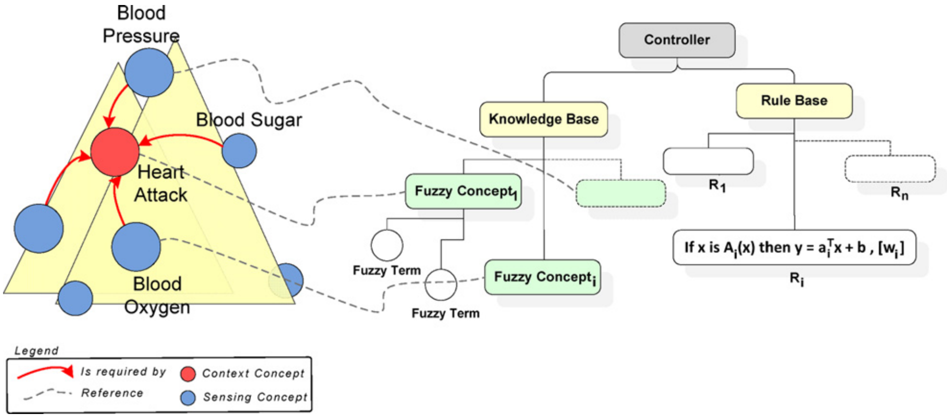

Fig. 3. A mapping between sensing and context concepts and a FIS/FCL files structure.

where R_i is the i-th rule, $x_1, x_2, \ldots, x_n$ are the input variables, $A_{i1}, A_{i2}, \ldots, A_{in}$ are the fuzzy sets assigned to corresponding input variables, variable y_i represents the value of the i-th rule output, and $a_i = [a_{i1}, a_{i2}, \ldots, a_{in}]$ and b_i are parameters of the consequent function. As said before, the antecedent fuzzy sets are usually achieved by projecting the membership degrees in the fuzzy partitions matrix U onto the axes of individual antecedent variable x_j to obtain a point-wise defined antecedent fuzzy set A_{ij}. Then we approximate it by a normal bell-shaped membership function [59]; indeed the uniform structure of bell-shaped function is suitable for identification, analysis and optimization. Hence, each fuzzy set A_{ij} is calculated from the sampled input data $x_j = [x_{1j}, \ldots, x_{nj}]^T$ and the fuzzy partition matrix $U = [u_{ij}]$ as follows:

$$A_{ij}(z) = \exp\left\{-\frac{1}{2}\left(\frac{z-\alpha_{iq}}{\beta_{iq}}\right)^2\right\} \tag{2}$$

where

$$\alpha_{iq}=\frac{\sum_{j=1}^{n} u_{ij}x_{qj}}{\sum_{j=1}^{n} u_{ij}} \quad \text{and} \quad \beta_{ij} = \sqrt{\frac{\sum_{j=1}^{n} u_{ij}(x_{qj}-\alpha_{iq})^2}{\sum_{j=1}^{n} u_{ij}}} \tag{3}$$

represent the mean and standard deviation of the bell-shaped membership function, respectively.

On the other hand, the computation of parameters $a_i = [a_{i1}, a_{i2}, \ldots, a_{in}]^T$ and b_i in the consequent part requires a deepened study, in order to evaluate the firing strength w_i of the i-th rule and the value of y_i [60].

Goal is to evaluate the final output of the TS fuzzy model y_i for an arbitrary x_j input sample, which is calculated using the following formula [60]:

$$\hat{y}_k = \sum_{i=1}^{c}\left[\underline{w}_i(\underline{x}_k)(\underline{x}_k\underline{a}_i + b_i)\right] \tag{4}$$

with $k = 1, 2, 3, \ldots, n$ and where $w_i(x_k)$ represent the firing strength of i-th rule for the k-th pattern. Thus, in order to compute the parameters of consequent part of a rule, a regression model of the compact form $\hat{Y} = X'[a_i^T, b_i] + \varepsilon$ is evaluated: herein ε is the approximation error, X' assumes the form: $X' = [w_1, x_k^T, 1, w_2 x_k^T 1, \ldots, w_c x_k^T, 1]$. Vectors $[a_i^T, b_i]$ are determined using the least-squares method [60].

