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PH.D. THESIS

Hybrid approaches based on Computational Intelligence and Semantic Web for distributed Situation and Context Awareness

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The majority of this thesis is based on certain parts of the following publications. As a coauthor, I was involved actively in the research, planning and writing these papers.

Chapters:

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- Giuseppe Fenza, **Domenico Furno**, Vincenzo Loia, "Enhanced healthcare environment by means of proactive context aware service discovery", in the proceedings of the 25th IEEE International Conference on Advanced Information Networking and Applications (AINA-2011) Biopolis, Singapore, March 22 - 25, 2011, ISBN: 978-0-7695-4337-6, pages 625-632.
- **Domenico Furno**, Vincenzo Loia, Mario Veniero, Marco Anisetti, Valerio Bellandi, Paolo Ceravolo, Ernesto Damiani,"Towards an Agent-based Architecture for managing Uncertainty in Situation Awareness", in the proceedings of 2011 IEEE Symposium on Intelligent Agents, April 11-15, 2011 - Paris, France, ISBN: 9781612840598, pages 1-6.
- Giuseppe Fenza, Enrico Fischetti, **Domenico Furno**, Vincenzo Loia, "A hybrid context aware system for tourist guidance based on collaborative filtering", in the proceedings of 2011 IEEE International Conference on Fuzzy Systems, June 27-30, 2011- Taipei, Taiwan, 978-1-4244-7315-1, pages 131-138.
- Carmen De Maio, Giuseppe Fenza, **Domenico Furno**, Vincenzo Loia, "Swarm-based approach to evaluate fuzzy classification of semantic sensor data", submitted to 8th IEEE International Workshop on Sensor Networks and Systems for Pervasive Computing, March 19-23, 2012 - Lugano, Switzerland.
- Carmen De Maio, Giuseppe Fenza, **Domenico Furno**, Vincenzo Loia, "Swarm-based semantic fuzzy reasoning for Situation Awareness Computing". In the proceedings of IEEE World Congress on Computational Intelligence, June 10-15, 2012 - Brisbane, Australia.
- Carmen De Maio, Giuseppe Fenza, **Domenico Furno**, Vincenzo Loia, "f-SPARQL extension and application to support context recognition". In the proceedings of IEEE World Congress on Computational Intelligence, June 10-15, 2012 - Brisbane, Australia.

Journals:

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- Carmen De Maio, Giuseppe Fenza, **Domenico Furno**, Vincenzo Loia, Sabrina Senatore, “OWL-FC: an upper ontology for semantic modeling of Fuzzy Control”. Journal of Soft Computing - A Fusion of Foundations, Methodologies and Applications, Springer, pp. 1-12, Issn: 1432-7643, Doi: 10.1007/s00500-011-0790-4.
- Giuseppe Fenza, **Domenico Furno**, Vincenzo Loia, Hybrid approach for context-aware service discovery in healthcare domain, Journal of Computer and System Sciences, Volume 78, Issue 4, July 2012, Pages 1232-1247, ISSN 0022-0000, 10.1016/j.jcss.2011.10.011.
- **Domenico Furno**, Vincenzo Loia, Alfredo Vaccaro, “Decentralised Smart Grids Monitoring by Swarm based Semantic Sensor Data Analysis”, submitted to the International Journal of Systems, Control and Communications (IJSCC) Published/Hosted by Inderscience Publishers. ISSN (printed): 1755-9340. ISSN (electronic): 1755-9359.

"The sciences do not try to explain, they hardly even try to interpret, they mainly make models. By a model is meant a mathematical construct which, with the addition of certain verbal interpretations, describes observed phenomena. The justification of such a mathematical construct is solely and precisely that it is expected to work."
(John von Neumann)

"And the only way to do great work is to love what you do. If you haven't found it yet, keep looking. Don't settle. As with all matters of the heart, you'll know when you find it. And, like any great relationship, it just gets better and better as the years roll on. So keep looking until you find it. Don't settle. [...] Stay hungry. Stay foolish."
(Steve Jobs)

"Motto for a research laboratory: what we work on today, others will first think of tomorrow."
(Alan J. Perlis)

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Abstract

The research work focuses on Situation Awareness and Context Awareness topics. Specifically, Situation Awareness involves being aware of what is happening in the vicinity to understand how information, events, and one's own actions will impact goals and objectives, both immediately and in the near future. Thus, Situation Awareness is especially important in application domains where the information flow can be quite high and poor decisions making may lead to serious consequences.

On the other hand Context Awareness is considered a process to support user applications to adapt interfaces, tailor the set of application-relevant data, increase the precision of information retrieval, discover services, make the user interaction implicit, or build smart environments.

Despite being slightly different, Situation and Context Awareness involve common problems such as: the lack of a support for the acquisition and aggregation of dynamic environmental information from the field (i.e. sensors, cameras, etc.); the lack of formal approaches to knowledge representation (i.e. contexts, concepts, relations, situations, etc.) and processing (reasoning, classification, retrieval, discovery, etc.); the lack of automated and distributed systems, with considerable computing power, to support the reasoning on a huge quantity of knowledge, extracted by sensor data.

So, the thesis researches new approaches for distributed Context and Situation Awareness and proposes to apply them in order to achieve some related research objectives such as knowledge representation, semantic reasoning, pattern recognition and information retrieval. The research work starts from the study and analysis of state of art in terms of techniques, technologies, tools and systems to support Context/Situation Awareness. The main aim is to develop a new contribution in this field by integrating techniques deriving from the fields of Semantic Web, Soft Computing and Computational Intelligence. From an architectural point of view, several frameworks are going to be defined according to the multi-agent paradigm.

Furthermore, some preliminary experimental results have been obtained in some application domains such as *Airport Security*, *Traffic Management*, *Smart Grids* and *Healthcare*.

Finally, future challenges is going to the following directions: *Semantic Modeling of Fuzzy Control, Temporal Issues, Automatically Ontology Elicitation, Extension to other Application Domains and More Experiments.*

Keywords

Situation Awareness, Context Awareness, Fuzzy Logic, Fuzzy Control, Swarm Intelligence, Semantic Web, Sensor Data Semantic Annotation, Knowledge Representation, Semantic Reasoning, Pattern Recognition, Information Retrieval, Multi-Agent Paradigms.

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List of Abbreviations

Acronym	Definition
AI	Artificial Intelligence
ARP	Attractive Research Pheromone
BSN	Body Sensor Network
CA	Context Awareness
CAPSD	Context Aware Proactive Service Discovery
CDM	Collaborative Decision Making
CI	Computational Intelligence
CoBrA	Context Broker Architecture
CoMSA	Cognitive Multiagent Situation Awareness
CP	Classification Pheromone
DL	Description Logic
EMA	Event Management Agency
FCL	Fuzzy Control Language
FIPA	Foundation For Intelligent Physical Agents
FIS	Fuzzy Inference System
FL	Fuzzy Logic
FLC	Fuzzy Logic Control
FP	Founded Pheromone
FSTO	Fuzzy Situation Theory Ontology
f-SPARQL	Fuzzy Simple Protocol and RDF Query Language
GUI	Graphical/Graphics User Interface
HCI	Human-Computer Interface
	Human Computer Interaction
I/O	Input/Output
IEEE	Institute Of Electrical And Electronics Engineers
IOPR	input and output parameters respectively
IR	Information Retrieval
ISBN	International Standard Book Number
ISO	International Standards Organisation
ISSN	International Standard Serial Number
JADE	Java Agent DEvelopment Framework
KM	Knowledge Management
MASON	Multi-Agent Simulator Of Neighborhoods (or Networks)
NIST	National Institute Of Standards And Technology
OGC	Open Geospatial Consortium
OWL	Ontology Web Language
OWL-S	Semantic Markup for Web Services
P2P	Peer-To-Peer

Acronym	Definition
PSO	Particle Swarm Optimization
R&D	Research & Development
RDF	Resource Description Framework
RDF/S	Resource Description Framework/Schema
RDFa	Resource Description Framework in attributes
RRP	Repulsive Research Pheromone
SA	Situation Awareness
SAW	Situation Awareness
SAWA	Situation Awareness Assistant
SbESA	Swarm based Enhanced Situation Awareness
SDK	Software Development Kit
SEA	Situations Evaluation Agency
SI	Swarm Intelligence
SOA	Service Oriented Architecture
SPARQL	Simple Protocol and RDF Query Language
SPINE	Signal Processing in Node Environment
SQL	Structured Query Language
	Structured Query Language (Database)
SSN	Semantic Sensor Network
SSW	Semantic Sensor Web
ST	Situation Theory
STO	Situation Theory Ontology
SWE	Sensor Web Enablement
SWRL	Semantic Web Rule Language
TDG	Track Data Generator
UML	Unified Modeling Language
URI	Universal Resource Identifier
URL	Universal Resource Locator (WWW)
W3C	World Wide Web Consortium (Also WWW3)
WAP	Wireless Application Protocol
WSO	Web Service Ontology
WWW	World Wide Web
XML	Extensible Markup Language

Chapter 1

What this thesis is all about?

The research work focuses on two main topics sometimes overlapping, sometimes slightly different: Situation Awareness (SA) and Context Awareness (CA).

SA deals with the perception of environmental elements with respect to time and/or space, the comprehension of their meaning, and the projection of their status after some variable has changed, such as time. SA involves being aware of what is happening in the vicinity to understand how information, events, and one's own actions will impact goals and objectives, both immediately and in the near future.

In computer science, SA refers to the perception of the environment critical to decision-makers in complex, dynamic areas from aviation, air traffic control, smart grids monitoring, power plant operations, military command and control, and emergency services such as fire fighting and policing; to more ordinary but nevertheless complex tasks such as driving an automobile or bicycle. Thus, SA is especially important in application domains where the information flow can be quite high and poor decisions may lead to serious consequences (e.g., airport security, piloting an airplane, functioning as a soldier, or treating critically ill or injured patients). Furthermore, lacking SA or having inadequate SA has been identified as one of the primary factors in accidents attributed to human error.

On the contrary CA refers to the idea that computers can both sense, and react based on their environment. Devices may have information about the circumstances under which they are able to operate and based on rules, or an intelligent stimulus, react accordingly.

Specifically, CA is considered a process to support user applications to adapt interfaces, tailor the set of application-relevant data, increase the precision of information retrieval, discover services, make the user interaction implicit, or build smart environments. In other words, CA is regarded as an enabling technology for ubiquitous computing systems. Therefore, context aware systems are concerned with the acquisition of context (e.g. using sensors to perceive a situation), the abstraction and understanding of context (e.g. matching a perceived sensory stimulus to a context), and application behavior based on the recognized context (e.g. triggering actions based on context). As the user's activity and location are crucial for many applications, context awareness has been focused more deeply in the research fields of location awareness and activity recognition.

The trend of research in the years since 2000 has seen a significant increase in works and publications relating to situation/context awareness [1]. This trend shows a growing interest in these fields and make them as fertile ground for research studies and applications.

Specifically, the aim of this thesis is to identify the main issues in these areas and propose new approaches to improve current results and lay the foundations for new studies and experimentations.

1.1 Research focus

The research studies in Situation/Context Awareness have highlighted that the main issues related to these areas are:

- the need to support the acquisition and aggregation of dynamic environmental information from the field (i.e. sensors, cameras, etc.)
- availability of formal approaches to knowledge representation (i.e. situations, contexts, concepts, relations, etc.) and the information acquired;
- availability of automated and distributed systems with considerable computing power to support the reasoning through special purpose software.

Furthermore, the studies carried out so far came to the conclusion that in scientific literature there is no framework that addresses these issues in a systematic way. In other words, it highlights the lack of approaches measured with respect to real cases that address above issues and that are closely dependent on a "good" situation/context awareness. Therefore, the focus of research in this sense is strategically oriented towards the definition of integrated frameworks pointing on approaches increasingly based on the synergic application of the most innovative results in Knowledge Representation, Discovery, Management and Processing.

1.2 Research significance and objectives

The contribution or added value provided by the research herein discussed concern the design and implementation of distributed architectures (frameworks) for context/situation awareness. These frameworks enable to integrate different methodologies, technologies and techniques in context/situation aware systems or environments.

In particular, semantic web technologies and languages are used to address the problems of acquiring, aggregating, representing, discovering, exchanging and sharing huge amount of raw data acquired by several sensors and/or devices.

On the other hand, multi-agent distributed paradigm with the integration of soft computing and/or computational intelligence methodologies and techniques are employed to improve real-time reasoning and/or distributed reasoning on semantically annotated sensor data.

With regard to macro objectives achieved by the proposed research work, the author identifies the following:

- identification of semantic models useful to support the dynamic representation, aggregation and processing of sensor data;
- definition of general approaches for Situation and Context Awareness based on the combination of semantic technologies and computational intelligence techniques;
- designing of multi-tier architecture capable to support automation and distribution requirements of Situation/Context Awareness architectures. The goal is to improve the acquiring, modeling and reasoning activities by means of task-oriented agents;

- study and analysis of the impact of hybrid approaches, based on semantic technologies and computational intelligence techniques, in the field of Situation/Context Awareness, especially in terms of approximate reasoning.

Finally, one of the main aims of this research work is to make the proposed frameworks able to support and enhance situation and context awareness in several domains.

1.3 Approach, method and applications

The proposed frameworks are based on three general approaches, that is to say, two for SA and one for CA.

In particular, the two proposed approaches for SA are based on the Endsley model described as “the perception of the elements in the environment within a volume of time and space, the comprehension of their meaning and the projection of their status in the near future” [2][3]. So they involve three high level stages or steps: perception, providing the ability to perceive the environment; comprehension, dealing with the integration of perceived information in order to determinate their relevance to the goals; and finally projection, aimed at evaluating current situations and forecasting future situation events and dynamics in order to anticipate future events and their implications. Specifically, the second methodology for SA represents an evolution of the first one.

On the other hand, the proposed general approach for CA is based on the idea that context aware systems are concerned with the acquisition of context (e.g. using sensors to perceive a situation), the abstraction and understanding of context (e.g. matching a perceived sensory stimulus to a context), and application behavior based on the recognized context (e.g. triggering actions based on context). In particular, the approach is aimed to attain environment monitoring by means of sensors to provide relevant information or services according to the identified context and also consists of three main phases.

The general strategy foresees to act in a flexible way on the above three stages or phases of each approach in order to cover a large range of Situation/Context Aware applications in different domains. Therefore, in these stages or phases is expected to employ methods and techniques from Semantic Web and soft computing integrated in distributed multi-agent architectures. In particular, methods of inference based on a physical model of the world and run-time collaboration of various entities (agents) that combine the knowledge model with observed data to derive conclusions are applied.

Finally, in order to show the applicability of the proposed approach in real scenarios, it will be instantiate in the following application domains: *Airport Security*, *Traffic Management*, *Smart Grids and Healthcare.*

1.4 Relevant literature

Many situation models [4] appear in the situation awareness literature. Certain models are capable of reasoning about situation knowledge [5]. Using prepositional logic, the authors in [6] describe situations as concepts, consider the compatibility relations among situations, and, apply rules in order to infer the situation of an entity. The work discussed in [7] deals with consistent situations with respect to situation calculus axioms. In addition, in [8] the authors discussed about core ontologies representing situations, but with lack of enhanced semantics, thus, restricted knowledge reasoning. Furthermore, the authors in [9] modeled the user context as situations. They proposed a method to retrieve such situational knowledge by applying a logical matching method against system and user expectations related to current/future situations. Situation conceptual modeling has also been attempted in several information models, especially in the era of situation awareness and situation calculus. Significant work related to conceptual Description Logics, situational modeling and reasoning has been reported by the authors in [10]. Finally, the authors in [11] deal with situational context recognition through data fusion techniques. Naturally, the closest field to the approach proposed in the thesis is represented by current ontology-driven approaches to SAW [12]. SAWA (Situation Awareness Assistant) by Matheus et. al. [8], an ontology-driven SAW application originating from the military domain, provides an overview of the overall system architecture its SAW ontology is used in. However, Matheus et. al. merely depict the functional building blocks of their system, a discussion of the technical software architecture elaborating on the problems identified in the previous section is missing. In this respect, the work by Chen et. al. [13] is similar—CoBrA (Context Broker Architecture) provides an ontology-driven system architecture for pervasive context aware environments. However, Chen et. al. do not discuss the aspects of reusability and scalability when developing such a highly-dynamic, ontology-driven system.

On the other hand most of the existing approaches for context-aware service discovery and selection rely on a key-value-pair [14][15] or keyword-based [16] service matching process. Context information are also represented by key-value-pairs and may be supplemented by simple if-then-rules. On the other hand, the COSS [17] and CAPEUS [18] approaches utilize an extensible set of ontologies for context and service description and therefore provide a common understanding of the represented information in contrast to the other solutions. In the last years, several research initiatives have been proposed, which attempt to enable more enhanced discovery and composition of services, by combining semantic web, agent-oriented and context-aware computing. Lee et Helal [19] recognizes the limitations of existing service discovery approaches and try to exploit context-awareness to accomplish the aim. The authors introduce the notion of context attributes, as part of the service description, which allow dynamic evaluation of contextual parameters to improve service discovery. The WASP project [20] extends the functionality of UDDI by introducing semantic and contextual features. Current standardization efforts regarding service directories like UDDI [21] and ebXML[1]. For instance, in [22], the authors achieve service categorization based on their WSDL descriptions, which proves restrictive, when trying to address issues like mobility of services, semantic discovery and context-awareness. Therefore, research initiatives have tried either to enhance the functionality of service directories [23] or to identify new research challenges [24]. The work in [25] paper proposes a novel framework which exploits fuzzy logic in order to abstract and classify the underlying data of web services as fuzzy terms and rules. The aim is to increase the efficiency of the discovery of web services and to allow imprecise or vague terms in the search query. Synergic exploitation of purely logic and approximate services matchmaking approach have been proposed in LARKS [26] and OWLS-MX [27]. Specifically, these works use both explicit and implicit semantics by complementary means of logic based and approximate matching. On the contrary, the approach proposed in the thesis presents an hybrid system whose main aim is related to provide an integrated environment that combines theoretical support and technologies in the Computational Intelligence domain. In particular, the work trains itself by performing activities of fuzzy context data analysis in order to support user's context identification by means of fuzzy rule extraction. Fur-

[1] ebXML, http: // www. ebxml. org

thermore, according to semantic technologies the work enriches semantic web services specification by means of pre-condition definition. In this manner context/service matchmaking algorithm may be defined according to retrieved context information. Indeed, the main idea of the work is related to enhanced context awareness by means of ontology concepts and computational intelligence techniques in order to obtain qualitative context modeling and services matchmaking. 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.

1.5 Thesis Outline

The thesis work is described according to the following structure.

Part I: Theoretical and Technological Foundations

Chapter 2 *"Fuzzy Logic & Fuzzy Systems"* – discusses preliminary concepts about fuzzy logic and fuzzy systems that represent a foundation for most of the research work.

Chapter 3 *"Swarm Intelligence"* – provides an overview of Swarm Intelligence theory with emphasis on Swarm Intelligence properties and applications. In particular, it introduces some Swarm Intelligence aspects that will be subsequently exploited in the proposed application scenarios.

Chapter 4 *"Semantic Web Technologies and Ontologies"* – describes the basics of the semantic technologies, the ontologies and the semantic web standards exploited in this research work. In addition, this chapter discusses in more detail some extensions proposed by the author.

Part II: Proposed Approaches & Research Objectives

Chapter 5 *"Situation and Context Awareness Approaches"* – discusses three general approaches to support Situation and Context Awareness. In particular, the aim of the chapter is to lay the foundation for the instantiation of the aforementioned approaches in several application domains. Furthermore, it analyzes some research objectives met by the proposed approaches.

Part III: Architectural Overviews and Application Scenarios. The achieved research objectives have been evaluated in different application domains and case studies.

Chapter 6 *"Situation Awareness and Airport Security"* – proposes the instantiation of an approach (discussed in *Chapter 5*) for SA in the field of Airport Security, with the specific aim to support Airport Security operators to detect and/or prevent emergency situations. In particular, it discusses from an architectural and methodological point of view the benefits deriving from semantic representation and management of knowledge and from distribution of semantic data real-time processing among several task oriented agents.

Chapter 7 *"Situation Awareness and Traffic Jam"* – proposes the instantiation of an enhanced approach (discussed in *Chapter 5*) for SA in the field of Traffic Management, with the specific aim to detect Traffic Jam situations. In particular, it discusses a feasible framework based on the combination of Swarm Intelligence and fuzzy controls. Specifically, the main aim here is to distribute the classification of sensor observations for the detection of relevant patterns (i.e. traffic jam situations).

Chapter 8 *"Situation Awareness and Smart Grids"* – proposes the instantiation of the enhanced approach (discussed in *Chapter 5*) for SA in the field of Smart Grids, with the specific aim to overcome some drawbacks due to the ineffective capabilities, in terms of scalability and flexibility, of the conventional monitoring paradigms. So the main aim of this chapter is to discuss an innovative decentralized and not-hierarchical monitoring architecture exploiting swarm intelligence and fuzzy data analysis in order to overcome the aforementioned problems.

Chapter 9 *"Context Awareness and Healthcare"* – proposes the instantiation of a general approach (discussed in *Chapter 5*) for CA in the field of Healthcare. This instantiation results in a context aware architecture whose main aim is related to support proactive context identification and context-aware healthcare services discovery. Through a sequence of phases the proposed system trains itself by means of unsupervised context data analysis aimed at profiling the user's context.

Chapter 10 *"Conclusion and Future Work"*.

Part I: Theoretical and Technological Foundations

Chapter 2

Fuzzy Logic & Fuzzy Systems

Fuzzy Logic was conceived and started [28][29][30], by Lotfi A. Zadeh, Full Professor in Computer Science at the University of California in Berkeley. Zadeh introduced Fuzzy Logic (FL) as a multi-valued logic that, different from classical approaches, enables intermediate values to be defined between typical evaluations like true/false, yes/no, high/low, etc.. Starting from these considerations, notions such as “rather tal” or “very fast” can be formulated mathematically and handled by computers in order to apply a more human like way of thinking in the programming of computers [31]. Fuzzy Logic theory is based on the concept of fuzzy set. Fuzzy sets can be thought of as an alternative to conventional concepts of set membership and logic which has its origins in ancient Greek philosophy and that are strongly based on the notion of precision. In particular, Aristotle and other philosophers made several efforts to define a precise mathematics through a formal theory of logic based on the so called “Laws of Thought”. One of these laws, the “Law of the Excluded Middle”, states that each proposition must either be *True* or *False*. However, when this law was introduced by Parminedes, around 400 B.C., different objections arose: for example, Heraclitus thought that some things could be simultaneously True and not True. This thought was better formalized by Plato who laid the foundation for what would become fuzzy logic. Indeed, Plato asserted the existence of a third region overlapping the concepts of True and False. Moreover, before Zadeh introduced the Fuzzy Logic, other modern philosophers echoed Plato’s sentiments, such as, for instance, Marx, Engels and Hegel. However, it was Lukasiewicz who first proposed a systematic alternative to the bi-valued logic of Aristotle [32]. Precisely, he started to create systems based on multi-values in 1920, exploiting a third value “possible” to face the Aritstotle’s paradox of the sea battle. Successively, other mathematicians tried to deal with multi-valued logics that contradict the “Law of the Excluded Middle”. Nevertheless, Fuzzy Logic represents the most stable and used theoretical approach for dealing with events and phenomenons characterized by high levels of uncertainty and imprecision. Indeed, starting from Mamdani’s experiences, the Zadeh’s idea has been strongly used for design complex systems such as industrial controllers, decision making systems.

2.1 Essentials

FL is part of Soft Computing area [33][34] together with neural networks, evolutionary computation and probabilistic approaches. The main benefit provided by fuzzy logic is the ability to mimic the human brain in order to effectively exploit ways of reasoning that are approximate and tolerant for imprecision and uncertainty. As a consequence, this approach enables for designing systems capable of reproducing human capabilities and yielding high performance in terms of computational efficiency. Indeed, the tolerance for imprecision and uncertainty, provided by fuzzy methods, underlies the remarkable human ability to sense and understand inaccurate information such as: distorted speech, decipher sloppy handwriting, comprehend nuances of natural language, summarize text, and recognize and classify images.

Fuzzy Logic achieves aforementioned benefits by "computing with words" rather than numbers. Indeed, while variables in mathematics assumes numerical values, in fuzzy logic applications, the non-numeric linguistic variables are usually exploited to ease the expression of rules and facts. A linguistic variable such as age may have a value such as young or its antonym old. Linguistic variables represent the atomic element useful for defining the so called fuzzy reasoning. In particular, the linguistic variables are used for composing *fuzzy rules*, the main method provided by fuzzy logic for capturing and reproducing the human knowledge. Although rule-based systems have a long history of use in artificial intelligence, what is missing in such systems is machinery for dealing with fuzzy consequents or fuzzy antecedents that strongly characterize the human thinking. The fuzzy rule based approach has been exploited for implementing applications belonging to different fields, such as image-understanding applications, medical diagnosis systems, classification, clustering and in industrial processes control. Hereafter, the details related to the different components making up the fuzzy theory will be provided. In detail, it will be presented fuzzy sets and their properties, FL operators, hedges, fuzzy proposition and rule-based systems, and inference engine, defuzzification methods, and the design of an FL decision system. Precisely, we will recall FL concepts starting from the fundamentals and examples presented in [35].

2.2 Fuzzy Sets and Membership Functions

The first step towards the formal definition of fuzzy logic and systems is the introduction of fuzzy sets, the fundamental brick of fuzzy reasoning. In detail, a fuzzy set can be considered as an extension of a conventional crisp set. Indeed, whereas crisp sets enable only full membership or no membership at all, fuzzy sets allow to deal with partial membership of sets' elements. Formally, in a crisp set, membership or nonmembership of element x in set A is described by using a function $\mu_A(x)$, where $\mu_A(x) = 1 \text{if} x \in A$ and $\mu_A(x) = 0 \text{if} x \not\in A$. Fuzzy set theory extends this concept by defining partial membership. Precisely, a fuzzy set A on a universe of discourse U is featured by a membership function $\mu_A(x)$ taking values in $[0,1]$. The elements which have been assigned the number 1 can be interpreted as the elements that are in the set A; the elements which have assigned the number 0 as the elements that are not in the set A; the elements which have assigned a value between 0 and 1 can be considered as partially belonging to the set A. Conventionally, a fuzzy set A in U may be represented by means of a set of ordered pairs, where each pair consists of a generic set element x and its grade of membership: $A = \{(x, \mu_A(x)) | x \in U\}$. The collection of x values characterized by a strictly positive membership $(\mu_A(x) > 0)$ represents the so-called *support of the fuzzy set*. Various types of membership functions are used for definining fuzzy sets. These shapes include triangular, trapezoidal, generalized bell shaped, Gaussian curves, polynomial curves, and sigmoid functions. Triangular curves are defined through a membership function depending upon three parameters a, b, and c, as highlighted in Eq. (2.2.1).

$$f(x;a,b,c) = \begin{cases} 0 & for \quad x < a \\ \dfrac{x-a}{b-a} & for \quad a \le x < b \\ \dfrac{c-x}{c-b} & for \quad b \le x \le c \\ 0 & for \quad x > c \end{cases} \tag{2.2.1}$$

Figure 1. Trapezoidal membership function.

Trapezoidal curves (see Figure 1) depend on four parameters and are defined as shown in Eq. (2.2.2).

$$f(x;a,b,c,d) = \begin{cases} 0 & for \quad x < a \\ \dfrac{x-a}{b-a} & for \quad a \le x < b \\ 1 & for \quad b \le x < c \\ \dfrac{d-x}{d-c} & for \quad c \le x \le d \\ 0 & for \quad d \le x \end{cases} \quad c = 1 \tag{2.2.2}$$

$$S(x;a,b,c) = \begin{cases} 0 & for \quad x < a \\ \dfrac{2(x-a)^2}{(c-a)^2} & for \quad a \leq x < b \\ 1 - \dfrac{2(x-c)^2}{(c-a)^2} & for \quad b \leq x < c \\ 1 & for \quad x > c \end{cases} \tag{2.2.3}$$

Gaussian curves (see Figure 2) depends upons the parameters σ and c and they are defined as shown in Eq. (2.2.4)

$$f(x;\sigma,c) = e^{\left(\frac{-(x-c)^2}{2\sigma^2}\right)} \tag{2.2.4}$$

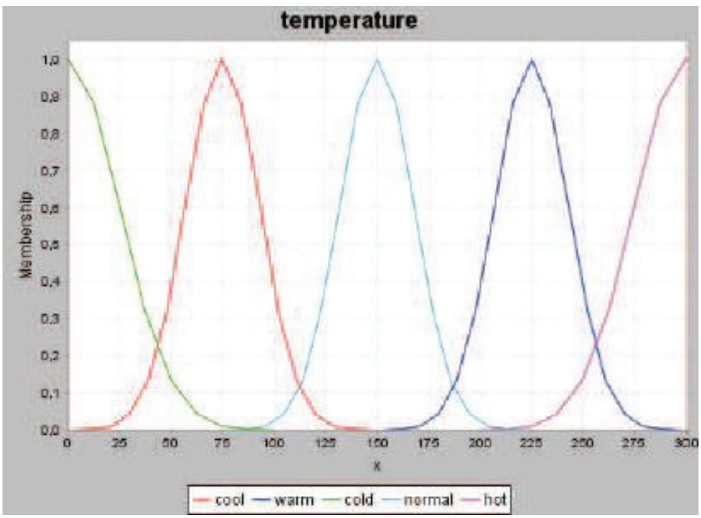


Figure 2. Gaussian membership function.

Other than conventional functions, fuzzy designers can define customized membership functions for dealing with events or phenomena not able to be represented by means of aforementioned shapes.

In order to show the difference between fuzzy and crisp set, let us consider a crisp set containing the collection of people characterized by a given height. This set is defined on a universe of discourse be from 40 inches to 90 inches and it contains all people with height 72 or more inches, whereas all people with height of less than 72 inches are belonging to its complement. The crisp set membership function for set tall is shown in Figure 3.

The corresponding fuzzy set with a smooth membership function is shown in Figure 4.

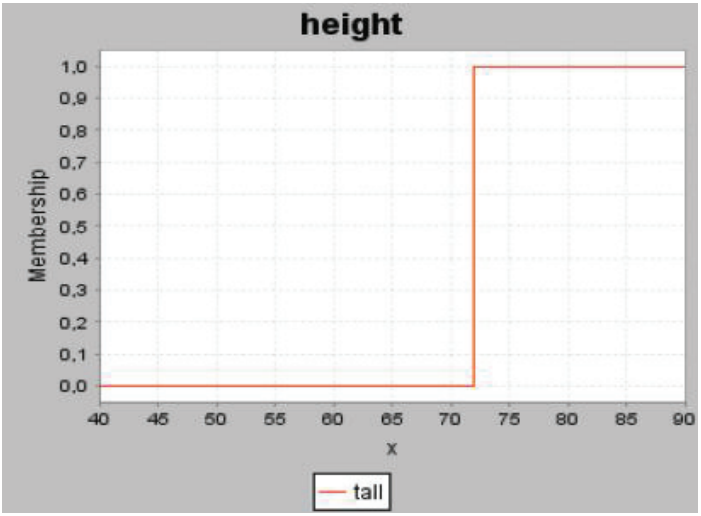


Figure 3. Crisp Membership Function.

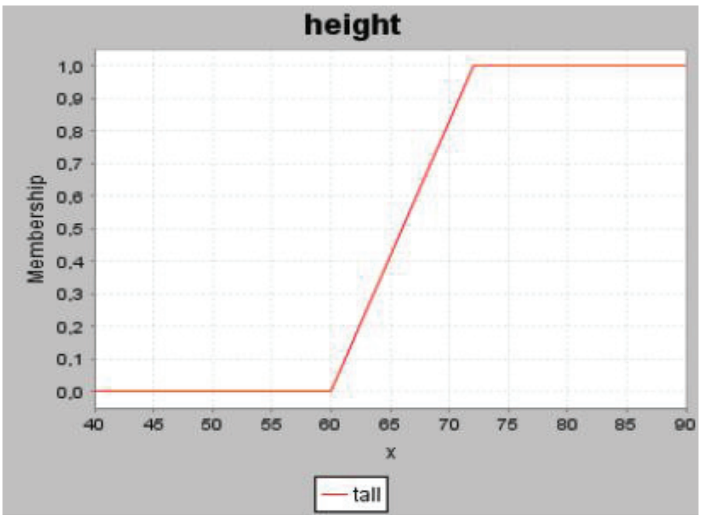


Figure 4. An example of fuzzy membership function.

The curve defines the transition from not tall and shows the degree of membership for a given height. This example shows that a given element can be a member, simultaneously, of a fuzzy set and its complement.

As will be shown in the follows, in order to define a qualitative fuzzy inference engine, fuzzy sets can be grouped in so-called *linguistic variables*. These variables are used to associate the membership functions modeling fuzzy sets with a terms collection enabling the *word computing*. This kind of computation is based on the definition of *fuzzy rules*, an extension of conventional IF…THEN rules, enhanced with fuzzy reasoning. Formally, a linguistic variable x in the universe of discourse U is characterized by $T(x) = \{T_x^1, T_x^2, T_x^3, \dots, T_x^k\}$ and $\mu(x) = \{\mu_x^1, \mu_x^2, \mu_x^3, \dots, \mu_x^k\}$, where $T(x)$ is the term set of x, that is, the set of names of linguistic values of x, with each T_x^i being a fuzzy set with membership function μ_x^i defined on U. In this way, fuzzy sets can map commonsense linguistic labels such as *slow*, *fast*, *small*, *large*, *heavy*, *low*, *medium*, *high*, *tall*, etc..

Hereafter, a linguistic variable modeling the height concept is introduced. In detail, if a universe of discourse from 40 inches to 90 inches is considered, then, to describe height, three term values such as *short*, *average*, and *tall* can be defined by using appropriate membership functions shown in Figure 1. In detail, this figure shows that a person with height 65 inches will have membership value 1 for set medium, whereas a person with height 60 inches may be a member of the set short and also a member of the set medium; only the degree of membership varies with these sets. Consequently, as the figure highlighted, the terms *short*, *medium*, and *tall* are not used in the strict sense but, instead, they can be overlapped and imply a smooth transition between different heights.

Hereafter, the fuzzy logical operations will be defined as preliminary concepts for introducing the fuzzy rules, the core of fuzzy reasoning.

2.3 Logical Operations and Rules

Fuzzy set operations generalize the conventional crisp set operations. As a consequence, to define fuzzy set logical operators, let us first recall crisp set operators and define them by using an approach based on membership functions. The most simple crisp set operations are union, intersection, and complement, which essentially correspond to OR, AND, and NOT bi-valued logical operators, respectively.

Let A and B be two crisp sets then their union, denoted $A \cup B$, contains all elements in either A or B; that is, $\mu_{A\cup B} = 1 \text{ if } x \in A \text{ or } x \in B$. At the same way, the intersection of A and B, denoted $A \cap B$, contains all the elements that are simultaneously in A and B; that is $\mu_{A\cup B} = 1 \text{ if } x \in A \text{ and } x \in B$. Finally, the complement of A is denoted by $\overline{A}$, and it contains all elements that are not in A; that is $\mu_{\overline{A}} = 1 \text{ if } x \notin A$, and $\mu_{\overline{A}} = 0 \text{ if } x \in A$. The truth tables for presented operators are shown in Figure 5.

AND			OR			NOT	
A	B	A∪B	A	B	A∪B	A	$\overline{A}$
0	0	0	0	0	0	0	1
0	1	0	0	1	1	1	0
1	0	0	1	0	1		
1	1	1	1	1	1		

Figure 5. Truth tables for AND, OR and NOT.

At the same way of the operations on crisp sets, in order to intersect, unify and negate fuzzy sets, it is necessary define operators that reflects on fuzzy sets the same behaviour of the AND, OR, and NOT operators on crisp sets.

Typically, the min, max, and complement operations as described in Eq. (2.3.1) are used to define the the AND, OR, and NOT operators on fuzzy sets.

$$\begin{aligned} \mu_{A\cup B} &= \max[\mu_A(x), \mu_B(x)] \\ \mu_{A\cap B} &= \min[\mu_A(x), \mu_B(x)] \\ \mu_{\bar{A}} &= 1 - \mu_A(x) \end{aligned} \tag{2.3.1}$$

however, min and max are not the only ways to describe the intersection and union of two fuzzy sets. Zadeh proposed to compute fuzzy union and fuzzy intersection in a more theoretical way, respectively, by means of S-norm and T-norm operators as described in the Eq. (2.3.2):

$$\begin{aligned} \mu_{A\cup B} &= S(\mu_A(x), \mu_B(x)) \\ \mu_{A\cap B} &= T(\mu_A(x), \mu_B(x)) \end{aligned} \tag{2.3.2}$$

the T-norm operator is a function $\mathrm{T}: [0,1] \times [0,1][0,1]$ which satisfies the following requirements:

- *boundary*: $T(0,0) = 0,\ T(a,1) = T(1,a) = a$ (this feature ensures the right generalization of crisp sets);
- *monotonicity*: $T(a,b) \leq T(c,d) if a \leq c and b \leq d$ (this feature states that a decrease in the membership values in A and B cannot lead to an increase in the membership value of the intersection of sets A and B);
- *commutativity*: $T(a,b) = T(b,a)$ (this feature specifies that the order in which fuzzy sets are connected does not matter);
- *associativity*: $T(a, T(b,c)) = T(T(a,b), c)$ (this feature enables us to take the intersection of any number of fuzzy sets and any order of pairwise groups).

The S-norm or T-conorm operator used to compute the fuzzy union operation is dual to T-norm operator. As consequence, it satisfies the following requirements:

- *boundary*: $S(1,1) = 1, S(a,0) = S(0,a) = a$;
- *monotonicity*: $S(a,b) \leq S(c,d)\ if\ a \leq c\ and\ b \leq d$;
- *commutativity*: $S(a,b) = S(b,a)$;
- *associativity*: $S(a, S(b,c)) = S(S(a,b), c)$;

A typical example of a pair of S-norm and T-norm operators is given from the bounded sum and bounded product defined in Eq (2.3.3):

$$x \oplus y = \min[1, x + y]$$
$$x \otimes y = \max[0, x + y - 1] \qquad (2.3.3)$$

However, as already said, the most part of applications use $\min$ for fuzzy intersection, $\max$ for fuzzy union, and $1 - \mu_A(x)$ for complementation.

In the next section, Fuzzy inference systems will be described. The beginning step in the building of a fuzzy inference system is the forming of a rule base consisting of IF-THEN rules. Each rule defines a relationship between the input and output fuzzy sets. A singleton fuzzy rule assumes the form if x is A, then y is B, where the *if* part of the rule (if x is A) is called the *antecedent* or *premise* whereas the *then* part of the rule (then y is B) is called the *consequent* or *conclusion*. The fuzzy relation between A and B is given by the membership function $\mu_{A \to B}(x, y) \in [0,1]$ which identifies the degree of presence or absence of association or interaction between the elements x and y. Formally, let U and V be two universes of discourse, a fuzzy relation $R(U, V)$ is a set in the product space $U \times V$ characterized by the membership function $\mu_R(x, y)$, where $x \in U$ and $y \in V$, and $(x, y) \in [0,1]$.

Interpreting an if-then rule involves two distinct steps:

1. the first step evaluates the antecedent part, i.e., it consists in fuzzifying the input and applying any necessary fuzzy operators;

2. the second step executes implication, i.e., it consists in applying the result of the antecedent to the consequent, which results in evaluation of the membership function $\mu_{A \to B}(x, y)$.

In fuzzy logic, there are different interpretations of the fuzzy relation $\mu_{A \to B}(x, y)$. The most famous ones are the minimum and the product implications, defined, respectively, as follows:

$$\mu_{A \cup B} = \mu_A(x)\mu_B(x)$$
$$\mu_{A \cap B} = \min[\mu_A(x), \mu_B(x)] \qquad (2.3.4)$$

In particular, the first one was proposed by Mamdani, the second one by Larsen. The minimum and product inferences are referred as engineering implications and they have nothing to do with traditional prepositional logic.

2.4 Fuzzy Inference System

Starting from fuzzy rule definition, a formal approach to fuzzy inference systems can be provided. Indeed, a fuzzy inference system (FIS) essentially defines a non-linear mapping of the input data vector into a scalar output, using fuzzy rules. The mapping process involves input/output membership functions, FL operators, fuzzy if-then rules, aggregation of output sets, and a so-called defuzzification operator. A general model of a fuzzy inference system (FIS) is depicted in Figure 6. As shown, a FIS contains four components: the rule base, the fuzzifier, the inference engine and the defuzzifier. In details, the rule base contains linguistic rules that are typically provided by human experts. However, it is also possible to extract rules also from numeric data. The fuzzifier module maps input numbers into corresponding fuzzy memberships. This task is required in order to activate rules that are in terms of linguistic variables. The inference engine defines mapping from input fuzzy sets into output fuzzy sets and it determines the firing strength for each rule. Finally, the defuzzifier operator is used to map the output fuzzy sets into a crisp number.

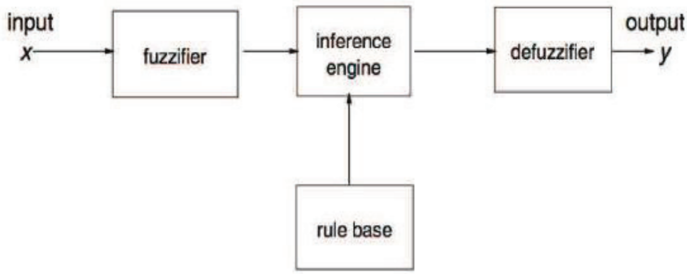


Figure 6. Block diagram of a fuzzy inference system.

An FIS with multiple outputs can be considered as a collection of independent multi-input, single-output systems. A schematic diagram of the inference process computed by a multi-input/multi-output FIS is shown in Figure 7.

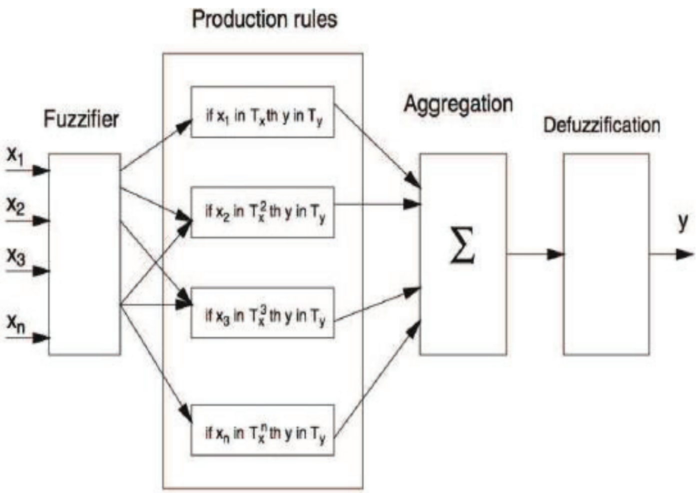


Figure 7. Schematic diagram of a fuzzy inference system.

In the figure, $x = (x_1, x_2, \dots, x_n)^T$ represents the input vector and $y = (y_1, y_2, \dots, y_m)^T$ be the output one. Each linguistic variable x_i in the universe of discourse U is characterized by $T(x) = \{T_x^1, T_x^2, \dots, T_x^k\}$ and $\mu(x) = \{\mu_x^1, \mu_x^2, \dots, \mu_x^k\}$ where each T_x^i is a fuzzy member and each μ_x^i is a membership function defined on U. In details, the $T(x)$ is the so-called *term set* of x, that is, the set of names of linguistic values of x.

Hereafter, a more detailed description of an inference process is given. In particular, the discussed fuzzy inference process is known as *Mamdani fuzzy inference method*. Indeed, there are also other approaches in literature. Among them, it is possible to cite the Sugeno's method. In details, Sugeno suggested a fuzzy inference method similar to Mamdani system except for the evaluation of the output membership functions. Indeed, in Sugeno's method, the output membership function is a constant or a linear function, respectively, if it is a zero-order or first-order Sugeno model. More in details, a fuzzy rule for the zero-order Sugeno method is of the form if x is A and y is B then $C = K$, where A and B are fuzzy sets in the antecedent and K is a constant, whereas, the first-order Sugeno model has rules of the form if x is A and y is B then $C = px + qy + r$, where A and B are fuzzy sets in the antecedent and p, q, and r are constants.

2.4.1 Step 1: Fuzzy Inputs

The first step in evaluating the output of a FIS is to take input values and compute the degree to which they belong to each of the fuzzy sets. The fuzzifier block performs the mapping from the input feature space to fuzzy sets in a certain universe of discourse. A specific value x_1 is then mapped to the fuzzy set $T_{x_i}^1$ with degree $\mu_{x_i}^1$, to fuzzy set $T_{x_i}^2$ with degree $\mu_{x_i}^1$, and so on. In order to perform this mapping, it is possible to use fuzzy sets of any shape, such as triangular, Gaussian, π-shaped, etc..

2.4.2 Step 2: Apply Fuzzy Operators

Once the inputs have been fuzzified, the successive task is to interpret the rule base. Interpreting an if-then rule is a two part process: (a) compute the firing strength of the antecedent part of the rule and (b) apply the implication method, using the degree of support for the entire rule to shape the output fuzzy set. Here, the first step is described. In details, when the antecedent part of a rule is composed by more than one clause, it is necessary to apply a fuzzy operator in order to compute a numerical value which represents the result of the whole antecedent part. This value is typically a number between 0 and 1 and represents the composite firing strength of the rule.

2.4.3 Step 3: Apply the Implication Method

The implication method is defined as the shaping of the output membership functions on the basis of the firing strength of the rule. The input for the implication process is a numerical value obtained by the evaluation of the antecedent part. Instead, the output is a fuzzy set. The most common methods are the minimum and the product. They can be represented, respectively, by Eq. (2.4.1) and (2.4.2).

$$\mu_y^i(w)' = \min(\alpha_i, \mu_y^i(w)) \tag{2.4.1}$$

$$\mu_y^i(w)' = \alpha_i \mu_y^i(w) \tag{2.4.2}$$

where w is the variable that represents the support value of the membership function.

2.4.4 Step 4: Aggregate all Outputs

After firing strengths of the rules were obtained, it is necessary to combine the corresponding output fuzzy sets into one composite fuzzy set by means of the so-called *aggregation* operation. In details, aggregation takes all fuzzy sets returned by the implication process for each rule and combines them into a single fuzzy set. This output fuzzy set is used as the input to the defuzzification process. Aggregation occurs only once for each output system variable. A characteristic of aggregation operator is to be commutative. For this reason, the order of rule execution is not important. The commonly used aggregation method is the max method. If there are two rules with output fuzzy sets represented by two fuzzy sets $\mu_y^1(w)$ and $\mu_y^2(w)$, then, combining the two sets, it is possible to obtain the output decision showed in Eq. (2.4.3):

$$\mu_y(w) = \max(\mu_y^1(w)\mu_y^2(w)) \tag{2.4.3}$$

it is worth noting that the last result is a membership curve.