4.2. Context Aware Services Discovery Phase

Context Aware Service Discovery Phase represents the runtime process. This section outlines main tasks: context identification, healthcare services modeling and matchmaking. As shown in Fig. 4, on the left side the context identification activity take place, here by means the results of the previous phase (see Section 4.1). In particular, degree of fulfillment of rules set is evaluated in order to recruit context identified features. On the right side of Fig. 4, characterization of healthcare services based on OWL-S formalism (mainly Input–Output-Precondition-Result) is depicted. Then, in the middle of Fig. 4, the activities of context identification and healthcare services modeling converge in the matchmaking task. Next subsections give more details about these tasks.

4.2.1. Context identification

In order that context aware services discovery takes place, user context identification task must to be accomplished. This task relies on two data sources: the data sensing coming from *Context Sensing User Domain* components (see Fig. 1); and *Context Fuzzy Rule Bases* carried out from previous *Context Training Phase*.

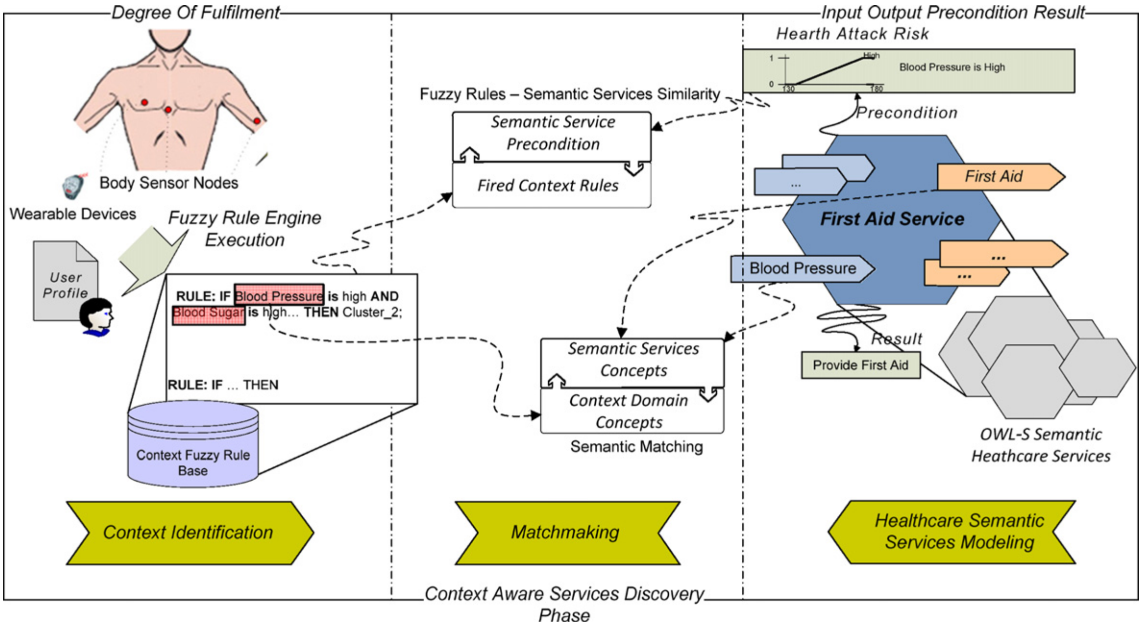

Fig. 4. Main phases of the workflow during Context Aware Services Discovery Phase.

Now, context identification is performed by means of the evaluation of degree of fulfillment among all fuzzy rules available in *Context Fuzzy Rule Base*. Since terms in the rules previously extracted (see Section 4.1.3) are the basic building blocks of a rule, the degree of fulfillment of a rule depends ultimately on the degrees of fulfillment of the terms occurring in the rule. We view contexts as the information that describes the constraints on the properties of a sensing data in order to be accepted for further consideration. More specifically, *Context Sensing Agents* are able to interpret fuzzy classifiers carried out from previous phase and to perform sensing (data acquisition and fuzzification), to work as actuators (defuzzification and final results) and to achieve fuzzy inference activities. We specify different levels of acceptance with fuzzy membership functions.

The outputs of the *Context Identification* activity is the set of rules fired with a degree of fulfillment higher than a specified threshold. Just to give an example, let's consider the following rule:

***IF** Blood Pressure **is** high **AND** Sugar Pressure **is** high **AND** Blood Oxygen **is** low **THEN** Cluster_1*

This is a typical fuzzy rule and it is composed of two following parts:

- the antecedent of the fuzzy rule is composed of context domain ontology concepts;
- the consequent of the fuzzy rule is the membership degree to a cluster, for instance, *Cluster_1*.

Obviously more than one rules may be fired with different membership degrees. In the example let us suppose that context identified is just the right one (i.e., Fainting Risk, etc.). Since the data context are modeled by means of ontologies the concepts in the rules are associated with their semantic specification. In the above example, underlying concepts in the context are: Blood Pressure, Sugar Pressure, Blood Oxygen and so on. These concepts together with the cluster membership degree are useful in order to support matchmaking between identification context fuzzy rules and healthcare semantic services as described follow (see Section 4.2.3).

4.2.2. Healthcare semantic services modeling

This work emphasizes the availability of semantic web services specification in order to support matchmaking activity during the *Context Aware Service Discovery Phase*. In particular, the architecture exploits the OWL-S description [65], for describing the web services capabilities. OWL-S is a Web Ontology Language (OWL) for Semantic Web Services which supports the dynamic discovery, invocation and composition of web services. It includes three essential layers of specification to wholly describe the capabilities of a service:

- the ***Service Profile*** provides a concise representation of web service capabilities (i.e. what the service does), through the advertising of the functionalities;
- the ***Service Model*** gives a detailed description of how the service operates, specifically describing the transformations (i.e. the processes) that it undertakes;

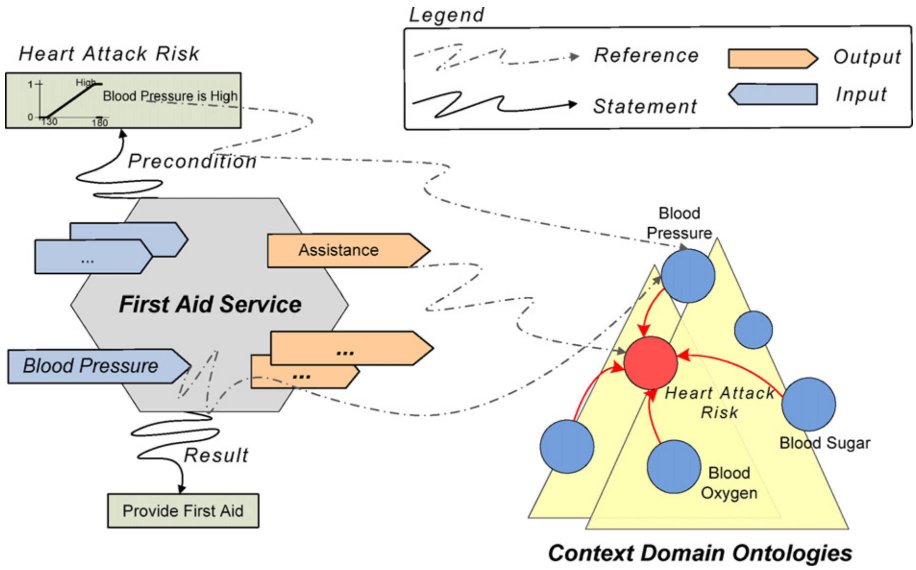

Fig. 5. An illustrative example of healthcare semantic service IOPR specifications.