2.4.5 Step 5: Defuzzify

In order to get a crisp value for output fuzzy set obtained by the aggregation operation, a defuzzification process is computed. Therefore, the input to the defuzzification process is the aggregate output fuzzy set, whereas, the output is a single crisp number. In literature, several methods for defuzzification are described. In the sequel, some of them are discussed.

2.4.5.1 Centroid defuzzification method

In this method, the defuzzifier returns as output of the FIS the center of gravity (centroid) y_i, of the aggregated fuzzy set. Formally, for a continuous fuzzy set B, the centroid is given by the following equation:

$$\frac{\int_S y_i \mu_B(y)dy}{\int_S \mu_B(y)dy} \tag{2.4.4}$$

where S denotes the support of $\mu_B(y)$. Often, discretized variables are used so that y' can be approximated as shown in Eq. (2.4.5), which uses summation instead of integration.

$$y' = \frac{\sum_{i=1}^{n} y_i \mu_B(y)}{\sum_{i=1}^{n} \mu_B(y)} \tag{2.4.5}$$

The centroid defuzzification method finds the balance point of the solution fuzzy region by calculating the weighted mean of the output fuzzy region.

It is the most widely used technique because, when it is used, the defuzzified values tend to move smoothly around the output fuzzy region. The technique is unique, however, and not easy to implement computationally. The method of centroid defuzzification is depicted in Figure 8.

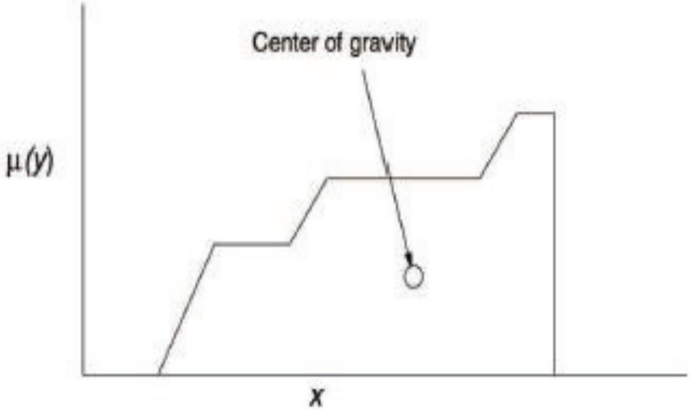


Figure 8. Centroid defuzzification method.

2.4.5.2 Maximum-decomposition method

In this method, the defuzzifier examines the aggregated fuzzy set and chooses that output y for which $\mu_B(y)$ is the maximum, as shown in Figure 9. Unlike the centroid method, the maximum-decomposition method has some properties that are applicable to a narrower class of problems. The output value for this method is sensitive to a single rule that dominates the fuzzy rule set. Also, the output value tends to jump from one frame to the next as the shape of the fuzzy region changes.

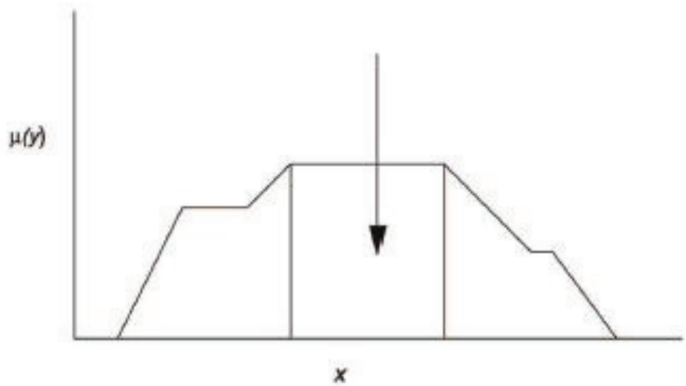


Figure 9. Maximum-decomposition defuzzification method.

2.4.5.3 Center of maxima method

In a multimode fuzzy region, the center-of-maxima technique finds the highest plateau and then the next highest plateau. The midpoint between the centers of these plateaus is selected as shown in Figure 10.

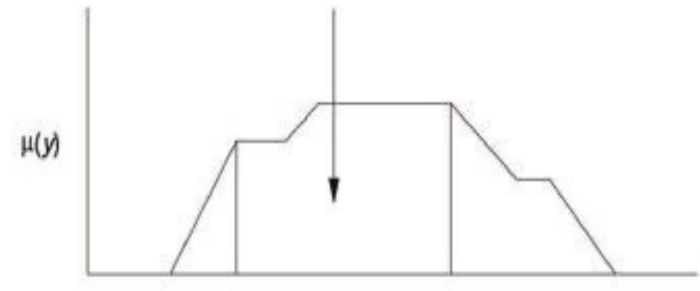


Figure 10. Average maximums defuzzification method.

2.4.5.4 Height defuzzification

In this method, the defuzzifier first evaluates $\mu_{B_i}(y)$ at y_1, and then computes the output of the FIS. Output y_h is computed as:

$$y' = \frac{\sum_{i=1}^{n} y_i \mu_B(y)}{\sum_{i=1}^{n} \mu_B(y)} \tag{2.4.6}$$

where m represents the number of output fuzzy sets obtained after implication and y_i, represents the centroid of fuzzy region i. This technique is simple to apply because the centers of gravity of commonly used membership functions are previously known.

Example: let consider a fuzzy inference system with two inputs $(n = 2)$ and one output $(m = 1)$. The two inputs represent the number of years of *education* and the number of years of *experience*, whereas the output of the system is the variable *salary*. Let consider x_1 be the number of years of education, $T(x_1) = \{low, medium, high\}$ be its term set, and $[0 - 15]$ the universe of discourse. Let consider x_2 as the number of years of experience, $[0 - 30]$ as the universe of discourse, and $T(x_2) = \{low, medium, high\}$ as the corresponding term set. Similarly, let consider the output *salary* as the linguistic variable y in the universe of discourse $[20,200]$ and the term set $T(y) = \{very\ low, low, medium, high, very\ high\}$. In details, the universe of discourse represents the minimum and maximum in thousands of dollars cashed as salary. The membership functions for the input and output variables are, respectively, in Figure 11, Figure 12 and Figure 13.

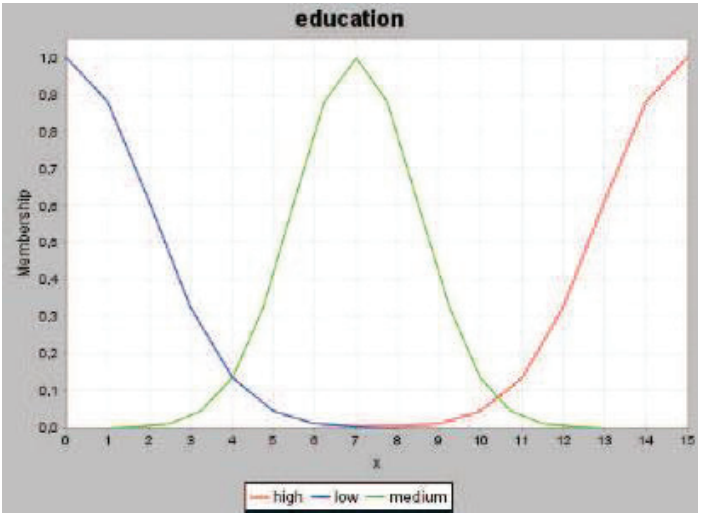


Figure 11. Fuzzy membership functions for input 1.

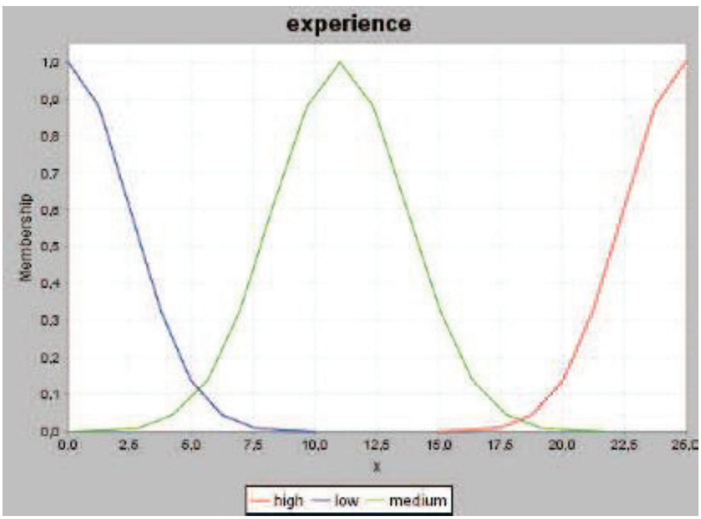


Figure 12. Fuzzy membership functions for input 2.

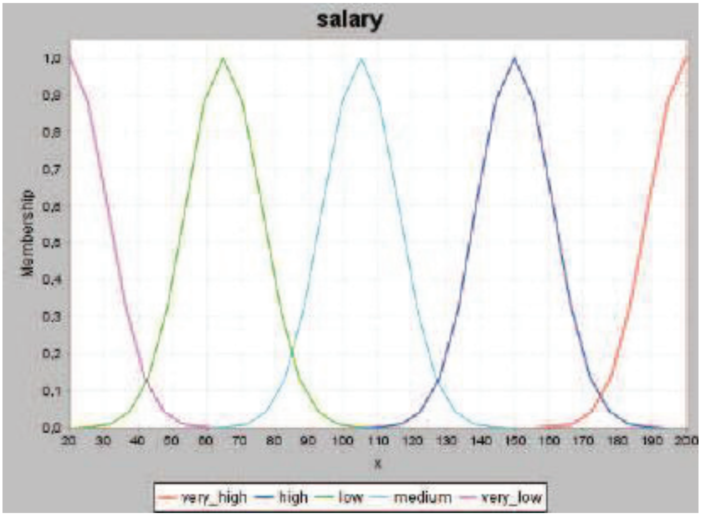


Figure 13. Fuzzy membership functions for output 1.

The fuzzy rule base R contains a set of fuzzy rules, i.e.,

$$R = (R_1, R_2, \dots, R_n) \tag{2.4.7}$$

where the i^{th} fuzzy rule is

$$R_i = if\,(x_1 \; is \; T_{x_1} and \dots x_p \; is \; T_{x_p}) then (y \; is \; T_y) \tag{2.4.8}$$

in this example, the set of rules is the following:

R_1: *if education is low and experience is low, then salary is very low*
R_2: *if education is low and experience is medium, then salary is low*
R_3: *if education is low and experience is high, then salary is medium*
R_4: *if education is medium and experience is low, then salary is low*
R_5: *if education is medium and experience is medium, then salary is medium*
R_6: *if education is medium and experience is high, then salary is high*
R_7: *if education is high and experience is low, then salary is medium*
R_8: *if education is high and experience is medium, then salary is medium*
R_9: *if education is high and experience is high, then salary is very high*

In Figure 14, it is possible to see the inference process when the education is equals to 10 years and experience is equals to 18 years. In particular, it is worth noting that only rules R_3 and R_7 are fired.

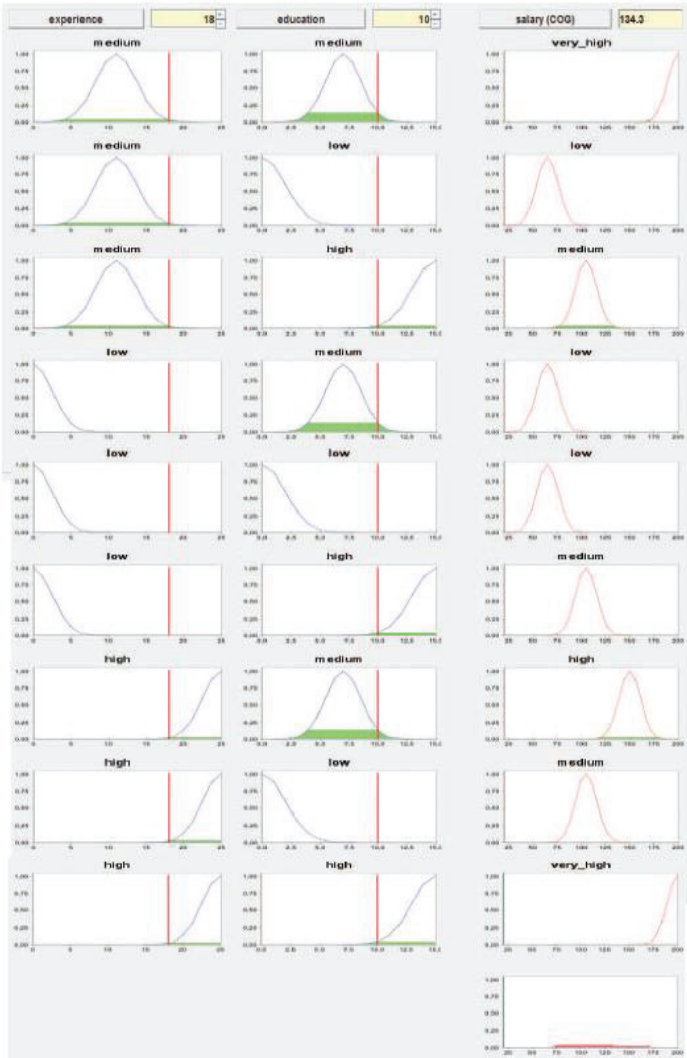


Figure 14. Fuzzy Rules.

The fuzzy inference process defines the mapping surface $y = f(x_1, x_2)$, which is illustrated in Figure 15.

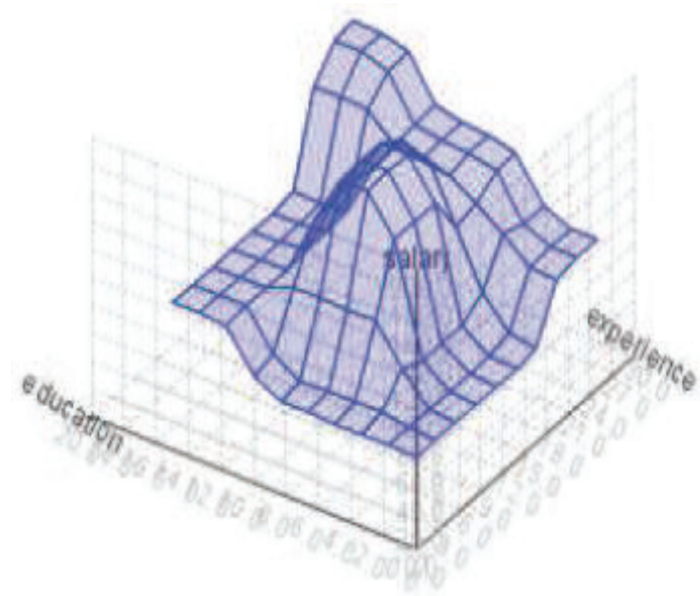


Figure 15. Fuzzy Surface.

2.5 Hedges

A *linguistic hedge* is an operation that changes the initial meaning of a fuzzy set. In fuzzy production rules, hedges play the same function of adjectives and adverbs in English sentences. Examples of hedges for a fuzzy set hot can be very hot, more or less hot, and extremely hot. There are different kinds of hedges: some intensify the features of a given fuzzy set such as very and extremely, others dilute the membership curve such as somewhat, rather and quite, other ones such as about, closeto and approximately approximate a scalar to a fuzzy set and, finally, the hedge not computes the complement of the relative fuzzy set. Hereafter, a formal definition of each kind of hedge is given. In particular, a concentrator hedge can be formally defined as follows:

$$\mu_{con(A)}(x) = \mu_A^n(x) \qquad (2.5.1)$$

where $n \geq 1$. This hedge simply replaces the exponent of the intensification function with a real positive number greater than unity. An example of general concentrator with $n = 3$ is given in Figure 16.

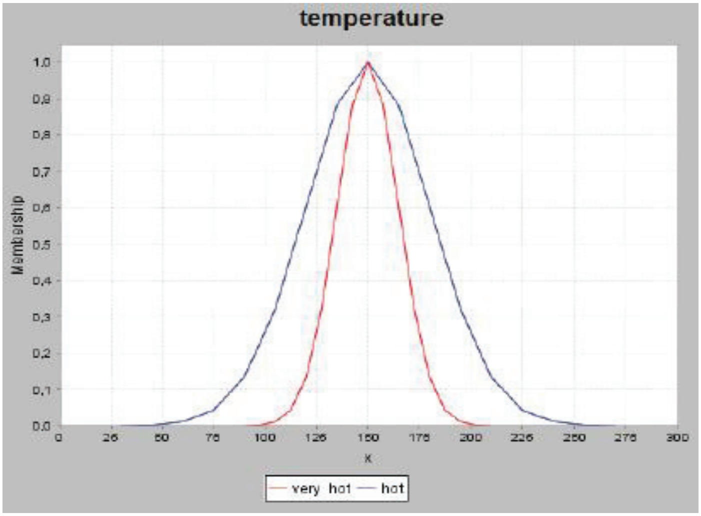


Figure 16. Concentrator hedge.

A generalization of the dilator hedge, instead, simply replaces the exponent of the intensification function with a real positive number less than unity, expressed as a fraction $(1/n)$. Therefore, it is possible to define a generalized dilator edge as follows:

$$\mu_{dil(A)}(x) = \mu_A^{\frac{1}{n}}(x) \tag{2.5.2}$$

where $n \geq 1$.

An example of generalized dilator hedge is depicted in Figure 17. Other examples are $\mu_a^{1.3}(x)$ used frequently to implement the hedge *slightly*, and, the hedge *somewhat* which dilutes the fuzzy shape by considering the square root of the membership function at each point along the set $\mu_a^{0.5}(x)$.

Another kind of hedges are the so-called *contrast hedges*. They change the nature of fuzzy regions by making the region either less fuzzy (intensification) or more fuzzy (diffusion). Hedges such as *positively*, *absolutely*, and *definitely* are intensification hedges because they change a fuzzy set by raising the truth values above (0.5) and decreasing all the truth values below (0.5).

An example is shown in Figure 18. These hedges can be formally defined as follows:

$$\mu_{inf}(A) = \begin{cases} 2(\mu_A^2(A)) & if\ \ \mu_A(A) \geq 0.5 \\ 1 - 2(\mu_A^n(A)) & otherwise \end{cases} \tag{2.5.3}$$

On the contrary, a hedge such as *generally* is a diffusion hedge (see Figure 19), since it changes the fuzzy surface by reducing all truth values above and increasing all truth values below.

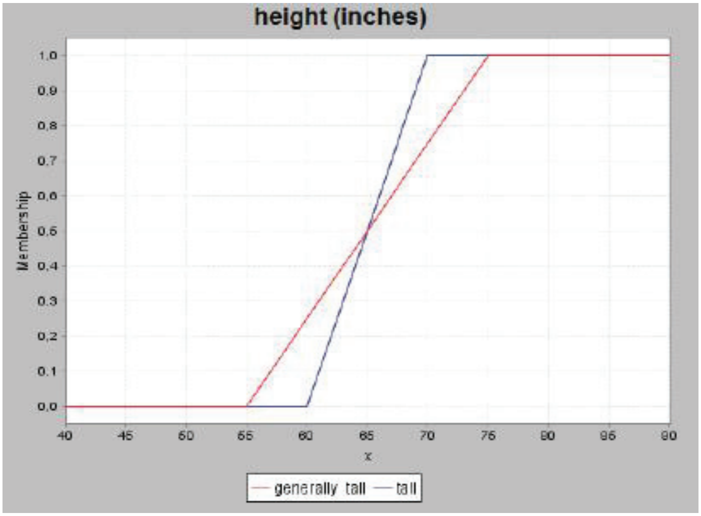


Figure 17. Dilator hedge.

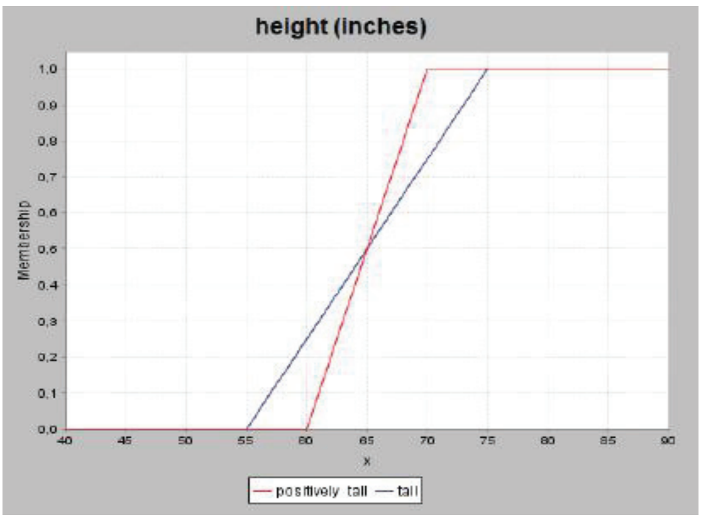


Figure 18. Intensification hedge.

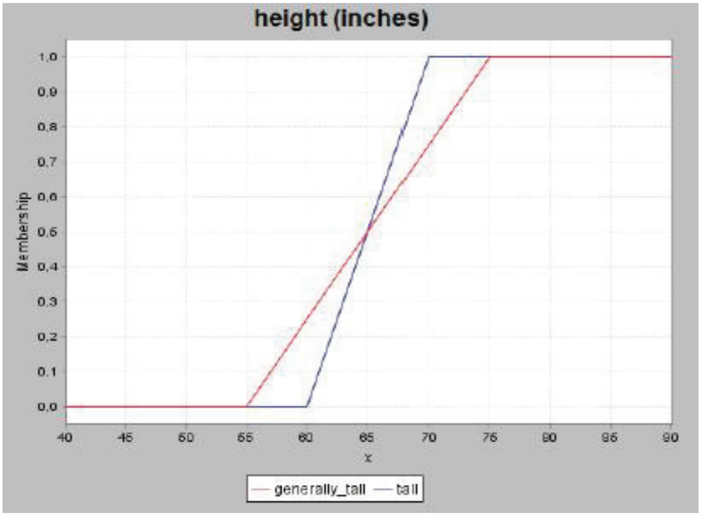


Figure 19. Diffusion hedge.

These hedges are computed by the following equation:

$$\mu_{def}(A) = \begin{cases} \frac{1}{2}(\mu_A^{\frac{1}{2}}(A)) & if \ \ \mu_A(A) \geq 0.5 \\ 1 - 2(\mu_A^{\frac{1}{2}}(A)) & otherwise \end{cases} \quad (2.5.4)$$

the last kind of hedges presented in this chapter are the approximate ones. They are an important class of transformers because they restrict existing bell-shaped fuzzy regions, but also they can be used to convert scalar values into bell-shaped fuzzy regions. The most common approximate hedge is the *about* hedge, used to create a space that is proportional to the height and width of the generated fuzzy space.

In the following chapters, fuzzy control and fuzzy systems concepts and their semantic modeling and representation will be applied, in combination with other computational intelligence techniques, in order to support and improve approximate reasoning processes involved in situation and context awareness.

2.6 Conclusions

In this chapter the author presents some preliminary concepts about fuzzy logic and fuzzy systems. In particular, the discussion focuses on concepts of fuzzy sets, membership functions and fuzzy inference, since they will be referenced throughout the dissertation. So, this chapter provides a foundation for most of the research work and in particular for the application scenarios discussed later.

Chapter 3

Swarm Intelligence

Swarm Intelligence (SI) is a relatively new area of study, related to the field of distributed control. Swarm intelligence seeks to use the behavior and control mechanisms found in nature especially in social insects to control multiple robots and to solve problems. The central idea behind swarms is that local interactions between simple agents can create complex global behavior. The control is completely decentralized with every agent responsible for its individual actions. Being a young field of research, the applications and problems being solved with swarm intelligence are easier than those of the more matured areas of distributed control. Most research involving swarms has focused on resource gathering or pattern formation through self-organization [36][37].

Specifically, SI refers to systems which accomplish complex global tasks through the simple local interactions of autonomous agents. The control is completely distributed among the individual agents with no leader coordinating any of the activities. Swarm intelligence [38] is "a property of systems of non-intelligent robots exhibiting collectively intelligent behavior.

3.1 What is it known as Swarm Intelligence?

According to Dorigo [39], it is called Swarm Intelligence to:

"The discipline that deals with natural and artificial systems composed of many individuals that coordinate using decentralized and self-organization. In particular, the discipline focuses on the collective behaviours that result from the local interactions of the individuals with each other and with the environment".

According to Beni [40], there is a quantitative definition of swarm intelligence. He claims swarm intelligent behavior occurs among N interacting agents only when N reaches some critical number N_c. $W(N)$, the work achieved by N interacting agents, can be described by a function with a critical point at N_c. $W_0(N)$, the work achieved by N independent agents, is 0 for all values of N.

Sugawara and Watanbe [36] generalized this definition to say that swarm intelligence occurs whenever $W(N) > W_0(N)$ or N interacting agents perform more work than an equivalent number of N independent agents. Performance gains through swarming occurs when a critical mass of agents come together and enter a positive feedback loop. For example, the defensive capabilities of a single bee are insignificant, but an entire swarm can protect the hive from most animal attackers.

3.2 Biological Inspirations

Ant colonies efficiently forage for food and build intricate nests with no single, controlling queen. Birds fly in formation without centralized leadership or explicit communication. Herd animals like cows do not follow one leader of the pack. These simple biological agents coordinate extremely complex behavior without any help from a global perspective or centralized controller.

How do birds flock and fly in a choreographed like fashion diving and swooping in unison? Trying to answer this question, Reynolds [41] created a boid model to explore the swarming relationship of birds. All boids follow three simple rules. First a boid cannot get too close to any over boid to prevent mid-are collisions. Second, a boid must copy the rest of the flock by averaging the other local boids velocities and directions. Third, the boid must try to minimize exposure to the outside of the flock by trying to fly toward the perceived center. The simulation results closely resembled the behavior of real birds in flight. This experiment was one of the first to show how simple interactions could create a global control pattern.

It is worth noting the difference between biological inspiration and trying to emulate the behavior of biological systems.

The point of this research is to glean the best aspects of biological societies and collectives and apply them to technological problems.

Creating a system that exactly mimics the behavior of biological collectives is an excellent simulator for biological research but not the best form of robotic control.

The goal is to exploit the millions of years of natural evolution that has produced solutions to problems very similar to the technological ones currently faced by science.

3.3 Emergence and Self-organization

SI relies upon the emergent properties of its components to manifest itself. Emergence [38] is the process by which complex patterns form out of the interaction of simpler rules. To label an event as being emergent it should be hard to predict from a description of the lower level components. For example, it would be difficult to imagine the resulting flocking from seeing only a single boid and its rules. There has been much research into the fields of social science [42], physics, biology, and engineering [38][39] concerning emergent properties.

Self-organization [43][44] takes form by processes performed by simple individuals which, by either competition or cooperation, create an organized global structure. Individuals make actions based on what they receive from the local environment, without actually knowing or concerning themselves about global structure. Since each action is a reaction to what is happening around the individual, it is not necessary to have a manager who is responsible for assigning tasks, which on the other hand would have been almost impossible in larger colonies. Examples of such self-organized systems are: fish schooling [45], formation [46], synchronization [47] and mapping [43].

In other words, self-organization is another term used to describe systems composed of discrete, individual components that create a global action through interaction. In chemistry, the term is used to describe reaction diffusion system and autocatalytic networks [48]. It has been applied to sensor networks [49] and evolutionary computation [50].

3.3.1 Feedback: Positive and Negative

Self-organized systems builds upon two opposite forces; attraction and repulsion. These forces occur in biologically inspired systems when quantity of some sort is sent back into the system to increase or decrease the magnitude of that same quantity. By e.g. looking at the intake of food in a colony it is important to have a good balance. If they have too little, they with starve, but on the other hand, if they have too much food they have to throw the bad food away. Nature finds this balance by rewarding and revoking behaviors. This concept of attraction and repulsion is in biologically systems presented as positive and negative feedback.

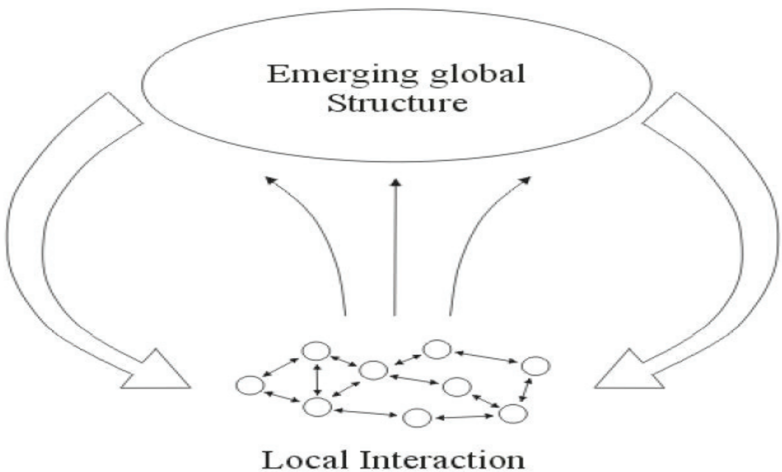


Figure 20. Global behaviors arise from local interactions.

3.4 Collective Behavior

Another widely used term in swarm intelligence is collective behavior (adaptation) [51]. Collective behavior can be defined as actions which differ from the already existing social structure of the group. There may be actions which are not in conformity with each other, or violates certain norms in the system. The fact that the actions violate the standards can be caused by different things. They may be unclear or contradict each other and from an outside perspective not make much sense. Such actions often occur when spontaneous changes happen in the environment and they quickly have to react. In nature and for ants, this could happen when a nest is destroyed the ants need to reconstruct it [52], or they get attacked by other insects and have to defend their nest, food or other resources.

3.4.1 Cooperation

Collective tasks are either non-cooperative or cooperative. Non-cooperative tasks are typically tasks which don't need any kind of cooperation between the individuals performing the tasks and can be successfully performed by one single individual given unlimited time [39][52].

It would however be more efficient if individuals cooperated. Examples of such non-cooperative tasks are: sorting [53], searching [54][55], map making [56][57], harvesting [54], vacuuming [58]. Cooperative tasks are tasks which can't be completed by one single individual. The goal can only be achieved by two or more individuals working together [43]. Examples of such cooperative tasks are: formation marching [47], material transport [59], tandem movement [60], box-pushing [61][62][63]. Cooperation (and in some cases competition) is the essential behavior of any type of swarm intelligence. To survive in the world, the ants need to cooperate. The same applies when they are building the nest. Building a nest consist of two steps: (1) First, the ant need to find leaves. The leaves are too heavy for one ant to handle, so they need to make a long line, and pull together. If it still is too heavy, more ants will help by making a second row of ants. They will connect with the ant in front of them, and they will together pull it as one bigger unit. They pull the leaf until it lies next to the other leaves that form some of the upcoming nest. (2) The next step is to use the silk which the larva produces by gluing the leaves together. Also here is one single ant not strong enough to carry one larva by itself [43].

By looking at the behavior of ants, we can see how this constitutes to a swarm behavior. They depend on helping each other to solve problems like building nests, finding food and fighting against enemies, to name a few. One of the many assets to swarm behavior is that it relies on simple mechanisms, which is great for robotics, and that it can be applied and implemented in several different contexts. It is a great source for inspiration.

3.4.2 Communication

Communication is the most fundamental property that must be present for either competition or cooperation to occur between individuals. Communication can be both direct and indirect. Direct communication is exchanging information between individuals where all the participants are involved and are present at the same time. For us humans, this can be associated with things we say or write, and in social insects, transmitting signals through touch. Indirectly communication has a more defuse definition. It can be anything from body language (behavior), force, symbolic elements or time spent [61]. The research suggests that social insects base almost all exchange information through indirect communications, such as described about ants and honey bees later in this section.

3.4.2.1 Stigmergy

Stigmergy [43][52] is a mechanism in indirect communication and in general, self-organized systems. It was first observed in social insects by Pierre-Paul Grasse in 1950's [64]. The concept of stigmergy is that an individual must always take into account the changes that have occurred in the environment and act on the basis of these. If one individual modifies the environment, the same individual or another individual get stimulated and responds to the changes by performing actions based on the new environmental settings [61]. Stigmergy is a necessity in any dynamic swarm system because of the scaling issue in direct communication.

3.4.2.2 Division of Labor

Division of labor [65][66] is a pattern of variation between individuals in a colony. Each individual eventually becomes specialized in parts of the tasks performed by the colony as they continue doing work which they are good at. Division of labor is both fundamental and necessary for a colony to function effective as a group. The determination of which tasks each individual will perform is based on two patterns: age and size/shape.

3.4.2.3 Pheromones

The most common form of communication among social insects are the use of pheromones [39][67]. Pheromones are chemical signals sent out from one individual to trigger a reaction behavior on the receiving individuals of the same species. These chemical signals can be used in many different occasions; trail-following [68], defense [69][66], mating and retrieving food.

3.4.2.4 Communication among Honey Bees

The communication among bees was discovered by Karl von Frisch, who got a Nobel Prize for it in 1973. He discovered that the bees are communicating with each other through the language of dance. A bee can perform different type of dances, which gives different information. The two most common dances are the round dance and the waggle dance. The round dance is often used when a food source is close to the hive, between 50 and 150 meters away. The way a bee performs the round dance, is by walking around in circles, suddenly turn 180 degrees, and then start walking forwards. This round dance says that the food source is nearby, but it doesn't say anything about where it is located. The waggle dance however, is the most known. This is a complex dance, which describe both the direction and the distance. The dance is performed by walking around in two small circles and shaking its body whenever it is in the middle. However, the main purpose of these dances is to recruit the other bees, and tell them where food sources or possible new nest sites are located.

3.4.2.5 Communication among Ants

The structure of an ant colony is flat, which means that there is no leader in the group. Each ant perform actions based on observations in the local environment (the stigmergy principle), thereby creating a global structure, since all are following much of the same reactive patterns. Even though they perform action based on changes in the environment, there is a rough division among them. In a colony there are three main types of ants; queen, drone and worker. Common for all ants is that they base communication on using pheromones, and detects them by using their antennas (similar to smell). Their antennas are equipped with features to both notice direction and intensity of pheromones. When an ant finds a new food source, it will lay down pheromones at the way back to the hill [68]. The intensity of the path created will increase as more ants follow the path and find the food source using the same principle of laying down pheromones on the way back. This principle will also lead to finding the shortest path when faced with several. However, the pheromones do not last forever. When the food source diminishes, fewer ants lay down pheromones, and the path will eventually disappear[39][52].

3.4.2.6 Shortest Path

The ants are able to always find the shortest path to a food source, by using the concept of pheromones. If there are two paths to the same food source, where one is longer than the other, the ants will soon find the shortest path. This happens when the ants put down pheromones on their way back from the food source to the ant hill. Since the longer path takes more time to walk, it will also take longer time to build up a solid pheromone path than it would do with a shorter path. This way it will start with a 50% chance of choosing the shortest path, and increase more as time goes by, and more ants put down pheromones on the shortest path.

An example of the construction of a pheromone trail while searching for a shorter path is shown in Figure 21, which was first presented in [70]. In Figure 21a, there is a path between the food and the nest established by the ants. In Figure 21b, an obstacle is inserted in the path. Thus, the ants spread to both sides of the obstacle, since there is no clear trail to follow (Figure 21c). As the ants go around the obstacle and find the previous pheromone trail, a new pheromone trail will be formed around the obstacle. This trail will be stronger in the shortest path than in the longest path, as shown in Figure 21d, as the shorter path receives a higher amount of pheromone in a time unit [71]. Although, all ants are moving at approximately the same speed and deposit a pheromone trail at approximately the same rate, it is the fact that it takes longer to contour the obstacle on their longer side than on their shorter side which makes the pheromone trail accumulate faster on the shorter side. It is the ant's preference to follow higher pheromone trail levels which makes this accumulation even faster on the shorter [72].

An interesting point is where the bees and the ants are each trying to find the best food sources. Let us say that we have two food sources, one good and one bad and where both bees and ants discovers them simultaneously. Then both bees and ant will eventually always choose the best food source. However, if they discover the bad food source first and then the good food source, ants will not be able to switch, but bees will. This is because of the pheromones that the ants lay down. Even though the ants discover the new and better food source, there still exists pheromones on the path to the poorer food source, and the ant will continue to go there until the food decrease. In other words, it is more difficult for the ant to quickly move from one food source to another, because of the pheromones they use.

3.5 Classification of Swarm Intelligence

Swarm intelligence has a marked multidisciplinary character since systems with the above mentioned characteristics can be observed in a variety of domains. Research in swarm intelligence can be classified according to different criteria (as discussed in the following subsections).

3.5.1 Natural vs. Artificial

It is normally to divide swarm intelligence research into two areas according to the nature of the systems under analysis. It is spoken therefore of natural swarm intelligence research, where biological systems are studied; and of artificial swarm intelligence, where human artifacts are studied.

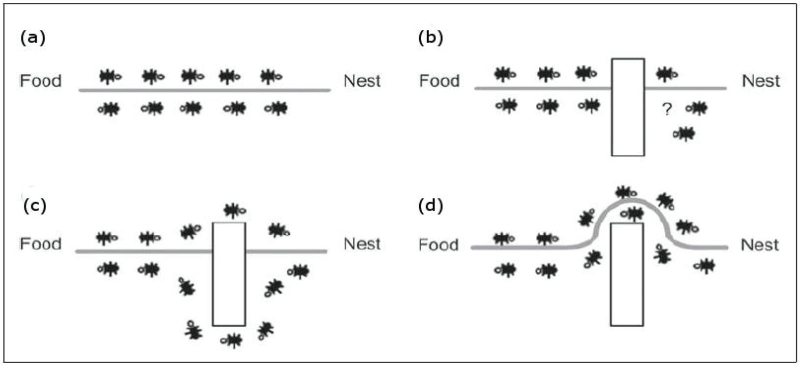


Figure 21. (a) Ants in a pheromone trail between nest and food; (b) an obstacle interrupts the trail; (c) ants find two paths to go around the obstacle; (d) a new pheromone trail is formed along the shorter path.

3.5.2 Scientific vs. Engineering

An alternative and more informative classification of swarm intelligence research can be given based on the goals that are pursued: it can be identified a scientific and an engineering stream. The goal of the scientific stream is to model swarm intelligence systems and to singularize and understand the mechanisms that allow a system as a whole to behave in a coordinated way as a result of local individual-individual and individual-environment interactions.

On the other hand, the goal of the engineering stream is to take advantage of the understanding developed by the scientific stream in order to design systems that are able to solve problems of practical relevance.

The two dichotomies natural/artificial and scientific/engineering are orthogonal: although the typical scientific investigation concerns natural systems and the typical engineering application concerns the development of an artificial system, a number of swarm intelligence studies have been performed with swarms of robots for validating mathematical models of biological systems. These studies are a kind of speculative nature and definitely belong in the scientific stream of swarm intelligence. On the other hand, one could influence or modify the behavior of the individuals in a biological swarm so that a new swarm-level behavior emerges that is somehow functional to the solution of some task of practical interest. In this case, although the system at hand is a natural one, the goals pursued are definitely those of an engineering application. In the following, an example is given for each of the four possible cases.

3.5.3 Natural/Scientific: Foraging Behavior of Ants

In a now classic experiment done in 1990, Deneubourg [73] and his group showed that, when given the choice between two paths of different length joining the nest to a food source, a colony of ants has a high probability to collectively choose the shorter one. Deneubourg has shown that this behavior can be explained via a simple probabilistic model in which each ant decides where to go by taking random decisions based on the intensity of pheromone perceived on the ground, the pheromone being deposited by the ants while moving from the nest to the food source and back.

3.5.4 Artificial/Scientific: Clustering by a Swarm of Robots

Several ant species cluster corpses to form cemeteries. Deneubourg was among the first to propose a distributed probabilistic model to explain this clustering behavior. In his model, ants pick up and drop items with probabilities that depend on information on corpse density which is locally available to the ants. Beckers et al. [74] have programmed a group of robots to implement a similar clustering behavior demonstrating in this way one of the first swarm intelligence scientific oriented studies in which artificial agents were used.

3.5.5 Natural/Engineering: Exploitation of collective behaviors of animal societies

A possible development of swarm intelligence is the controlled exploitation of the collective behavior of animal societies. No example is available in this area of swarm intelligence although some promising research is currently in progress: For example, in the Leurre[2] project, small insect-like robots are used as lures to influence the behavior of a group of cockroaches. The technology developed within this project could be applied to various domains including agriculture and cattle breeding.

3.5.6 Artificial/Engineering: Swarm-based Data Analysis

Engineers have used the models of the clustering behavior of ants as an inspiration for designing data mining algorithms. A similar work in this direction was undertaken by Lumer and Faieta in 1994 [75]. They defined an artificial environment in which artificial ants pick up and drop data items with probabilities that are governed by the similarities of other data items already present in their neighborhood. The same algorithm has also been used for solving combinatorial optimization problems reformulated as clustering problems.

3.6 Properties of Swarm Intelligence systems

A typical swarm intelligence system owns the following characteristics:

- It is composed of many individuals.
- The individuals are relatively homogeneous; that means they are either all identical or they belong to a few typologies.
- The interactions among the individuals are based on simple behavioural rules that exploit only local information that the individuals exchange directly or via the environment.
- The overall behaviour of the system results from the interactions of individuals with each other and with their environment, that is, the group behaviour self-organizes.

[2] http://leurre.ulb.ac.be/index2.html

The main property of a swarm intelligence system is its ability to act in a coordinated way without the presence of a coordinator or of an external controller. Many examples can be observed in nature of swarms that perform some collective behaviour without any individual controlling the group, or being aware of the overall group behaviour. In spite of the lack of individuals in charge of the group, the swarm as a whole can show an intelligent behaviour. This is the result of the interaction of neighbouring individuals that act on the basis of simple rules.

Most often, the behaviour of each individual of the swarm is described in probabilistic terms: Each individual has a stochastic behaviour that depends on his local perception of the neighbourhood.

Because of the above properties, it is possible to design swarm intelligence system that are scalable, parallel, and fault tolerant:

- Scalability means that a system can maintain its function while increasing its size without the need to redefine the way its parts interact. Because in a swarm intelligence system interactions involve only neighbouring individuals, the number of interactions tends not to grow with the overall number of individuals in the swarm: each individual's behaviour is only loosely influenced by the swarm dimension. In artificial systems, scalability is interesting because a scalable system can increase its performance by simply increasing its size, without the need for any reprogramming.

- Parallel action is possible in swarm intelligence systems because individuals composing the swarm can perform different actions in different places at the same time. In artificial systems, parallel action is desirable because it can help to make the system more flexible, that is, capable to self-organize in teams that take care simultaneously of different aspects of a complex task.

- Fault tolerance is an inherent property of swarm intelligence systems due to the decentralized, self-organized nature of their control structures. Because the system is composed of many interchangeable individuals and none of them is in charge of controlling the overall system behaviour, a failing individual can be easily dismissed and substituted by another one that is fully functioning.

3.7 Studies and applications of Swarm Intelligence

This section presents briefly a few examples of scientific and engineering swarm intelligence studies.

3.7.1 Clustering Behavior of Ants

Ants build cemeteries by collecting dead bodies into a single place in the nest. They also organize the spatial disposition of larvae into clusters with the younger, smaller larvae in the cluster centre and the older ones at its periphery. This clustering behaviour has motivated a number of scientific studies. Scientists have built simple probabilistic models of these behaviors and have tested them in simulation. The basic models state that an unloaded ant has a probability to pick up a corpse or a larva that is inversely proportional to their locally perceived density, while the probability that a loaded ant has to drop the carried item is proportional to the local density of similar items. This model has been validated against experimental data obtained with real ants. In the classification this is an example of natural/scientific swarm intelligence system.

3.7.2 Nest Building Behavior of Wasps and Termites

Wasps build nests with a highly complex internal structure that is well beyond the cognitive capabilities of a single wasp. Termites build nests whose dimensions (they can reach many meters of diameter and height) are enormous when compared to a single individual, which can measure as little as a few millimetres. Scientists have been studying the coordination mechanisms that allow the construction of these structures and have proposed probabilistic models exploiting stigmergic communication to explain the insects' behaviour. Some of these models have been implemented in computer programs and used to produce simulated structures that recall the morphology of the real nests. In the classification this is an example of natural/scientific swarm intelligence system.

3.7.3 Flocking and Schooling in Birds and Fishes

Flocking and schooling are examples of highly coordinated group behaviors exhibited by large groups of birds and fish. Scientists have shown that these elegant swarm-level behaviors can be understood as the result of a self-organized process where no leader is in charge and each individual bases its movement decisions only on locally available information: the distance, perceived speed, and direction of movement of neighbours. These studies have inspired a number of computer simulations that are now used in the computer graphics industry for the realistic reproduction of flocking in movies and computer games. In the classification these are examples respectively of natural/scientific and artificial/engineering swarm intelligence systems.

3.7.4 Ant Colony Optimization

Ant colony optimization is a population-based metaheuristic that can be used to find approximate solutions to difficult optimization problems. It is inspired by the above-described foraging behavior of ant colonies. In ant colony optimization (ACO), a set of software agents called "artificial ants" search for good solutions to a given optimization problem transformed into the problem of finding the minimum cost path on a weighted graph. The artificial ants incrementally build solutions by moving on the graph. The solution construction process is stochastic and is biased by a pheromone model, that is, a set of parameters associated with graph components (either nodes or edges) the values of which are modified at runtime by the ants. ACO has been applied successfully onto many classical combinatorial optimization problems, as well as to discrete optimization problems that have stochastic and/or dynamic components. Examples are the application to routing in communication networks and to stochastic version of well-known combinatorial optimization problem, such as the probabilistic travelling salesman problem. Moreover, ACO has been extended so that it can be used to solve continuous and mixed-variable optimization problems. Ant colony optimization is probably the most successful example of artificial/engineering swarm intelligence system with numerous applications to real-world problems.

3.7.5 Particle Swarm Optimization

Particle swarm optimization is a population based on stochastic optimization technique for the solution of continuous optimization problems. It is inspired by social behaviors in flocks of birds and schools of fish. In particle swarm optimization (PSO), a set of software agents called particles search for good solutions to a given continuous optimization problem. Each particle is a solution of the considered problem and uses its own experience and the experience of neighbor particles to choose how to move in the search space. In practice, in the initialization phase each particle is given a random initial position and an initial velocity. The position of the particle represents a solution of the problem and has therefore a value, given by the objective function. While moving in the search space, particles memorize the position of the best solution they found. At each iteration of the algorithm, each particle moves with a velocity that is a weighted sum of three components: the old velocity, a velocity component that drives the particle towards the location in the search space where it previously found the best solution so far, and a velocity component that drives the particle towards the location in the search space where the neighbor particles found the best solution so far. PSO has been applied to many different problems and is another example of successful artificial/engineering swarm intelligence system.