- the ***Service Grounding*** supplies the details on how interoperate with a service, mapping the messages to the syntactic WSDL compliant form.

The OWL-S Profile represents the high level description of the specifications of a semantic web service. It encloses a textual description and contact information, aimed at human interpretation. Moreover, it declares the functional description of an advertised web service, through its own IOPR (Input–Output-Precondition-Result) specifications. Indeed, a set of conditions holds in order to guarantee the proper execution of a service (Precondition), a set of post-conditions is defined too, after the service execution (Result), and finally the Input and Output describes I/O functional descriptions. The OWL-S Profile often maintains an abstract description of the actual specifications, whereas the lower level OWL-S modules generally provides more "functional" details about the service capabilities. Anyway, the role of the IOPR specifications in the OWL-S Profile is descriptive of the service, additional details to the IOPR information are further explained in the OWL-S Process description layer (whose description is out of the scope of this work).

In the execution phase of Context Aware Service Discovery Phase, the activity of Healthcare Services Modeling concerns the characterization of each available service by using IOPR specified in the OWL-S Profile. As highlighted in Fig. 5, IOPR components in the Service Profile refer context domain ontologies (as well as the identified context see Section 4.2.1). In particular, Fig. 5 shows an illustrative example of *First Aid Service* that may be dispatched when the context of *Heart Attack Risk* is identified (depending on precondition). The service may be called when preconditions are satisfied. More specifically, service shown in Fig. 5 dispatch user rescue to the Assistance. Usually, precondition are expressed by means of purely logic based languages, like: SWRL, RuleML or others. In Healthcare Services Modeling task, preconditions define the admissibility ranges for input parameters in terms of fuzzy sets, as shown in Fig. 5 for blood pressure. In other words, this task indexes each concepts in the IOPR and defines fuzzy sets for context parameters in the preconditions in order to evaluate degree of matching between identified context (previous task of the discovery phase) and services available as described follow.

4.2.3. Matchmaking

In the Context Aware Services Discovery Phase the key role is represented by the matchmaking activity.

The matchmaking activity is aimed at getting one or more web services that approximately meet the input request. The characterization of service advertisements and the definition of searching criteria are the crucial factors to determine the quality of the service/request matchmaking. The matchmaking between the advertisement of the web service and the consumer requirements converges toward the exploitation of ontologies and semantic inference techniques. Our work defines a hybrid approach which attains a synergy between the purely logic based and fuzzy modeling for the matchmaking of semantic web services. We stress the case when no exact match occurs, so the aim is to retrieve services that approximately match the request.

More specifically, the main goal of matchmaking in the reference domain concerns the possibility of finding a match between user context and healthcare service.

Therefore, the outputs of context identification and healthcare services modeling become the input for the matchmaking activity. In particular, in a system where the main goal is service personalization according to user context become primary takes advantage of similarity measures in order to achieve the matchmaking.

The goal here is to go over the semantic matchmaking between user context parameters and semantic web services inputs; in other words, we want to obtain a qualitative matchmaking by exploiting context data analysis and semantic web services capabilities.

In order to achieve this goal, we should find a way to match context identification fuzzy rules and healthcare semantic web services. Therefore, our idea is to combine the query for semantic matchmaking based on user context parameters with rules extracted by the phase of context identification. In particular, in the reference domain the rules generated by clustering on the user context and the healthcare services preconditions can present overlapping fuzzy sets that describe almost the same region in the domain of some model variable.

In such cases, we can say that these fuzzy sets represent more or less the same concept (i.e. blood pressure is high). Therefore, a similarity measure for identifying similar fuzzy sets can be exploited.

The definition of similarity between fuzzy sets [61] is the degree to which the fuzzy sets are equal. This definition is related to the concepts represented by the fuzzy sets. Overlapping fuzzy sets should have a similarity value greater than zero.

The similarity measure is based on the set-theoretic operations of intersection and union, to determine the similarity between fuzzy sets.