3.7.6 Swarm-based Network Management

The first swarm-based approaches to network management were proposed in 1996 by Schoonderwoerd et al. [76], and in 1998 by Di Caro and Dorigo [77]. Schoonderwoerd et al. proposed *Ant-based Control* (ABC), an algorithm for routing and load balancing in circuit-switched networks; Di Caro and Dorigo proposed AntNet, an algorithm for routing in packet-switched networks. While ABC was a proof-of-concept, AntNet, which is an ACO algorithm, was compared to many state-of-the-art algorithms and its performance was found to be competitive especially in situation of highly dynamic and stochastic data traffic as can be observed in Internet-like networks. An extension of AntNet has been successfully applied to ad-hoc networks. These algorithms are another example of successful artificial/engineering swarm intelligence system.

3.7.7 Cooperative Behavior in Swarms of Robots

There are a number of swarm behaviors observed in natural systems that have inspired innovative ways of solving problems by using swarms of robots. This is what is called swarm robotics. In other words, swarm robotics is the application of swarm intelligence principles to the control of swarms of robots. As with swarm intelligence systems in general, swarm robotics systems can have either a scientific or an engineering flavor. Clustering in a swarm of robots was mentioned above as an example of artificial/scientific system. An example of artificial/engineering swarm intelligence system is the collective transport of an item too heavy for a single robot, behavior also often observed in ant colonies.

3.8 Conclusions

There are many scientific motivations encouraging a number of varying fields to study swarm intelligence. For instance, biologists seek a deeper understanding of social insects and other animal societies. Some have even conjectured that the human body [78] and brain [38] are swarm intelligent systems composed of simple interacting agents.

Furthermore, the mechanisms behind swarming behavior can be applied to many distributed computational problems. Ant Colony Optimization (ACO) research draws inspiration from ant colonies and is used to solve discrete optimization problems. APO has been used to solve the traveling salesman problem, the sequential ordering problem, and the quadratic assignment problem [79][80]. Swarming algorithms utilizing the ant behaviors are being used to more quickly establish routing schemes in ad hoc wireless networks [81]. In relation to this thesis, swarm intelligence is being studied to advance the control and distribution of autonomous agents. It presents many new challenges and possible benefits to the field of SA.

Chapter 4

Semantic Web Technologies and Ontologies

Semantic technologies are a new paradigm — an approach that deals with the challenges of net-centric infrastructure, knowledge work automation, and building systems that know what they're doing. Semantic technologies are functional capabilities that enable both people and computers to create, discover, represent, organize, process, manage, reason with, present, share and utilize meanings and knowledge to accomplish business, personal, and societal purposes. Semantic technologies are tools that represent meanings, associations, theories, and know-how about the uses of things separately from data and program code. This knowledge representation is called ontology, a run-time semantic model of information, defined using constructs for:

- **Concepts** – classes, things;
- **Relationships** – properties (object and data);
- **Rules** – axioms and constraints;
- **Instances of concepts** – individuals (data, facts);

As described in [82], Semantic technologies have emerged as a central theme across a broad array of ICT research and development initiatives. Figure 22 visualizes the intersections of four major development themes in the semantic wave: networking, content, services, and cognition. Content and Cognition are the two theme emphasized in this research thesis. Specifically, R&D themes include:

- ***Content*** — Semantics to make information interoperable, improve search, enable content discovery, access, and understanding across organization and system boundaries, and improve information lifecycle economics;
- ***Cognition*** — Semantics to make knowledge executable by computer; augment capabilities of knowledge workers; enable robust adaptive, autonomic, autonomous behaviors;
- ***Services*** — Semantics to enable computers to discover, compose, orchestrate, and manage services, and link information and applications in composite applications;
- ***Networking*** — Semantics to enable computers to configure and manage dynamic, persistent, virtual systems-of-systems across web, grid & P2P.

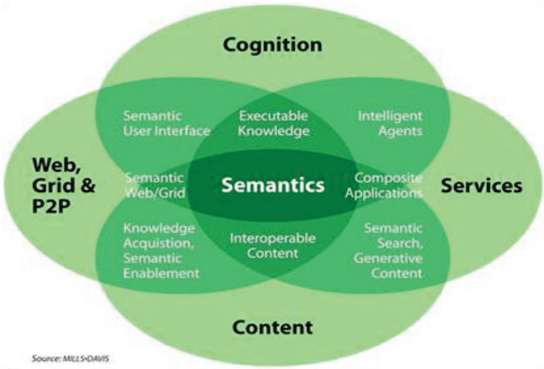


Figure 22. The central-role of semantic technologies.

In order to connect systems, integrate information and make processes interoperable, the first step is to integrate the knowledge about these systems, content sources, and process flows. Today, people do this offline, manually. Instead, in the Semantic Web vision both people and applications will connect knowledge in real time using automated and semi-automated methods. Semantically modeled, machine executable knowledge lets us connect information about people, events, locations, and times across different content sources and application processes. Instead of disparate data and applications on the Web, it is possible to get a Web of interrelated data and interoperable applications. Recombinant knowledge is represented as concepts, relationships and theories that are sharable and language neutral. Semantic technologies provide the means to unlock knowledge from localized environments, data stores, and proprietary formats so that resources can be readily accessed, shared, and combined across the Web. Actual limitations of the systems are spurring development of semantic platforms to provide meaning-based, concept-level search, navigation, and integration across varied content sources and applications found on PCs and other devices.

4.1 Semantic Models (Taxonomies and Ontologies)

The pursuit of data models that can adequately and accurately describe the vast array of relationships within an organization, body of information, or other knowledge domain space is an ongoing one. The challenge is heightened when trying to arrive at approaches that are machine computational, meaning that the models can be used by computers in a deterministic and largely autonomous way. Numerous knowledge representation technologies have been devised, some successfully and some not. As a result of these efforts, computer scientists have made significant progress toward finding out the most appropriate manner in which to express highly descriptive relationships and logical concepts existing within business environments, organizational interactions, and, to a larger extent, everyday society.

Overcoming the communication gaps resulting from reliance on numerous vocabularies remains a challenge. Technical challenges have until recently had to do with overlapping and redundant terminological inconsistencies. Without knowing it, business units, individuals, and others have expended scarce resources referring to identical elements using different terminologies and different relationship models, causing confusion and limiting communication possibilities. Identifying and reconciling these semantic distinctions is a fundamental reason for using semantic models. Figure 23 displays a spectrum of commonly used semantic models.

This diagram shows a range of models, from models on the lower left with less expressive or “weak” semantics to models on the upper right with increasingly more expressive or “strong” semantics. In general, the progression from the lower left to the upper right also indicates an increase in the amount of structure that a model exhibits. Included in the diagram are models and languages such as the relational database model and XML on the lower left. These models are followed by XML Schema, Entity-Relation models, XTM (the XML Topic Map standard), RDF/S (Resource Description Framework/Schema), UML (Unified Modeling Language), OWL (Web Ontology Language), and up to First Order Logic (the Predicate Calculus), and higher. In truth, the spectrum extends beyond modal logic but any such discussion is still largely theoretical as well as outside the scope of this document.

One of the simplest forms of semantic model is a taxonomy. A taxonomy might be thought of as a way of categorizing or classifying information within a reasonably well-defined associative structure. The form of association between two items is inherent in the structure and in the connections between items. A taxonomy captures the fact that connections between terms exist but does not define their nature. All the relationships become hierarchical “parent-child” links. Sometimes this hierarchical structure is called a “tree,” with the root at the top and branching downward. In hierarchies, there is an ordered connection between an item and the item or items below it.

A thesaurus is a higher order form of semantic model than a taxonomy because its associations contain additional inherent meaning. In other words, a thesaurus is a taxonomy with some additional semantic relations in the form of a controlled vocabulary. The nodes in a thesaurus are “terms,” meaning they are words or phrases. These terms have “narrower than” or “broader than” relationships to each other. A thesaurus also includes other semantic relationships between terms, such as synonyms.

Taxonomies and thesauri are limited in their semantic expressiveness because they offer only one dimensional axis on which to define relationships. As such, they are typically used to create a classification system, but they fall flat when trying to represent multidimensional and/or varied conceptual domains.

Concepts are the bearers of meaning as opposed to the agents of meaning. They are largely abstract and therefore more complex to model. Concepts and their relationships to other concepts, their properties, attributes, and the rules among them cannot be modeled using taxonomy. Other more sophisticated forms of models, however, can represent these elements. A semantic model in which relationships (associations between items) are explicitly named and differentiated is called an ontology. (In Figure 23, both conceptual models and logical theories can be considered ontologies, the former a weaker ontology and the latter a stronger ontology). Because the relationships are specified, there is no longer a need for a strict structure that encompasses or defines the relationships. The model essentially becomes a network of connections with each connection having an association independent of any other connection. Unlike a taxonomy, which is commonly shown as a “tree,” ontology typically takes the form of a “graph,” i.e., a network with branches across nodes (representing other relationships) and with some child nodes having links from multiple parents. This connective variability provides too much flexibility in dealing

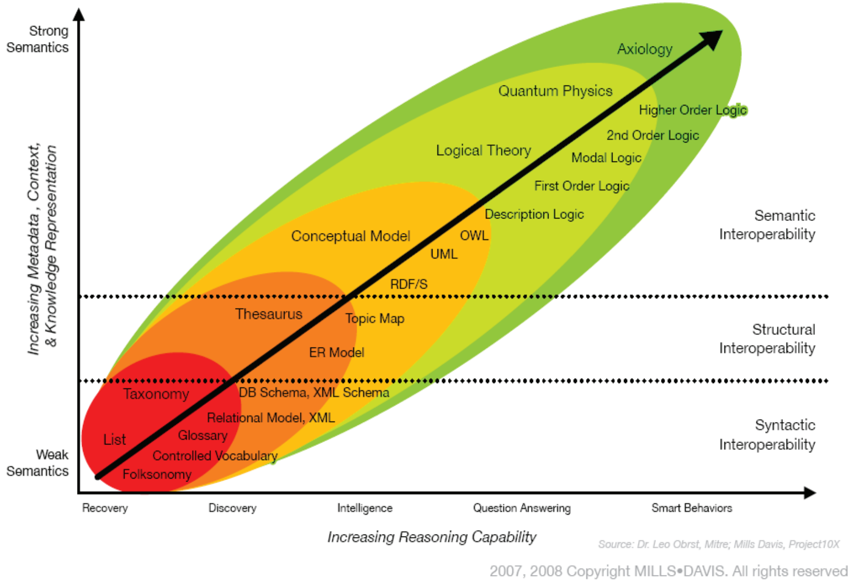


Figure 23. Spectrum of Knowledge Representation and Reasoning Capabilities.

with concepts, because many conceptual domains cannot be expressed adequately with either a taxonomy or a thesaurus. Too many anomalies and contradictions occur, thereby forcing unsustainable compromises. Moreover, moving between unlike concepts often requires brittle connective mechanisms that are difficult to maintain or expand.

Simple ontologies are mere networks of connections; richer ontologies can include, for example, rules and constraints governing these connections. Just as improvements in languages and approaches to model-based programming increased the ability to move from conceptual models to programmatic models without the need for human coding steps, similar advancements have taken place within ontological development. Whereas once ontologies were created primarily for human consumption, the development of robust protocols for expressing ontologies along with a growing infrastructure that support such models, provides increased capabilities for models to deduce the underlying context and draw logical conclusions based on these associations and rules.

The current state of the art on representing and using ontologies has grown out of several efforts that started in the 1980s. Early semantic systems initially suffered from a lack of standards for knowledge representation along with the absence of ubiquitous network infrastructures. With the advent of the World Wide Web and the acceptance of XML as a de facto standard for exchange of information on the Web, ontology efforts have started to converge and solidify. RDF, OWL, and Topic Maps (an ISO standard for representing networks of concepts to be superimposed on content resources) all use XML for serialization. This results in strongly typed representations (with public properties and fields contained in a serial format), making it easy to store and transport these models over the Web as well as integrate them with other web standards such as Web services. A cautionary note expressed by some in the knowledge management community is that there may be a proliferation of competing ontologies, which may in turn mean continued friction in achieving seamless sharing of structure and meaning across systems. Whereas different ontologies can be aligned for automated transformation from one model to another, it typically requires a good deal of human modeling to get to that point (aligning ontologies of any significant size can be similar to aligning large databases, a task that often requires significant planning and effort). These knowledge management professionals stress that significant benefits can result from using a widely shared foundational ontology, a subject that will be addressed in a later section.

4.2 Semantic Web Wedding Cake

Figure 24 is the Semantic Web layered architecture (Wedding Cake) presented by Tim Berners-Lee in 2000. Languages have increasing expressive power are layered on top of the other. The bottom layer is Unicode and URI, which form the basis of the architecture. Unicode makes people with different languages specify data in the same format. URI helps us indicate resources on the Web.

4.2.1 XML, Namespace, XMLSchema

The second layer from the bottom in Figure 24 consists of XML [83], namespace, and XML Schema. XML is the abbreviation of eXtensible Markup Language. It is a well-defined and flexible text format for electronic data publishing.

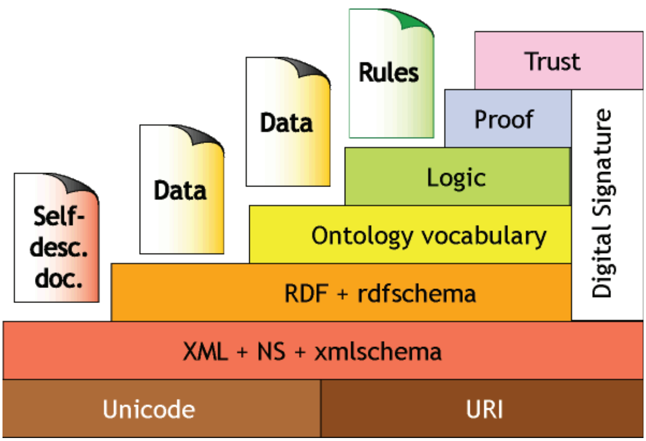


Figure 24. Semantic Web Wedding Cake (From Berners-Lee, XML 2000 Conference).

The structure of an XML document has to follow the defined standard so that it can be processed by computer automatically. Because of those characteristics, XML is suitable to be the underlying format for data exchange.

Namespace is used for resolving resources with the same name but in different URLs. With namespace, we can use the same name for resources in different documents. In XML Schema, there are some built-in datatypes definitions such as string, boolean, decimal, datetime, and etc. XML Schema helps us define data in those datatypes instead of just using strings. Therefore, all applications who know XML Schema can understand what is meant in a document written in that format. Conventionally, the namespace of XML Schema is named xsd, so when we want to represent an integer, we can write it as `<xsd:integer>100</xsd:integer>`. XML Schema provides the basic datatype system of the Semantic Web.

4.2.2 Resource Description Framework (RDF) & RDF-Schema

The next layer is RDF and RDF Schema. RDF [84] stands for Resource Description Framework, which provides a way to describe resources over the Internet. RDF is written in XML so that its underlying structure is based on XML syntax and structure. RDF can be used for knowledge sharing, resources cataloging and searching, etc. There are two major parts in RDF: Resources and Properties. Resources are identified using URIs, which can be a person, a book, or anything else. Properties are attributes used to describe a resource. A property's value can be a XML schema datatype or another resource. RDF expressions allow us to describe some resources by defining its related properties.

From another point of view, if we parse all contents in an RDF file, we can get the so called RDF, which is a set of triples composed of a resource's URI, a property, and a value. They are also called a subject, a predicate, and an object. All information in an RDF file can be represented as RDF triples. By the way, an RDF file can also be represented as a graph. If we set a subject as a node in a graph, and set its predicate as an outgoing edge from it to another node that represents its object, we can construct a graph representing the RDF triples. RDF also defined some data structures defined such as collection and container. RDF supports three type of container. They are rdf:Alt, rdf:Bag, and rdf:Seq. The collection data structure is also defined in RDF. RDF collection adopts the concept of list so that a collection is consist of a set of dummy nodes with first and rest properties to indicate real collection elements.

RDF Schema (abbreviated as RDF/S) is a schema language of RDF [85]. It is a semantic extension of RDF. RDF Schema vocabulary descriptions are written in RDF, so it is also an RDF document.

RDF Schema helps us define the relationships between resources and properties and add more semantics to the model described above. RDF/S supports defining the class and sub-classes relationship with the tags rdfs:Class and rdfs:subClassOf. It also supports defining domain and range of a property with the tags rdfs:domain and rdfs:range. Subproperties in RDF Schema is defined using the rdfs:subPropertyOf tag. RDF Schema can help people construct the relationships in a model.

RDF and RDF Schema provide the basic functionalities for semantic markup. However, their expressive power is not enough. The layer on top of them is ontology vocabulary. It provides more expressive power. Nowadays, some logics are adopted in this layer of the Semantic Web architecture. It is mainly based on Description Logics.

4.2.3 Ontology & Ontology Web Language

Ontology is a very important part in Semantic Web. It enables sharing, exchanging, and reusing knowledge by formalization of concepts of interest in a specific domain. When we want to describe something, we can use the definitions of an ontology to describe it. Therefore, concepts of the ontology can be used in communicating with each other. By referring to the same ontology, different entities can understand and talk to each other. Ontologies are very important in this work research. In this section, we introduce some current languages for ontology construction. Standardization of ontology languages has been an important issue in W3C for years. OWL (Web Ontology Language) [86] is their result and is going to become the new standard for ontology definition. OWL is a revision of DAML+OIL. There are some major modifications such as removing of synonyms for RDF and RDFS classes and properties, supporting versioning, renaming of some properties and classes, adding new classes and properties, and etc.

OWL has three sublanguages with different expressive power. They are OWL Lite, OWL DL, and OWL Full, respectively. OWL Lite supports classification hierarchy and simple constraints while having lower complexity, OWL DL is for users who need the maximum expressiveness without losing computational completeness, and OWL Full is the sublanguage with the maximum expressiveness and syntax freedom but no computational guarantees. OWL DL is an extension of OWL Lite, and OWL Full is an extension of OWL DL. So a legal OWL Lite ontology is also a legal OWL DL ontology and a legal OWL DL ontology is a legal OWL Full ontology too.

OWL is based on XML and RDF and all data in an OWL file can be represented as a set of RDF triples. An OWL document has four main parts in it. The first part is ontology header. It contains information about namespaces, version, imports, and compatibility with other OWL documents. The second part is class axioms. Class and subclass relationship definitions are in this part. The first letter of a class name should be capital. The third part is property axioms. Property definitions, which are domain and range, are defined here. The first letter of a property name should not be capital. The last part is individual (instance) axioms. Individuals of classes defined in the part of class axioms are declared here. By the way, all the four parts can be written in any order.

In OWL, we define classes using the <owl:Class> tag. A class can be subclass of one or multiple classes using <owl:subClassOf>. OWL has two built-in basic classes, owl:Thing and owl:Nothing, stand for top (everything) and bottom (empty set) respectively. Every user-defined class is implicitly a subclass of owl:Thing and every individual in OWL is in the set of owl:Thing individuals.

We can also define properties of a class. Like RDF, there are two kinds of properties in OWL. The ObjectProperty has points to a class or individual and DatatypeProperty points to a primitive datatypes such as integer, decimal, string, etc. These two kinds of property can be used to define properties or attributes of a class. We can model most of concepts in a rough way by combining the class and property.

Moreover, we can also define sub-properties of properties, transitive properties, and inverse properties of some other properties. For example, we can define ancestor as a transitive property, father as a sub-property of parent, child as an inverse property of parent.

Furthermore, OWL supports sameClassAs and samePropertyAs. They can help us to define classes or properties having the same content but different name. They are useful to define one concept with many different names. OWL also provides intersectionOf, complementOf, and disjointUnionOf, that helps us to form the concepts of models more completely.

In early 2004, W3C has announced that RDF and OWL are their recommendation for exchanging knowledge and representing information on the Web. In the announcement, they describe a infrastructure for sharing data on the Web. In the infrastructure, XML provides rules and syntax for structured documents, RDF forms a data framework for the Web, and OWL is used to publish and share ontologies. OWL adds more vocabularies for describing classes and properties in order to support advanced Web search, knowledge management, and software agents. In this research, is followed W3C's recommendation to build ontologies and construct knowledge bases.

4.3 Situation/Context Awareness and Semantic Sensor Web

Situation and context awareness applications employ sensor networks to collect large amounts of heterogeneous data in different and complex environments. Furthermore, the rapid development and deployment of sensor technology stress the problem related to the availability of too much and heterogeneous data. So, last trend emphasizes the semantic annotation of acquired sensor data. Semantic sensor data provides machine understandable contextual information. In particular, the Semantic Sensor Web (SSW) is an approach to annotating sensor data with spatial, temporal, and thematic semantic metadata. In other words, sensor data can be annotated with semantic metadata to increase interoperability between heterogeneous sensor networks, as well as to provide contextual information essential for situation/context awareness. Semantic web techniques can greatly help with the problem of data integration and discovery as it helps map between different metadata schema in a structured way. This technique builds on current standardization efforts within the Open Geospatial Consortium (OGC)[3] Sensor Web Enablement (SWE)[4] and extends them with Semantic Web technologies to provide enhanced descriptions and access to sensor data. Specifically, the SSW enhances meaning by adding semantic annotations to existing standard sensor languages of the SWE. These annotations provide more meaningful descriptions and enhanced access to sensor data than SWE alone, and they act as a linking mechanism to bridge the gap between the primarily syntactic XML-based metadata standards of the SWE and RDF/OWL-based metadata standards of the Semantic Web. In association with semantic annotation, ontologies and rules play an important role in SSW for interoperability, analysis, and reasoning over heterogeneous multimodal sensor data.

4.3.1 From Semantic Sensor Data to Situation/Context Awareness

The aim of this subsection is to highlight the existing relation between SSW and Situation/Context Awareness applications. Specifically, the author here is trying to clarify as semantic technologies and in particular standardization efforts, in this sense, to achieve a global semantic sensor web, have a meaningful impact on situation and context aware applications. Architectural overviews and application scenarios (described in the following sections) in this work concerns with the hybrid application of computational intelligence and semantic web technologies to achieve situation/context awareness in several applications. Specifically, an abstraction of the process, followed in the proposed application scenarios, to extract knowledge from sensor data is depicted in Figure 25.

Firstly, the process foresees the semantic annotation of acquired sensor data according to space, time and domain ontologies. In this regard, several ongoing initiatives are helping to build relevant ontologies within various communities, such as the US National Institute of Standards and Technology (www.nist.gov/), the W3C, and the OGC. NIST has initiated a project titled "Sensor Standards Harmonization" to develop a common sensor ontology based on the existing standards within the sensor domain, including IEEE 1451, ANSI N42.42, the Chemical, Biological, Radiological, and Nuclear (CBRN) Data Model, and the

[3] http://www.opengeospatial.org/

[4] http://www.opengeospatial.org/projects/groups/sensorwebdwg

OGC SWE languages. Several efforts are also underway to design an expressive geospatial ontology, including the W3C Geospatial Incubator Group (www.w3.org/2005/Incubator/geo/) and the Geographic Markup Language Ontology (http://loki.cae.drexel.edu/~wbs/ontology/ogc-gml.htm) of the OGC. OWL Time (www.w3.org/TR/owl-time/), a W3C-recommended ontology based on temporal calculus, provides descriptions of temporal concepts such as instant and interval, which supports defining interval queries such as within, contains, and overlaps. Domain-specific ontologies that model various sensor related fields such as weather and oceanography (www.oostethys.org/) are also necessary to provide semantic descriptions of thematic entities [87].

Secondly, the proposed process foresees the extraction of features and the detection of entities. Extracted features and detected entities characterize situations or contexts involved in the several applications. Specifically, the research work in this thesis leveraged on one side on Situation Theory Ontology (STO) to represent information about situations in situation aware applications and, on the other side, on Web Service Ontology (WSO) for context-aware discovery of web services in context aware applications. STO and WSO will be described in more detail in the following.

Finally, the process foresees semantic analysis and querying of situation or context awareness model to extract useful situation/context knowledge. In order to achieve these tasks the dissertation propose the use of an established RDF query language, namely SPARQL. Furthermore, the author proposes a flexible extension of this language to enable approximate querying of semantic data models, that is, f-SPARQL. Also, these semantic technologies will be discussed in the following of this chapter.

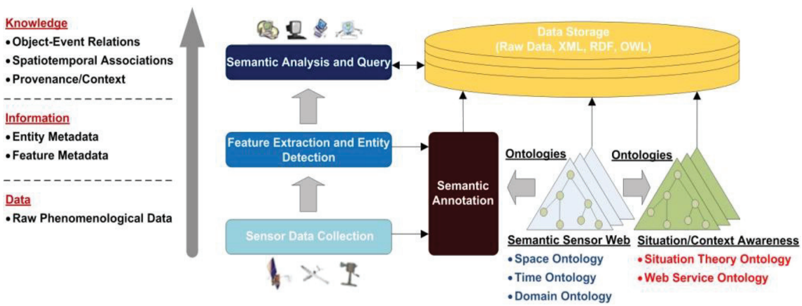


Figure 25. Semantic Sensor Data to Situation/Context Knowledge process.

4.4 Ontology-based Situation Theory

Although the notion of ‘‘situation awareness’’ is part of the data fusion lexicon [88], this term has been used with a number of different meanings.

The earliest formal notion of situation was introduced by Barwise and Perry to give a more realistic formal semantic for speech acts than what was available till then [89][90][91]. Furthermore, in [93] a formal framework for Situation Theory (ST) has been developed and successively extended by Devlin [93][94].

In ST, information about a situation is expressed in terms of infons. Infons are written as (4.4.1)

$$\sigma_i \equiv \ll R, a_1, \dots, a_n, \varphi \gg \qquad (4.4.1)$$

where R is an n-place relation and $a_1, \dots, a_n$ are objects appropriate for R. Since ST is multi-sorted, the word ''appropriate'' means that the objects are of the types appropriate for a given relation. The last item in an infon, φ, is the polarity of the infon. Its value is either 1 (if the objects stand in the relation R) or 0 (if the objects don't stand in the relation R). Infons may be recursively combined to form compound infons by using conjunction, disjunction and situation-bounded quantification.

To capture the semantics of situations, ST provides a relation between situations and infons. This relationship is called the supports relationship and relates a situation with the infons that ''are made factual'' by it. Given an infon σ and situation s the proposition ''s supports σ'' is written as $s \models \sigma$.

In [95] has been presented a formalization of Barwise's situation semantics [90] in terms of an ontology, with some parts using mathematics and rules, such an ontology has been named STO.

4.4.1 From a Fuzzy Extension of Situation Theory to Fuzzy Situation Theory Ontology

During the application of ontologies, more and more practitioners realized the difficulty in describing uncertain knowledge. SA is usually applied in very complex and dynamic environments and the uncertainty modeling becomes primary. For example, in Airport Security domain the uncertainty degree which a situation happens can become fundamental.

Fuzzy Situation Theory Ontology (FSTO) meta-model for SA can evolve in a natural way towards the approximation and uncertainty modeling. In this section, the author will try to explain how fuzziness has been introduced in the above model. Devlin states that ''infons are not things that in themselves are true or false. Rather a particular item of information may be true or false about a situation.'' [12].

Thus, in our interpretation, the polarity of a *infon* σ_i supporting a situation s_j can be one out of the terms defining a linguistic variable expressing infon's truth. For instance, let us say

$$(InfonTruth, \Im(G), [0..1], G, M) \qquad (4.4.2)$$

be the aforementioned linguistic variable where, G is the grammar generating terms in $\Im(G)$ and M is the semantic rule which associates each linguistic value with its meaning. The definition of the context free grammar G involves $(true, false)$ as primary terms (whose membership function definitions are depicted in Figure 26a), a finite number of hedges $(more\ of\ less,\ quite,\ really, \dots)$ whose evaluation in M is performed by means of concentration and dilation, the connectives and and or, and the negation not. Thus, the syntax of the linguistic variable given by the grammar is such that the set of terminal symbols in $\Im(G)$ consists of primary terms, modifiers, connectives and negations.

According to (4.4.3), an infon σ_i supporting a situation s_j is written as:

$$\sigma_{i,s_j} \equiv \ll R_i, a_1, a_2, \dots, a_n, \tau_{\sigma_{i,s_j}} \gg with\ \tau_{\sigma_{i,s_j}} \in \ \Im(G) \qquad (4.4.3)$$

stating that $R_i(a_1, a_2, \dots, a_n)\ is\ \tau_{\sigma_{i,s_j}}$ in s_j.

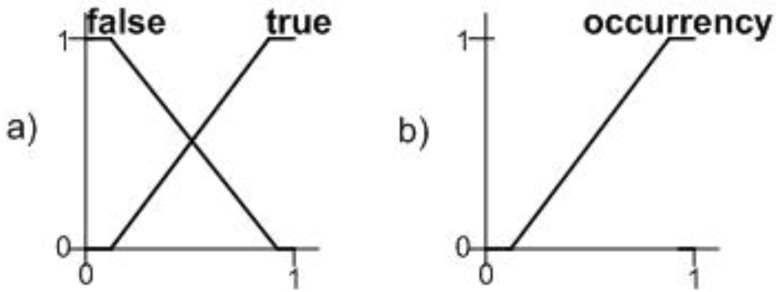


Figure 26. Membership functions definitions for a) Infon Truth and b) Occurrency.

By adopting this modeling approach, the semantic of *support* proposition $\models$ can be stated as

$$s_j \models_{ext} \{\sigma_{i,s_j}\} \iff \forall\, i:\ R_i(a_1, a_2, \dots, a_n)\ is\ \tau_{\sigma_{i,s_j}} \qquad (4.4.4)$$

This interpretation lead us to define a modeled situation occurrence as the evaluation of a corresponding fuzzy control rule:

IF $R_1\left(a_{1,1}, a_{1,2}, \dots, a_{1,n_1}\right)\ is\ \tau_{\sigma_{1,s_j}}$
AND …
AND $R_i\left(a_{i,1}, a_{i,2}, \dots, a_{i,n_i}\right)\ is\ \tau_{\sigma_{i,s_j}}$ THEN (4.4.5)
$s_j\ is\ occurring$

otherwise formalized as:

$$\mu_{occ}(s_j) = \bigwedge_i \mu_{\tau_{\sigma_{i,s_j}}}\left[R_i\left(a_{i,1}, a_{i,2}, \dots, a_{i,n_i}\right)\right] \qquad (4.4.6)$$

where $\bigwedge$ is a suitable t-norm operator and *Occurrency* is a fuzzy set modeled as depicted in Figure 26b.

FSTO formal definition for a situation model provides an efficient fuzzy-based interpretation model for infons and situations aimed at supporting approximate evaluation of situations thus satisfying predicibility requirements in complex and dynamic domains. This approach has been extended in order to meet the need for managing multiple perception sources, each of them characterized by a specific uncertainty model.

Namely, the infon ontological definition has been modified to introduce UncertainValues bound to a weighted UncertaintyModel concurring to the identification of both value and certainty of the elementary infon value (see Figure 27).

Let's be $\{\bar{\sigma}_h = \ll R_i, a_1, a_2, \dots, a_n, \delta \gg\}_{h \in H}$ the set of acquired infons instances contained in the facts base (a-box) relevant for s_j (for which it is possible to build a semantic graph matching the definition of s_j), then for each perception step producing an assertion about a given property or relation coming from a specific sensor associated to a given uncertainty model, the δ value of the corresponding infon $\bar{\sigma}_h$ during the evaluation process is calculated as (4.4.7)

$$\delta = \frac{\sum_{j=1}^{n} c_j v_j w_j}{n} \qquad (4.4.7)$$

where n is the number of different assertions made about the infon values under different sensors, c_j is the certainty of the asserted value v_j and, finally w_j is the weight of the uncertainty model of the source sensor. w_j is interpreted as the reliability of the uncertainty model associated to a given sensor and allows to take into account noisy measurements or assertions at the perception stage.

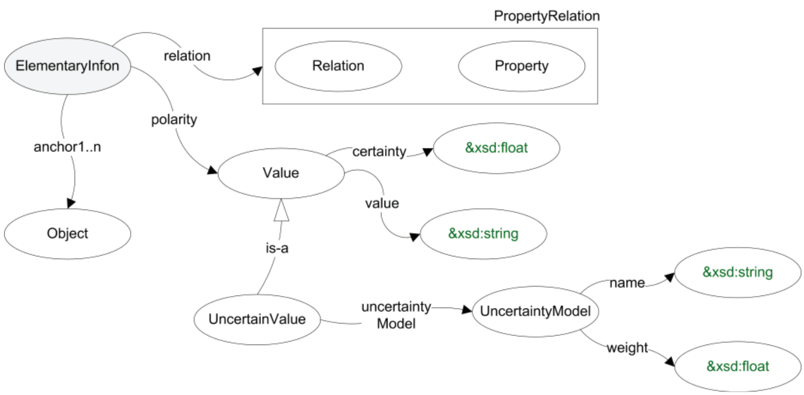


Figure 27. Elementary Infon ontological definition.

4.5 Web Service Ontology

Because of web services are useful in an open environment like the Internet in general and in context aware applications in particular, there must be a general agreement on how they are represented. It is therefore a need for a standardized framework that provides the necessary languages and guidelines to describe services and their capabilities.

Such a framework needs to be general enough so that it can be used to represent a variety of services, and at the same time restrict the usage to avoid ambiguous representation and unnecessary complexity.

OWL-S is an upper ontology whose root class is the Service class, which is associated with three other classes: ServiceProfile, ServiceModel and ServiceGrounding (see Figure 28). The description of services also requires a domain ontology because the main elements of a service description are concepts or individuals of a domain ontology.

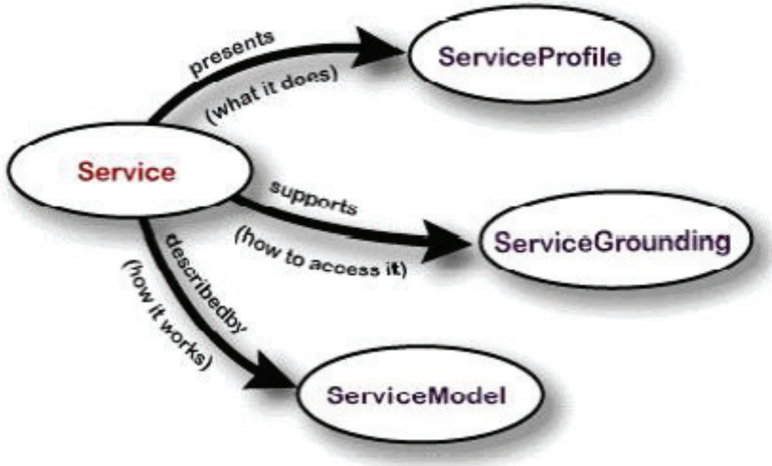


Figure 28. Top level of web services ontology.

4.5.1 Service Profile

The service profile describes the service for the purpose of discovery by providing several types of information:

- Human readable information
  - service name, service description, contact information
- Functionalities (IOPE)
  - parameter type identifiers,
  - identifiers of the input and output parameters of service methods,
  - preconditions
  - results
- Service parameters
  - identifier of a parameter (name, value) used by the service
- Service category
  - identifier of a category of service (category name, taxonomy, value, code).

4.5.2 Service Process

An OWL/S process model describes the composition or orchestration of one or more services in terms of their constituent processes. Process subclasses have been defined: an atomic process is a description of a service that expects one message and returns one message in response; a composite process consists of a set of process and a simple process. Each process can have any number of inputs to represent information under some conditions. The outputs of process provide the information to the requester under a number of preconditions, which must all hold in order for the process to be successfully invoked. Effects of process characterize facts that become given a successful execution of the service.

4.5.3 Service Grounding

The service grounding specifies the details of the access to the service such as message formats, protocols. This sub-class enables the transformation from inputs and outputs of atomic process into concrete atomic process grounding constructs.

4.6 Semantic Web Querying

It is possible today to utilize networks of sensors to detect and identify a multitude of observations, from simple phenomena to complex events and situations. SSW proposes that sensor data be annotated with semantic metadata that will both increase interoperability and provide contextual information essential for situational knowledge. In this scenario plays a key role the ability of analyzing and querying semantic sensor web models as well as situation/context awareness models in order to extract knowledge useful to achieve a good situation/context awareness in several application domains. Specifically, in the following subsections the author shortly presents SPARQL as base semantic query language and propose a flexible extension of it. The proposed extension allows the execution of approximate queries as well as clustering and classification of semantic individuals.

4.6.1 SPARQL

SPARQL (pronounced "sparkle", a recursive acronym for SPARQL Protocol and RDF Query Language) is an RDF query language, that is, a query language for databases, able to retrieve and manipulate data stored in Resource Description Framework format. It was made a standard by the RDF Data Access Working Group (DAWG) of the World Wide Web Consortium, and considered as one of the key technologies of semantic web.

SPARQL allows users to write unambiguous queries. For example, the query in Figure 29 returns the list of all CDs after 2000 in the dataset:

SPARQL QUERY

```
PREFIX cd: <http://example.org/cd/>
        SELECT ?title ?year
        FROM  <http://cd.com/listacd.ttl>
        WHERE {
                ?title cd:year ?year.
                FILTER (?year > 2000).
        }
```

Figure 29. An example of SPARQL query.

Like SQL, SPARQL selects data from the query data set by using a SELECT statement to determine which subset of the selected data is returned. Also, SPARQL uses a WHERE clause to define graph patterns to find a match for in the query data set.

A graph pattern in a SPARQL WHERE clause consists of the subject, predicate and object triple to find a match for in the data.

Figure 30. SPARQL general form.

SPARQL queries take general form showed in Figure 30; in particular it depicts the sections into which a query may be broken down and the clause or keyword which defines that section.

Finally, the SPARQL language specifies four different query variations for different purposes.

- SELECT query
  - Used to extract raw values from a SPARQL endpoint, the results are returned in a table format.
- CONSTRUCT query
  - Used to extract information from the SPARQL endpoint and transform the results into valid RDF.
- ASK query
  - Used to provide a simple True/False result for a query on a SPARQL endpoint.
- DESCRIBE query
  - Used to extract an RDF graph from the SPARQL endpoint, the contents of which is left to the endpoint to decide based on what the maintainer deems as useful information.

Each of these query forms takes a WHERE block to restrict the query although in the case of the DESCRIBE query the WHERE is optional.

4.6.1.1 f-SPARQL

SPARQL [96] can be used to express queries over RDF data sets. SPARQL FILTERs restrict solutions to those for which the FILTER expression evaluates to TRUE. Until now, however, standard SPARQL processes information only in a crisp way. Therefore, existing SPARQL implementations, such as ARQ1 and Sesame2, do not allow users to form queries with preferences or vagueness, which could be desirable for the following reasons [97]:

1. to express soft query conditions;
2. to control the size of the answers;
3. to produce a discriminated answer.

Example. *An advertisement company requires 30 models which are close to 175cm and not very young and not very old*.

Apparently, SPARQL can not efficiently express and answer such a request. To address this problem, the authors in [98] propose a flexible extension of SPARQL, called f-SPARQL. It allows, in FILTER constraint, the occurrence of fuzzy terms, e.g. young or tall, and fuzzy operators, e.g. close to or at most. The fuzzy terms and fuzzy operators along with the query variables form the so-called fuzzy constraints. Furthermore, we need to take into account the membership degree threshold for every fuzzy constraint. The reason for this is the fact that each tuple satisfies a fuzzy constraint to a certain degree and hence if no threshold specified, all tuples are retrieved always. To avoid reinvent the wheel, the authors in [98] develop a set of translation rules for converting flexible queries formalized with f-SPARQL into traditional crisp SPARQL queries, and thus we can still make use of existing SPARQL implementations. However, there is still a sweet nuisance if more than 30 models satisfied the fuzzy constraint user specified. This poses a new challenge in case we must rank these candidates according to a certain standard and select the top 30. The introduction of weights allows different fuzzy constraints to have different importance.

During research studies the author has implemented a framework to perform approximate queries quite similar to the approach described in [98]. f-SPARQL has been implemented in JAVA, it can be interpreted as a wrapper to ARQ implementation of SPARQL. Pratically, as highlighted in Figure 31, it translates a query f-SPARQL into a standards crisp query language SPARQL by exploiting α-cut on a membership function describing a fuzzy term of a fuzzy set, so that the query can be evaluated through the ARQ engine, and in the end, on obtained results are applied some transformations to achieve different goals.

In particular the author has addressed two issues that were not discussed in the article [98], that is:

- how to define fuzzy sets;
- how to make classification.

The solution of these issues has been inherited by jFuzzyLogic[5], a java package that implements the specifications of the Fuzzy Control Language (FCL).

[5] http://jfuzzylogic.sourceforge.net/html/index.html

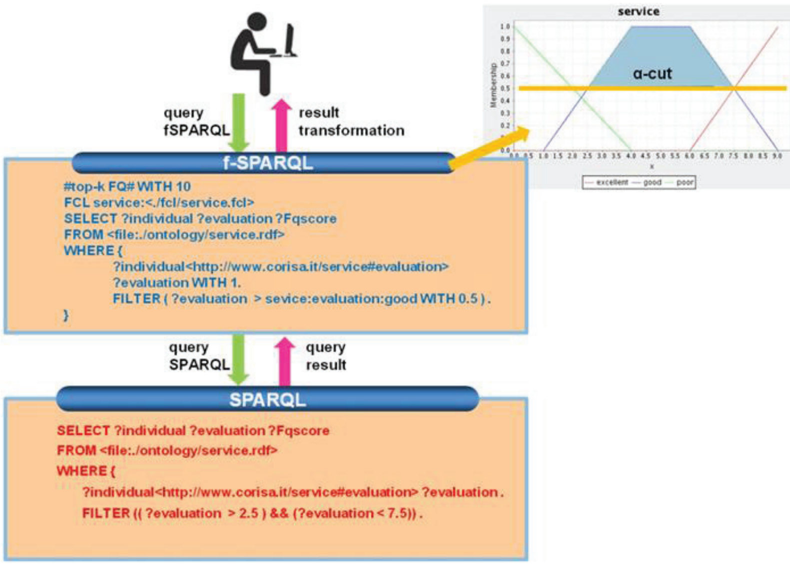


Figure 31. f-SPARQL query transformation process.

4.6.1.2 f-SPARQL facilities for Clustering and Classification

The implementation of f-SPARQL framework by the author has considered not only the important aspect of approximate querying in order to enhance conventional SPARQL querying, but it has also dealt with the possibility to enable fuzzy clustering and classification of semantic individuals. So, a further extension of f-SPARQL has been proposed by the author during his research studies. In particular, the proposed implementation of these facilities is based on Fuzzy c-means (FCM) algorithm [99]. In particular, the work considers N-dimensional centroids, where each dimension represents a Data Property corresponding to a feature on which we want to carry out clustering.

The clustering process involves two steps:

1. Identification of k centroids on dataset;
2. Classification of individuals according to centroids identified.

In order to accomplish the first step, in f-SPARQL framework has been defined a query, namely *“#CQ#”*. An example of this type of query is shown in Figure 32.

The first line (i.e., #CQ# 2 2 0.1 50) defines the methodology to detect centroids, specifying the number of centroids to found, the fuzziness value, the accuracy to achieve and the maximum number of iterations if during the execution, the desired accuracy is not reached, respectively.

In the example shown in Figure 32, we want to cluster individuals in two classes, so we set 2 centroids, with fuzzyness value 2, accuracy value 0.1, and a maximum number of iterations equal to 50.

f-SPARQL Query for Clustering

```
#CQ# 2 2 0.1 50
PREFIX pre:<http://www.corisa.it/butterflyDataset#>
ONPROPERTY pre:a pre:b
FROM file://C:/UniSA/Thesis/ontology/FuzzyOntologies/butterfly.rdf
```

Figure 32. f-SPARQL sample query for Clustering.

The *PREFIX* clause (as in the standard SPARQL query) associates short label with a specific URI. *ONPROPERTY* clause defines Data Property on which we want clustering. Furthermore, we can use the syntax *"ONPREOPERTY *"* in order to consider all data properties for clustering, when all individuals contain numeric values. Finally in the *FROM* clause we can specify the training dataset, on which we would retrieve the centroids.

Once obtained centroids, we are able to extract the fuzzy rules used for the fuzzy classification of individuals (i.e. the second step).

First, will need to define Fuzzy Sets and Fuzzy Term, so, for each cluster, we define functions from which to derive the membership degree. In particular, we define:

- as many fuzzy sets as the centroids' dimensions;
- each fuzzy set will be described by many fuzzy terms as the number of clusters.

The resulting linear functions are obtained by calculating for each individual of training data set, the similarity with respect to each centroid dimension.

Let $sim_{ijp} = \frac{1}{1+d_{ijp}}$, the similarity value, where d_{ijp} is the Euclidean distance with respect to dimension p and the index i and j correspond to i-th individual and j-th centroid, respectively.

In Figure 33 are shown the two fuzzy sets, a and b, resulting from the previous f-SPARQL Clustering query.

These functions can be automatically designed and store in an FCL-like file. Specifically, this file involves fuzzy sets and fuzzy term descriptions as well as the definition of a block of rules concerning with the clauses which must be fulfilled in order to assign an individual to a specific cluster. These rules will be after translated into f-SPARQL filters enabling us to perform the fuzzy classification of individuals.

As a result, a format for f-SPARQL Classification query has been defined. In particular, as depicted in Figure 34, this type of query consists of two parts; the first part, defining the classification rules and the second part, specifying the individuals to classify.

In the sample query in Figure 34 we want to classify, with respect to the two input centroids, only those individuals whose value for the Date Property "a" is greater than 4. Furthermore, we want the result to be sorted in a decreasing way relatively belonging degree to cluster "0". In particular we identify in the first part of query, the clause *CENTROIDS*, which will specify the value of fuzziness and the classification rules as filters f-SPARQL. On the other hand, the second part of query can be specified according to f-SPARQL.