Thus, if A and B are two fuzzy sets, the similarity between them $S(A, B)$ is:

$$S(A,B) = \frac{|A \cap B|}{|A \cup B|} \tag{5}$$

where $|.|$ denotes the cardinality of a set, and the $\cap$ and $\cup$ operators represent the intersection and union respectively.

Then if we generalize the computation achieved on a single vector of user context parameters, it is possible to obtain the fuzzy rule for the i-th cluster:

$$\text{If } (x_1 \text{ is } A_{i1}) \quad \text{and} \quad (x_2 \text{ is } A_{i2}) \quad \text{and} \quad \ldots \quad \text{and} \quad (x_n \text{ is } A_{in}) \quad \text{then } x \text{ is } \mu_i$$

the above rule just describe the matching between the membership value of features in the rule antecedent and the whole membership value with reference to the i-th cluster.

Essentially, the value $\mu_i(x)$ is that the fuzzy rule theory call the degree of fulfillment of the rule (DOF), that is, the truth value.

At this point we can introduce a measure for qualitative matchmaking, specifically given rule i-th and service SWS_f:

$$\deg_{MATCH}(SWS_f) = \max_i \left\{ \frac{\sum_{j=1}^{n} S(A_j, B_j)}{n} \cdot \mu_i(x) \right\} \tag{6}$$

where i is the i-th rule in the rule base, n is the number of user context parameters in the rule antecedent and the corresponding number of healthcare services preconditions, A_j is the fuzzy set corresponding to j-th user context parameter, B_j is the fuzzy set in healthcare service precondition describing the admissibility range for the same context parameter, S is the similarity measure defined in (6) and $\mu_i(x)$ is the membership degree to the i-th cluster (i.e. rule).

In the case study, described in the following section, we will show the benefits in terms of qualitative matchmaking deriving by the application of (7).

5. Case study

In this section the aim is to highlight the usefulness of the proposed approach in terms of context-driven service discovery and qualitative matchmaking. In particular, we will try to depict a real application of our approach. For this aim, let's consider the monitoring of the following user parameters: blood pressure, blood sugar and blood oxygen. Then, let's consider again the rule resulting from context identification phase:

IF *Blood Pressure* ***is*** *high* ***AND*** *Sugar Pressure* ***is*** *high* ***AND*** *Blood Oxygen* ***is*** *low* ***THEN*** *Cluster_1*

Fig. 6 shows a healthcare semantic web service with fuzzy sets on preconditions as admissibility ranges. Specifically the admissibility ranges for the user context parameters are, respectively: blood pressure [130–180], blood sugar [110–160] and blood oxygen [70–90].

By the application of (7) to the considered service SWS_f, we obtain:

$$\deg_{MATCH}(SWS_f) = \frac{0.9 + 0.8 + 0.7}{3} \cdot 0.8 = 0,64$$

If 0.64 is the maximum degree of considered service (see (7)) the value becomes the ranking result of it. The same evaluation is performed on the other available services.

Now, in order to show the real benefits deriving from the application of the proposed approach, we compare our matchmaking approach to purely logic-based matchmaking by evaluating the precision and recall. We remember that Recall is the number of relevant items retrieved, divided by the total number of relevant items in the collection. The highest value