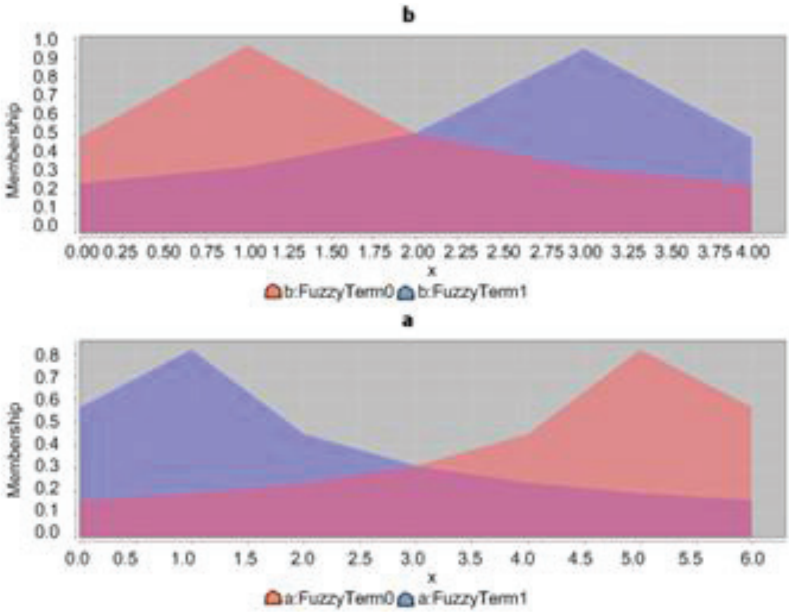


Figure 33. Example of fuzzy sets obtained by f-SPARQL Clustering query.

f-SPARQL Query for Classification

```
#CQ#
CENTROIDS {
    FUZZYNESS : 2.0 .
    c0 : ((?b >= write:b:FuzzyTerm0 WITH 0.0) && (?a >= write:a:FuzzyTerm0 WITH 0.0)).
    c1 : ((?b >= write:b:FuzzyTerm1 WITH 0.0) && (?a >= write:a:FuzzyTerm1 WITH 0.0)).
    ORDER BY DESC(c0)
}
FCL write:<./fcl/write.fcl>
SELECT ?individual ?b ?a
FROM <file:./ontology/butterfly.rdf>
WHERE {
    ?individual <http://www.corisa.it/butterflyDataset#b> ?b WITH 1.0 .
    ?individual <http://www.corisa.it/butterflyDataset#a> ?a WITH 1.0 .
    FILTER (?a > 4) .
}
```

Figure 34. f-SPARQL sample query for Classification.

4.7 Conclusions

This chapter synthesizes the semantic technologies that will be used and referenced throughout this thesis. In particular, ontologies and languages enabling the processes of semantic annotation and querying of sensor observations have been described.

These processes have a key role in the following of this thesis where situation and context awareness hybrid approaches will be discussed and application scenarios in different domains will be analyzed. Therefore, the aim of this chapter is to introduce the technological and ontological background behind the research of the work thesis.

Part II: Proposed Approaches & Research Objectives

Chapter 5

Situation and Context Awareness Approaches

As aforementioned, the research work focuses on two main topics: Situation Awareness and Context Awareness. The aim of this chapter is to clarify the author's interpretation about these two topics. In particular, SA in the vision of the author is based on the Endsley model for SA described as "the perception of the elements in the environment within a volume of time and space, the comprehension of their meaning and the projection of their status in the near feature" [100]. Whereas, CA is interpreted as the capability of devices (especially, mobile devices) to acquire context (e.g. using sensors to perceive a situation), abstract and understand context (e.g. matching a perceived sensory stimulus to a context), and apply behavior based on the recognized context (e.g. triggering actions based on context).

Specifically, in this chapter the author defines two general approaches for SA and a general approach for CA according to the aforementioned definitions. Then in the following of this thesis the proposed general approaches will be instantiated in several application domains and case studies will be discussed.

On the other hand, these general approaches have been applied in order to face with different problems such as: knowledge representation, semantic reasoning, pattern recognition, information retrieval, etc.. So, the aim of the author is to emphasize in which terms the proposed approaches have a positive impact on these problems.

This chapter introduces two general approaches for Situation Awareness (see Section 5.1 and Section 5.2) and a general approach for Context Awareness (see Section 5.3) referenced throughout this research work. Subsequently, some specific research objectives achievable by the application of the proposed approaches will be discussed (see Section 5.4).

5.1 Cognitive Multiagent Situation Awareness (CoMSA)

This approach for Situation Awareness is based on the Endsley model [100], therefore, three main phases have been identified (see Figure 35 below): perception, providing the ability to perceive the environment; comprehension, dealing with the integration of perceived information in order to determinate their relevance to the goals; and finally projection, aimed at evaluating current situations and forecasting future situation events and dynamics in order to anticipate future events and their implications.

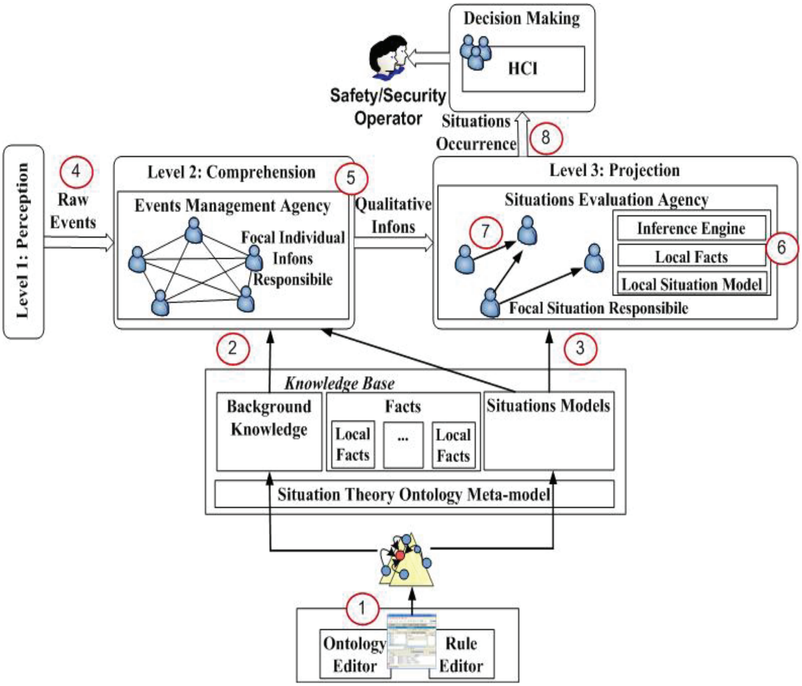


Figure 35. Logical Process of CoMSA Approach.

Figure 35 illustrates the overall process of this approach for SA. Essentially, it consists of the following steps:

1. application domain individuals and relevant situations modeling;
2. from the analysis of domain knowledge and the identification of focal individuals instantiating a network of agents suitable for the generation of infons (according to STO or FSTO) related to focal individuals;
3. from the analysis of situation models to monitor and the identification of focal individuals instantiating a network of agents for the monitoring of the situation for each relevant element of the scene;
4. the raw data acquired from sensors are semantically annotated (according to SSW) and transformed in domain events;
5. the statements identified (understood), as a result of events occurring, are forwarded in form of infons to the projection layer;
6. each agent responsible for a given situation has a local knowledge of the facts (infons/situations), necessary and sufficient for the assessment of situations under its responsibility;

7. the identified situations are transmitted among the agents providing only the qualitative result of the evaluation, and leaving to the inference engine the possible derivation of infons;
8. qualitative information on the occurrence of a given situation are transmitted to operators/systems in order to support decision making activities.

Therefore, CoMSA approach foresees on one side the exploiting of semantic technologies for the domain modeling and the semantic annotation of sensor observations; on the other side, it foresees the exploiting of situation theory meta models, firstly to dynamically organize the network of agents and secondly to support distributed semantic reasoning (or semantic fuzzy reasoning). So each agent in the network performs a specific task and cooperate with others in order to detect the occurrence of a relevant situation as a result of the simultaneous occurrence of a set of infons supporting it.

From a practical point of view, semantic modeling of domain may be achieved by domain or thematic ontologies, whereas semantic annotation of sensor observations may be realized by using semantic sensor web ontologies. On the other hand, STO or FSTO may be successfully employed to model situations and support reasoning, whereas multi-agent frameworks (e.g. JADE[6]) are available to simplify the implementation of multi-agent systems.

Anyway, in this approach the organization of agents network is strongly related to the instantiation of focal individuals, concerning with static and dynamic objects involved in the observed scenario, as well as the relevant situations to monitor. Furthermore, domain and situations modeling is not supported by automatic tool or unsupervised techniques, so it is necessary the support of expert knowledge to achieve these tasks.

In these sense, the approach for SA discussed in the following section, tries to overcome these problems by exploiting data analysis and computational intelligence techniques.

In the following of this thesis, a case study based on this approach and applied to the Airport Security application domain will be widely discussed.

5.2 Swarm-based Enhanced Situation Awareness (SbESA)

SbESA approach, proposed in this section, concerns with an evolution of CoMSA approach. Specifically, also this approach is based on Endsley model for SA, so it involves perception, comprehension and projection phases, but each of this phase presents substantial changes and evolutions with respect to CoMSA approach.

Figure 36 illustrates the overall process of this approach for SA. Essentially, it consists of the following steps:

1. The first step consists in a training phase, whose aim is to analyze semantic sensor observations in order to identify relevant situations (patterns). Specifically, in this phase an unsupervised clustering algorithm on sensor data is executed; furthermore, a classifier is designed according to clustering results. So the output of this phase is represented by a set of classification rules for the identified relevant situations;

[6] http://jade.tilab.com/

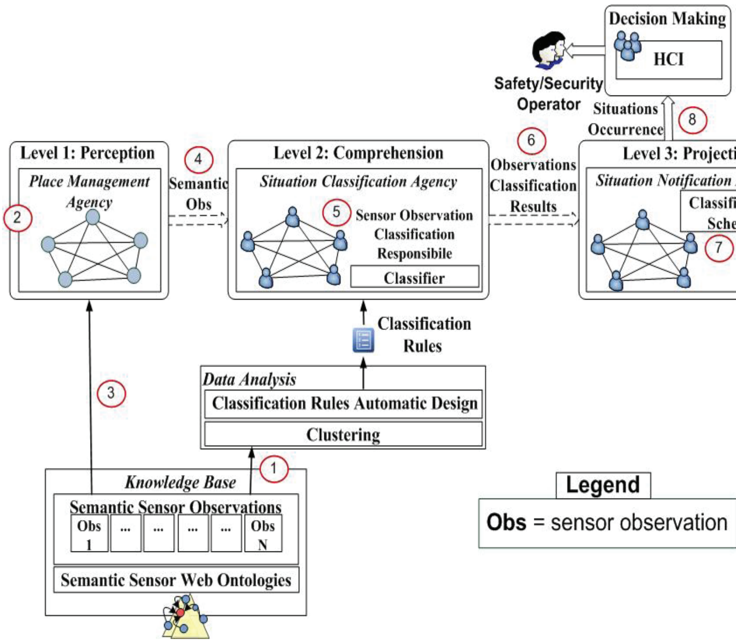


Figure 36. Logical Process of SbESA Approach.

2. a network of place agents is instantiated. In particular, we have a place agent for each sensor;
3. each place agent is responsible of acquiring and managing observations related to a sensor;
4. a population of classification agents receives semantic sensor observations by place agents;
5. each classification agent performs the classification of semantic observations corresponding to a sensor and determine their belonging to a relevant situation;
6. a population of notification agents receive the observations classification results;
7. notification agents notify classification results according to previously received classification results and to their classification schema (e.g. distributed classification schema, composed classification schema, etc.);
8. qualitative information on the occurrence of a given situation are transmitted to operators/systems in order to support decision making activities.

This approach foresees the use of semantic technologies for the semantic annotation of sensor observations and relevant situations; on the other hand, it foresees the execution of a training phase consisting in the execution of an unsupervised clustering algorithm in order to organize sensor observations according to relevant situations (patterns). Then it foresees the application of a technique for the automatic extraction of classification rules from clustering data. These classification rules are exploited in a next step of the process in order to bind sensor observations to relevant situations.

A peculiarity of SbESA approach is represented by the simultaneous deployment of different types of agent populations with different tasks and whose communication is not necessarily direct. In other words, the agents in this proposed approach may coordinate their activity and communicate their results through markers in a shared dynamic environment. Thanks to this idea the approach allows a distributed classification of sensor observations aimed to infer relevant situations in a specific domain.

From a concrete point of view, semantic modeling of sensor network as well as semantic annotation of sensor observations may be realized by using SSW ontologies, whereas STO or FSTO may be successfully employed to model relevant situations. On the other hand, f-SPARQL framework may be employed to support unsupervised clustering and classification of semantic sensor observations. Finally Swarm Intelligence theory (see Section 3.2, Section 3.3 and Section 3.4) may be the solution for a collective, decentralized, self-organized multi-agent system. In this sense, the coordination of agents may be addressed with stigmergetic interactions, that is, agents move and dynamically organize themselves by using artificial pheromones and each node in the distributed sensor network is interpreted as a location where agents may deposit or sense pheromones (see Section 3.4.2). Multi-agent simulation environments (e.g. MASON[7]) are available to simplify the implementation of swarm-based systems.

This approach also consider the employment of ontologies to dynamically instantiate the network of place agents (one for each sensor), but the number and typologies of population agents as well as the number of agents for each population are considered as configuration parameters. On the other hand, thanks to the training phase as first step of the process this approach allows to identify relevant situations in unsupervised way, that is, without expert knowledge.

During the dissertation, two case studies based on this approach and applied to Traffic Jam Management and Smart Grids application domains will be widely discussed.

5.3 Context Aware Proactive Service Discovery (CAPSD)

The proposed approach for CA is based on the idea that context aware systems are concerned with the acquisition of context (e.g. using sensors to perceive a situation), the abstraction and understanding of context (e.g. matching a perceived sensory stimulus to a context), and application behavior based on the recognized context (e.g. triggering actions based on context). In particular, the approach is aimed to attain environment monitoring by means of sensors to provide relevant information or services according to the identified context and consists of three phases: User Context Analysis and Identification, Semantic Web Services Definition and Context Aware Brokering.

Figure 37 illustrates the overall process of CAPSD approach. Essentially, it consists of the following steps:

1. acquisition of services context by Domain Services Modeling Agency;
2. Domain Services Modeling Agency models services adding context information to their definition;

[7] http://cs.gmu.edu/~eclab/projects/mason/

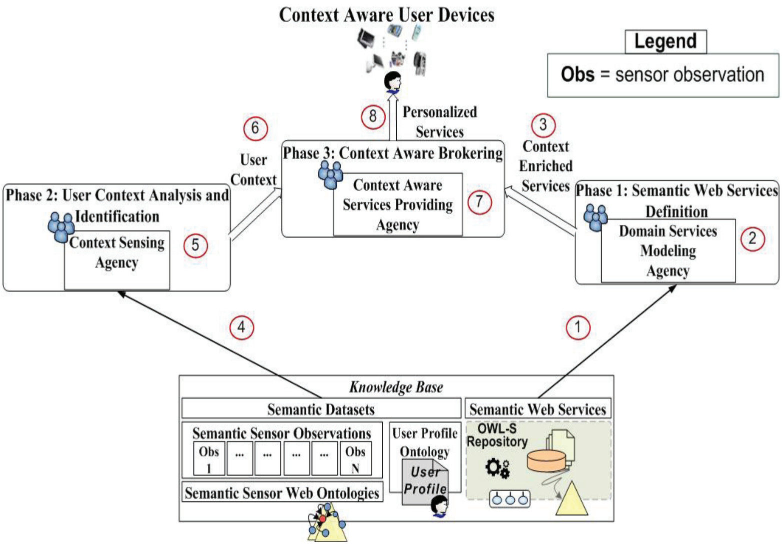


Figure 37. Logical Process of CAPSD Approach.

3. Domain Services Modeling Agency sends a list of Context Enriched Services to Context Aware Services Providing Agency;
4. user context (i.e. static or dynamic) is acquired by Context Sensing Agency;
5. Context Sensing Agency performs context analysis and identification;
6. Context Sensing Agency sends Identified User Context information to Context Aware Services Providing Agency;
7. Context Aware Services Providing Agency performs a matchmaking algorithm in order to filter the list of Context Enriched Services according to Identified User Context information;
8. Context Aware Services Providing Agency provides user applications with a list of personalized services.

This approach foresees the use of domain ontologies to model static (e.g., user profile, preferences, etc.) and dynamic context (i.e., sensor observations) data. Furthermore, it foresees the use of semantic web services in order to enrich services with context information. On the other hand, soft computing techniques should be employed in order to analyze and identify user context as well as for semantic web services matchmaking.

From a technological point of view, user context may be modelled according to Semantic Sensor Web ontologies whereas OWL-S may be successfully employed for the semantic modelling and definition of web services. Furthermore, fuzzy data analysis with the generation of fuzzy classifiers may be useful to automatically recognize user context. The process of unsupervised fuzzy data analysis enable to enrich context modelling with qualitative representation of underling data. Finally, in order to evaluate matchmaking among user context and context services, techniques based on hybrid approaches combining description logic and fuzzy logic should be considered. Task oriented agents perform all the aforementioned activities with the aim to elicit highest suitable services among the available ones. Also in this case, multi-agent frameworks may be considered for the implementation of multi-agent systems.

In the following of the dissertation, a case study based on this approach and applied to Healthcare application domain will be widely discussed.

5.4 Research Objectives

The following subsections describe some research objectives that have been addressed in this research work by applying the general approaches described above. Specifically, Figure 38 depicts the existing relation between approaches and research objectives such as knowledge representation, semantic reasoning, pattern recognition and information retrieval. In addition, for each approach are listed the key elements whose application has a meaningful impact on the related research objectives.

5.4.1 Knowledge representation

Knowledge representation aims at designing computer systems that reason about a machine-interpretable representation of the world, similar to human reasoning. Knowledge-based systems have a computational model of some domain of interest in which symbols serve as surrogates for real world domain artefacts, such as physical objects, events, relationships, etc. [101]. The domain of interest can cover any part of the real world or any hypothetical system about which one desires to represent knowledge for computational purposes.

As highlighted in Figure 38, all the proposed approaches address the knowledge representation research objective. In general, sensor observations and domain elements are modeled according to Sensor Web Ontologies. Furthermore, CoMSA approach achieves situations modeling (in terms of infon) according to Fuzzy Situation Theory Ontology, whereas CAPSD approach proposes to exploit semantic representation of web services. In conclusion, each approach presented in this work proposes to use ontologies as a set of symbols to represent a set of facts within a knowledge domain.

5.4.2 Semantic reasoning

Semantic reasoning enable to represent implicit knowledge deriving it from explicit knowledge expressed by an ontology.

In order to achieve semantic reasoning, a symbol vocabulary (ontology) should be combined with a system of logic to enable inferences about elements in the knowledge representation to create new knowledge representation sentences. Logic is usually used to supply formal semantics of how reasoning functions should be applied to the symbols in the knowledge representation system.

Logic is also used to define how operators can process and reshape the knowledge.

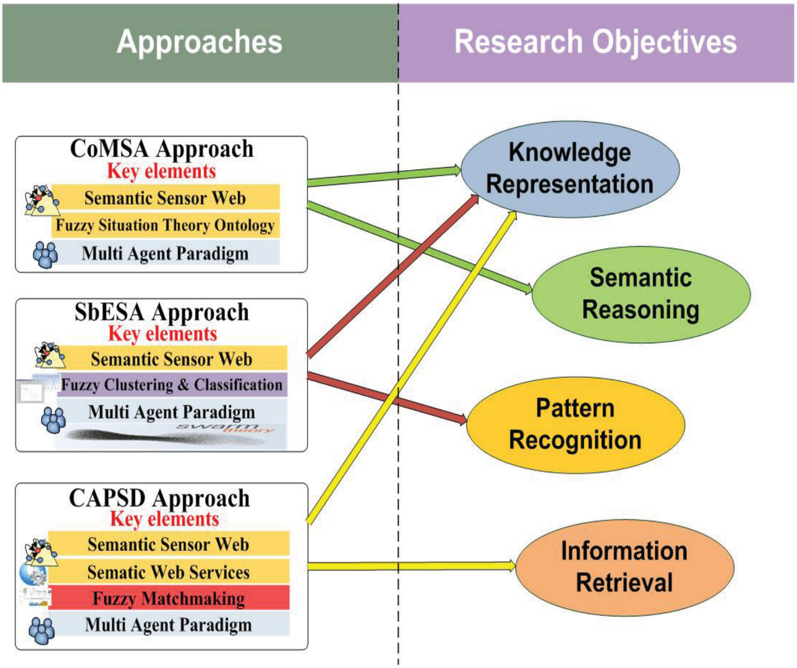


Figure 38. Relation between approaches and research objectives.

Specifically, CoMSA approach propose the application of semantic rules in order to infer emerging situations as result of the simultaneous occurrence of their supporting relations. Semantic reasoning may become a critical task as the knowledge base grows, so CoMSA approach propose to exploit agent paradigm in order to distribute reasoning about situations.

In particular, in this approach semantic representation of the domain elements is used in order to automatically instantiate the network of agents responsible for semantic reasoning.

Furthermore the aforementioned approach also propose to apply a combined approach based on description logic and fuzzy logic in order to enhance semantic reasoning. In particular, it foresees the exploitation of FSTO in order to enable fuzzy reasoning about situations and enhance reasoning with the capability of prevent the occurrence of situations.

5.4.3 Pattern recognition

SA involves the ability to recognize, interpret, and integrate key patterns in the environment to accurately assess one's current status and projection of future status. Especially, if we interpret SA as a classification problem, there is a clear relationship between SA and pattern recognition. With refers to the proposed approaches, pattern recognition is achieved in SbESA approach as well as in CAPSD approach. In particular, SbESA approach in the training phase identifies situations as result of sensor observations clustering execution. Afterwards classifiers are automatically designed and the classification of new sensor observations is performed in each node of the sensor network. The peculiarity of this approach is represented by the application of Swarm Intelligence theory in order to distribute and optimize the classification of sensor observations thanks to agents interacting locally with one another and with their environment. These agents follow very simple rules, and although there is no centralized control structure dictating how individual agents should behave, local, and to a certain degree random, interactions between such agents lead to the emergence of "intelligent" global behavior, unknown to the individual agents, that is, the recognition of relevant situations (patterns) in sensor network observations.

On the other hand, the approach for context awareness attains pattern recognition in the phase of User Context Analysis and Identification where user data clustering is performed in order to extract patterns for user context identification.

5.4.4 Information retrieval

An information retrieval process begins when a user enters a query into the system. Queries are formal statements of information needs, for example search strings in web search engines. In information retrieval a query does not uniquely identify a single object in the collection. Instead, several objects may match the query, perhaps with different degrees of relevancy. Specifically, the proposed approach for CA actually carries out an information retrieval process where the user query is represented by user context (dynamically extracted during Context Analysis and Identification phase) and objects are represented by semantic web services (defined in the second phase). In particular, this approach proposes to exploit a semantic representation of user context as well as a semantic representation of web services in order to achieve a semantic matchmaking.

Semantic matchmaking is a task whereby queries (i.e. user context) and resources (i.e. semantic web services) advertisements are expressed with reference to a shared specification of a conceptualization for the knowledge domain at hand (i.e. an ontology). Furthermore, this approach proposes to exploit fuzzy logic in order to abstract and classify the underlying data of semantic web services as fuzzy terms and rules. The aim is to increase the efficiency of the information retrieval process allowing imprecise or vague terms both in the search query and in the web services' definitions.

5.5 Conclusions

In this chapter of the thesis, the author discusses three general approaches to support Situation and Context Awareness. In particular, two of these approaches concern with SA and are based on the Endsley model [100]. Essentially, SbESA approach may be considered an evolution of CoMSA approach; it foresees the application of different techniques in order to reach the same goal.

On the other hand the third approach concerns with a possible realization of context aware computing based on the idea that context aware systems are concerned with the acquisition of context (e.g. using sensors to perceive a situation), the abstraction and understanding of context (e.g. matching a perceived sensory stimulus to a context), and application behavior based on the recognized context (e.g. triggering actions based on context). Finally, the author analyzes some research objectives met by the proposed approaches.