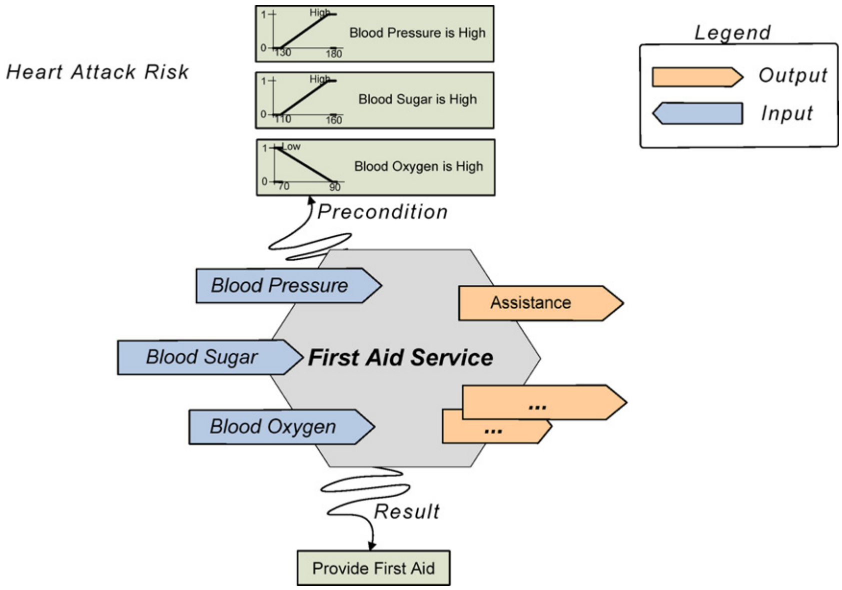

Fig. 6. An example of healthcare semantic web service with admissibility range on preconditions.

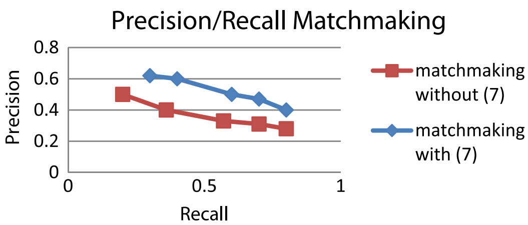

Fig. 7. A sample Precision/Recall Matchmaking graph.

Table 1
Precision and Recall data set.

Total number of services	60
Relevant Services for Heart Attack Risk Service	4
Relevant Services for Fainting Risk Service	7
Relevant Services for Flu Risk Service	12
Relevant Services for Ictus Risk Service	17
Relevant Services for tachycardia Risk Service	20

Table 2
Precision and Recall results.

Query	Precision without (7)	Recall without (7)	Precision with (7)	Recall with (7)
Relevant Services for Heart Attack Risk Service	0.5	0.2	0.62	0.3
Relevant Services for Fainting Risk Service	0.4	0.36	0.6	0.4
Relevant Services for Flu Risk Service	0.33	0.57	0.5	0.6
Relevant Services for Ictus Risk Service	0.31	0.7	0.47	0.7
Relevant Services for tachycardia Risk Service	0.28	0.8	0.4	0.8

of recall is achieved when all relevant items are retrieved. Whereas, Precision is the number of relevant items retrieved, divided by the total number of items retrieved. The highest value of precision is achieved when only relevant items are retrieved. Let's consider the data set in Table 1:

Table 2 shows results of compare between the approaches with and without the application of (7).

Fig. 7 shows Precision/Recall curves of matchmaking services and it is evident that by applying context aware service discovery (like as our approach) the precision is quite better nevertheless the recall increases. Furthermore, the results highlight that purely logic based matchmaking isn't able to obtain maximum value of Recall.

6. Conclusion and future work

This chapter presents a general approach for a context aware architecture which main aim is related to support autonomous services selection by means of hybrid approach to matchmake user context and available services in the healthcare domain. Through a sequence of phases the system train itself by means of unsupervised theoretical model aimed at profiling the user's context. Hybrid approach empowers the services matchmaking capability that doesn't relies on a purely logic based matchmaking. The use of ontologies is fundamental for the usability of the system: they enable the semantic description of data and the inter-relationships among concepts. On the other hand ontologies enable services characterization in term of context that are able to manage. Final result is a flexible architecture for the context aware provisioning of semantic services which appropriately meet the user's needs.

A future extension of this approach foresees two aspects. In particular, the first one is related to the introduction of time entity in the modeling of the Context Training Phase. The second one regards the evaluation of underlying data in which services may be used by means of training task execution on the data acquired during the service usage monitoring. The case study carried forward in the whole modeling process, provides an idea of flexibility of this model and demonstrates its admissibility. It represents an effective research and validation strategy for investigating a real-life context.

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