In the following of this thesis, the aim of the author is to present some application scenarios, consisting in the instantiation of the aforementioned approaches, in several application domains.

Part III: Architectural Overviews and Application Scenarios

Chapter 6

Situation Awareness and Airport Security

Nowadays, Airport Security is one of the biggest issues for travelers. The millions of air passengers who pass through airports every day require high levels of security. The continuous evolution and growth of threats - from terrorism and organized crime, to drug trafficking, mass immigration and cyber attacks - force security organizations to be constantly equipped to contend with the changing risks. Security requirements raising at international level reflect the expectations and demands of the world's citizens. Analyzing and addressing involved risks calls for rigorous methods, proven technological capability and the appropriate organizational and human resources [102]. This convergence between defense and security has prompted the need for new solutions and technologies to support collaborative decision making by enabling organizations to share existing information and communication systems.

Out of the others, Airport Security domain reveals a growing trend towards Collaborative Decision Making (CDM) information systems. Here, security operators relies on decision making tools to face the problem of the information overload induced by the large amount of data provided by multiple heterogeneous and highly-dynamic information sources.

It is broadly recognized that Situation Awareness (SA) is a crucial factor in decision-making. Maintaining a coherent situation awareness with respect to all relevant entities residing in a region of interest is essential for achieving successful resolution of an evolving situation. Situation-aware information systems support operators by the aggregation of the available information to meaningful situations [103]. Indeed, primary basis for situation awareness is the acquired knowledge about objects within the region of interest, typically provided by "sensors" (both mechanical and human) that perform object identification and characterization. Nevertheless, this task involves the monitoring and identification of relationships among objects in collaborative dynamic environments.

In order to automate reasoning on the acquired environmental knowledge we remark the leading role of the semantic technologies [104][105][106]. Ontologies are recognized as a promising technology to realize such systems, because of their semantically-rich kind of knowledge representation. In this sense, several systems for SA support the management of various information sources (sensor data, textual information, databases, etc.) for purposes such as information exchange and graphical presentation to facilitate decision making.

Moreover, another important requirement generally unsatisfied is represented by the capability to cope with uncertainty for situation awareness in complex, real application domains. Indeed, the use of soft computing techniques applied to the modeling of situation awareness to improve cognitive decision making [107][108]and operating performance is an important new trend.

The approach discussed in this chapter is strongly based on CoMSA approach (see Section 5.1), so it achieves some of the research objectives described in Section 5.4, that is to say, knowledge representation and semantic reasoning.

Specifically, the chapter deals with the definition of an architectural framework in the domain of Airport Security and discusses an application scenario. It is mostly based on the adoption of a synergic approach of agent-based architecture and semantic modeling of situations introducing fuzziness in order to satisfy the aforementioned requirements in modeling airport security situation awareness.

It is particularly organized as follows: Section 6.1 present the state of the art of both application domain and cognitive approaches to situation awareness. Section 6.2 describes the Agent-based Distributed Inference System designed and developed to support soft computing cognitive awareness in an airport collaborative decision making framework. Section 6.3 and Section 6.4 present, respectively, the general depicted approach to Airport Security SA modeling and main experimental results of the system under discussion. Finally, Section 6.5 close the chapter.

6.1 Situation Awareness Relevance for Airport Security

6.1.1 Situation Awareness

The notion of "situation awareness" has been used with a number of different meanings. In our discussion, we refer to SA as the perception of environmental elements within a volume of time and space, the comprehension of their meaning, and the projection of their status in the near future.

SA involves being aware of what is happening all around in order to understand how information, events, and performed actions will impact specific goals and objectives, both now and in the near future. Having complete, accurate and up-to-the-minute SA is essential where technological and situational complexity are a concern for the human decision-maker. SA has been recognized as a critical, yet often elusive, foundation for successful decision-making across a broad range of complex and dynamic systems, including aviation and air traffic control.

In this work, the first goal is to formalize main concepts of situation awareness involved in a specific scenario of Airport Security using a language that is both computable by computer and commonly supported.

To achieve this goal, we first need to identify appropriate concepts that can be classified as part of the situation awareness domain. Out of the others, in the following sections, we will stress the concept of relationship among things (objects) involved in a specific situation as a key element in SA. Relations will be intended from the point of view of an entity as a focal object in the situation, and capture how other surrounding entities relate to it. In what follows, we will detail this formalization.

A relevant source of information on situation awareness is the situation theory developed by Barwise [109][110] and Perry [111][112], successively extended by Devlin [93][113]. Computer support for logic is a popular theme in computer science, and there are many languages that have been developed for this purpose. Moreover, situation theory has already been expressed in terms of some existing logical languages. However, few of these languages have even been standardized, and fewer still are commonly supported by popular software tools and systems. Currently, the only languages that have such support are Semantic Web [104] languages: Resource Description Framework [105] and Web Ontology Language [106], on its turn based on RDF. OWL improves RDF by adding many new logical capabilities. One of the most important new capability is the ability to define classes in terms of other classes using a variety of class constructors such as unions, intersections and property values. Accordingly, we have chosen OWL as the reference language for situation theory formalization in our particular domain. OWL comes with three increasingly-expressive sublanguages: OWL Lite, OWL DL, and OWL Full, however all of them share the fundamental features of being self-descriptive, able to decouple facts from the containing document as well as to reduce to simple, elementary statements.

Concepts expressed in OWL and the ones expressed using description logic inference rules, together, enable the construction of a formal ontology for situation awareness. In the proposed approach work, the author mainly refers at a founding upper ontology expressed by means of OWL to model situation awareness, that is, Situation Theory Ontology [29], and extend it in order to allow effective and improved SA modeling for Airport Security able to manage domain uncertainty introducing approximation and uncertainty modeling capabilities. This extension results in:

- a reformulation of the infon [114] concept of STO according to fuzziness and interpretation;
- an extension of STO ontological model in order to allow:
  - the modeling of ontological fuzzy sets;
  - the modeling of STO infon complying with the interpretation;
  - the modeling of STO situation complying with the interpretation.

A formal definition of this extension is described in Section 4.4.1 and the author has called it Fuzzy Situation Theory Ontology (or FSTO).

6.1.2 Airport Security

Nowadays, airport unexpected situations stress both security of operators and air navigation service providers, as well as travelling passengers. Indeed unexpected situations disrupt the smooth running of air transport operations, frequently with widespread impact. For instance, crew and passengers being late, aircraft not prepared in time, services unavailable and/or infrastructure malfunctioning generate sporadic, even though sometimes systematic, delay, inconvenience and, more generally, inefficiency. Furthermore, new types of threats (terrorism, organized crime, etc.) can make risky the normal conduction of airport operations.

Sharing current information on such events, communicating it to those involved and taking collaborative decisions is essential to minimize such disruption, maintaining efficient operations and consistently maximizing the effective usage of airport infrastructures.

Collaborative Decision Making (CDM) aims at achieving a common awareness shared by inexpensive systems and processes as well as supporting collaboration among key partners in order to enhance real-time decision making at an airport, substantially driving to more efficient operations.

CDM affects the decision-making process by managing aircraft and security operations through a wider, network-oriented approach. Plans are shared, the air traffic picture is drawn, means to minimize disruption are devised and decisions to maintain fluid operations developed and executed.

Airport CDM tries to replace the current central planning paradigm with a collaborative process. To establish such a process, information owned by individual partners is shared among all in a useful system-wide representation.

When all airport partners have access to up-to-date information, a common situation awareness will be established. As all partners involved will have a global overview, they can improve their pre-tactical and tactical planning processes [102].

To achieve enhanced common situation awareness, the following pre-requisites are required:

- agreed relevant data should be shared between all partners involved at the right time;
- shared data should have enough quality to simplify improved traffic predictability and planning capabilities for all involved partners;
- decisions should be made by the partner best placed to make them;
- decisions made should be shared with all other partners.

6.2 Agent-Based Distributed Inference System

In this section the author presents a model of an architecture for cognitive awareness together with a general description of the roles involved.

As shown in Figure 39 the proposed architectural model consist of two main parts:

- Knowledge Management (KM System),
- Security.

KM System is in charge of managing the whole domain knowledge, whereas Security realizes airport operator point of view. This layer performs the following tasks:

- Track Data Generator (TDG). It acquires raw data from field (i.e. sensors, radars, etc.) and transforms them in ontological format;
- Event Management Agency (EMA). It generates useful information to check airport situations. In particular it works on instantaneous information concerning Airport situations and dispatches them toward security division roles interested to specific info (situations).

The Security division instead is, in turn, composed by the following roles:

- Situations Evaluation Agency (SEA). It carries out reasoning on situation awareness applied to a crisis scenario for Airport Security (i.e. runway conflicts, airport vehicles conflicts, etc.);
- Human Computer Interaction (HCI). It interfaces the security operator, showing him log on airport situations and alerts signal when needed.

In the proposed application scenario, SEA refers to Runway Conflict Scenario, since that the author is concerned to the situation where a conflict on runway has occurred.

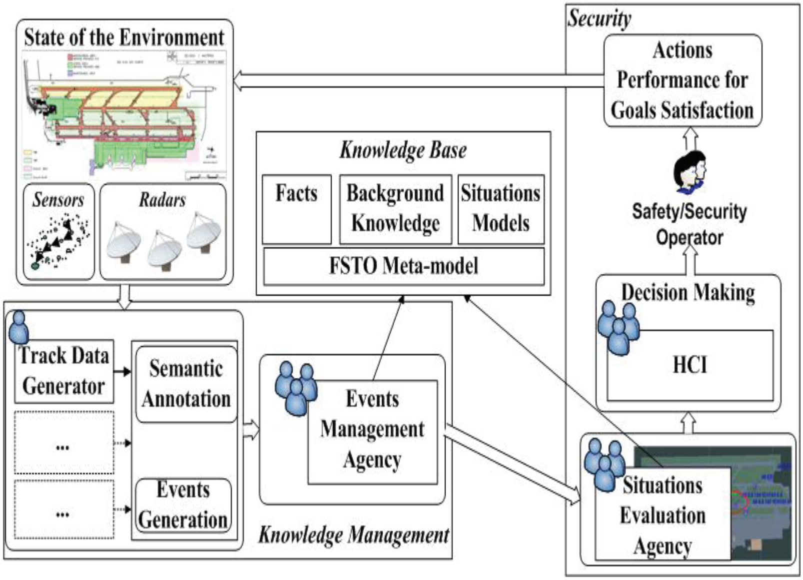


Figure 39. Architectural Overview for cognitive awareness in Airport Security.

A typical process flow in the proposed architecture foresees the following steps:

9. TDG acquires raw data from air and ground radars annotating them as ontological events. After that, it sends generated information to EMA.
10. EMA receives data from TDG, transforms it in Situation info and dispatches it to SEA specialization (i.e. ScenarioRunwayConflict);
11. SEA reasons on a situation of interest for Airport Security (i.e. Scenario Runway Conflict) and notifies the awareness results to HCI;
12. HCI shows log relating to an observed situation and eventually reasons on a situation of interest for Airport Security (i.e. ScenarioRunwayConflict) and, by chance that, it shows an alert message.

6.3 Representing Airport Security Situations

In this section we present a use case relating to a specific Security scenario of Airport domain.

The case study we will draw in the follow is characterized by simplifications introduced through the field complexity.

Specifically, we will refer to Fuzzy Situation Theory Ontology (FSTO) in order to draw out elements and situations involved in a simplified scenario.

6.3.1 Use case scenario

The faced use case involves two aircraft in two distinct phases on a shared runway:

- landing phase. The phase where the aircraft starts to loss quote before to knock down and free the runway;
- holding point approaching phase. The phase where the aircraft starts to move from the apron toward the several taxiway before arriving at the last holding point incident on the runway.

In Figure 40 the author presents a snapshot of the scenario concerning with the observed security situation.

Airport regulation for this scenario requires the two phases to be performed exactly in the previously listed order.

Therefore, in normal conditions the aircraft in holding point approaching phase can hold the runway only after that the landing aircraft has left it. Hence, the aim here is to monitor all situations that can occur in order to avoid undesired risky behaviors.

6.3.2 Background knowledge

To model relevant situations to be monitored in the selected scenario we first have to shortly depict the domain elements involved in the above scenario. These elements are listed below.

- Aircraft: it is a vehicle which is able to fly by being supported by the air;
- Runway: it is a strip of land at an airport on which aircraft can take off and land. Runway's part of the maneuvering area;
- Holding Point: it is a geographically or electronically defined location used for aircraft stationing. It represents a crossing point between taxiways so it can be incident on runway as well;
- Exit point: it is a geographically or electronically defined location used to drive an aircraft end-landing towards a rapid exit taxiway.
- Clearance Point: it is a geographically or electronically defined location used in end-landing aircraft in order to state the safe release of the runway.
- EndCrossing Point: it is a geographically or electronically defined location indicating the end of runway crossing for an aircraft.

Relevant attributes for listed elements will include: location, speed and time. Basing on aforementioned definitions we can now describe the identified interesting situations allowing to monitor the risky scenario.

We remember that in our interpretation of situation theory, information about a situation is expressed in terms of infons as defined in (4.4.2) and (4.4.3).

6.3.2.1 AircraftLandingOnRunway Situation

In this situation an aircraft is in landing phase on a runway. The considerable relations involved are:

R11. inDirectionOf(X, Y): it points out a binary relation where the first parameter X is the subject, that is the aircraft, and the second parameter Y is the target object, that is the Runway where the aircraft should land. The infon for this relation is:

<< inDirectionOf, Aircraft, Runway, quite true >>;

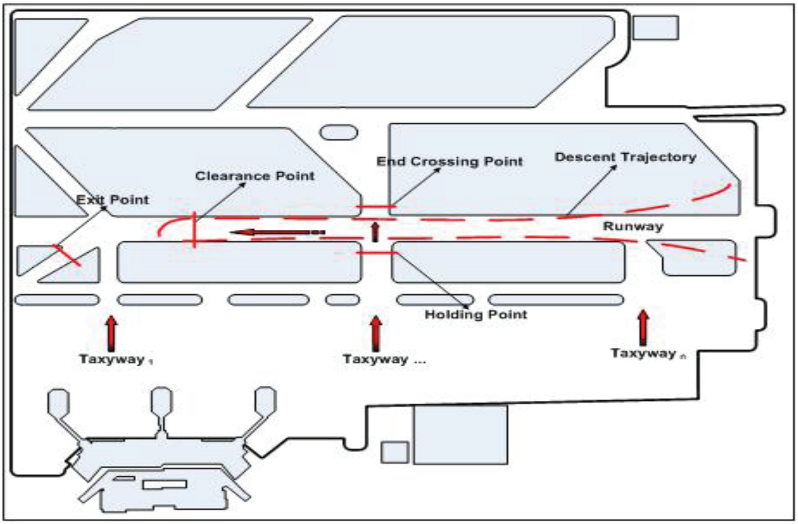


Figure 40. Use Case Scenario Snapshot.

R12. isApproachingToLandingZone(X, Y): it is a binary relation where the first parameter X is represented by an Aircraft and the second parameter Y is represented by a Runway. The landing zone is represented by a descent trajectory resembling a cone. This trajectory end is determined by a clearance point meaning that an aircraft stopped on holding point can cross the runway. The infon for this relation is:

<< isApproachingToLandingZone, Aircraft, Runway, quite true >>.

6.3.2.2 AircraftCrossingOnRunway Situation

In this situation an aircraft is over the last Holding Point before the runway, that is, the aircraft has crossed the runway. The considerable relations involved are:

R21. isArrivedToHoldingPoint(X, Y): it points out a binary relation where the first parameter X is the subject, that is the Aircraft, and the second parameter Y is the target object, that is the Holding Point where the aircraft should stop. The infon for this relation is:

<< isArrivedToHoldingPoint, Aircraft, HoldingPoint, quite true >>;

R22. isMoving(X): it points out an unary relation where the single parameter X is represented by an Aircraft in movement. The infon for this relation is:

<< isMoving, Aircraft, not false >>;

R23. isStopBar(X): it is an unary relation where the single parameter X is represented by the Holding Point and the aim of this relation is to verify if the Holding Point is the last before runway. The infon for this relation is:

<< isStopBar, HoldingPoint, true >>;

R24. connected(X, Y): it is a binary relation where the first parameter X is represented by the Holding Point and the second one Y is the Runway where it is connected. The infon for this relation is:

<< connected, HoldingPoint, Runway, true >>;

R25. isArrivedToEndCrossingPoint(X, Y): it points out a binary relation where the first parameter X is the subject, that is the Aircraft, and the second parameter Y is the target object, that is the EndCrossing Point where the aircraft should arrive. The infon for this relation is:

<< isArrivedToEndCrossingPoint, Aircraft, EndCrossingPoint, false >>.

6.3.2.3 RunwayConflicts Situation

This situation is the one that must be observed in order to raise possible conflicts on a runway. In its general form it can be stated as the result of the intersection between the two aforementioned situations:

intersectionOf(AircraftLandingOnRunway, AircraftCrossingOnRunway) => RunwayConflicts

more specifically, the corresponding model form is depending on the two aforementioned supported situations, together with the assertion that the involved aircrafts and runways are different. Let us say:

S1. AircraftLandingOnRunway (X_1, Y_1) where X_1 is the landing aircraft and Y_1 is the targeted runway;

S2. AircraftCrossingOnRunway (X_2, Y_2) where X_2 is the crossing aircraft and Y_2 is the traversed runway.

In order to define the RunwayConflictsSituation, two more relevant relations will be stated, together with the corresponding infons:

R31. differentIndividual(X_1, X_2);

R32. sameIndividual(Y_1, Y_2).

In the following figures (Figure 41, Figure 42, Figure 43), we depict three different phases in runway conflict anomalies evaluation. In particular, we show a table with fuzzy infons for the aforementioned situations, followed by a snapshot of observed airport scenario in a specific time slice. Let us observe that:

- in the first phase, with a high degree of AircraftLandingOnRunway occurrency and a medium degree of AircraftCrossingOnRunway occurrency, due to A101 moving towards the holding point, we obtain a medium-high degree of RunwayConflict occurrency (see Figure 41);
- in the second phase, with a high degree of AircraftLandingOnRunway occurrency and a high degree of AircraftCrossingOnRunway occurrency we obtain a high degree of RunwayConflict occurrency (see Figure 42);
- in the third phase, with a low degree of AircraftLandingOnRunway occurrency and a low degree of AircraftCrossingOnRunway occurrency we obtain a low degree of RunwayConflict occurrency (see Figure 43).

PHASE 1										
Instant	AircraftLandingOnRunway(A104, R35L)			AircraftCrossingOnRunway(A101, R35L)						RunwayConflict(A101, A104, R35L)
T	R11	R12	S1	R21	R22	R23	R24	R25	S2	RC_Occurrency
5	0,8	0,8	0,8	0,5	0,7	1	1	0	0,5	0,5
6	0,8	0,8	0,8	0,5	0,7	1	1	0	0,5	0,5
7	0,9	0,9	0,9	0,7	0,7	1	1	0	0,7	0,7
8	0,9	0,9	0,9	0,7	0,7	1	1	0	0,7	0,7

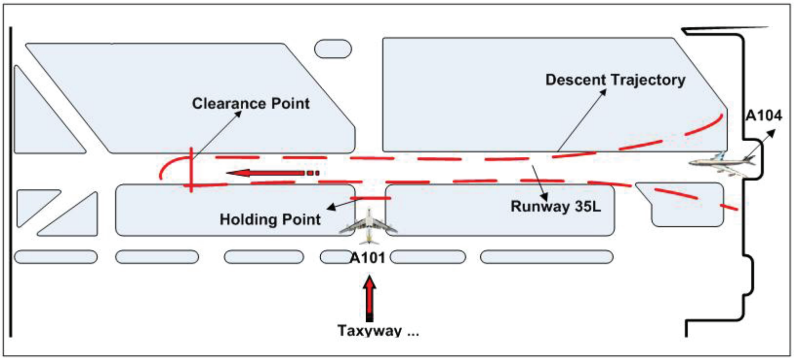


Figure 41. Phase with a landing aircraft and another one approaching to holding point.

PHASE 2										
Instant	AircraftLandingOnRunway(A104, R35L)			AircraftCrossingOnRunway(A101, R35L)						RunwayConflict(A101, A104, R35L)
T	R11	R12	S1	R21	R22	R23	R24	R25	S2	RC_Occurrency
9	1	1	0,999	0,9	0,6	1	1	0	0,6	0,6
10	1	1	0,999	0,9	0,6	1	1	0	0,6	0,6
11	1	1	0,999	1	0,5	1	1	0	0,5	0,5
12	1	1	0,999	1	0,5	1	1	0	0,5	0,5
13	1	1	0,999	1	0,6	1	1	0	0,6	0,6
14	1	1	0,999	1	0,6	1	1	0	0,6	0,6
15	1	1	0,999	0,9	0,8	1	1	0,1	0,8	0,8
16	1	1	0,999	0,8	0,8	1	1	0,2	0,8	0,8
17	1	1	0,999	0,7	0,8	1	1	0,3	0,7	0,7

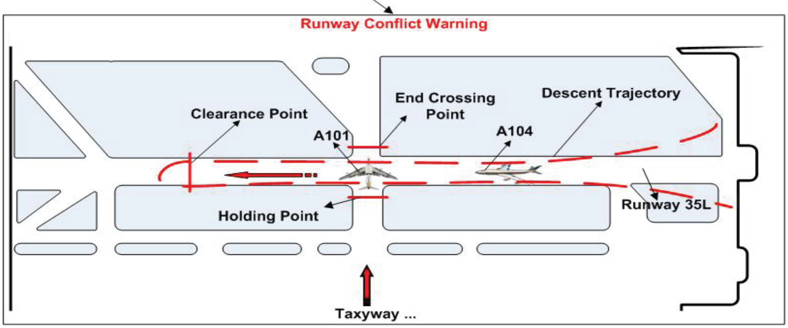


Figure 42. Phase showing a critical situation (a simultaneous landing / crossing).

PHASE 3										
Instant	AircraftLandingOnRunway(A104, R35L)			AircraftCrossingOnRunway(A101, R35L)						RunwayConflict(A101, A104, R35L)
T	R11	R12	S1	R21	R22	R23	R24	R25	S2	RC_Occurrency
18	1	1	0,999	0,5	0,8	1	1	0,5	0,5	0,5
19	1	1	0,999	0,4	0,8	1	1	0,6	0,4	0,4
20	1	1	0,999	0,4	0,8	1	1	0,6	0,4	0,4
21	0,9	1	0,9	0,3	0,8	1	1	0,7	0,3	0,3
22	0,9	1	0,9	0,3	0,6	1	1	0,7	0,3	0,3
23	0,9	1	0,9	0,3	0,6	1	1	0,7	0,3	0,3
24	0,8	0,9	0,8	0,3	0,6	1	1	0,7	0,3	0,3
25	0,8	0,9	0,8	0,2	0,6	1	1	0,8	0,2	0,2
26	0,8	0,8	0,8	0,2	0,6	1	1	0,8	0,2	0,2
27	0,7	0,8	0,7	0,2	0,6	1	1	0,8	0,2	0,2
28	0,7	0,8	0,7	0,1	0,6	1	1	0,9	0,1	0,1
29	0,7	0,7	0,7	0,1	0,6	1	1	0,9	0,1	0,1
30	0,7	0,7	0,7	0	0,8	1	1	0,5	0	0

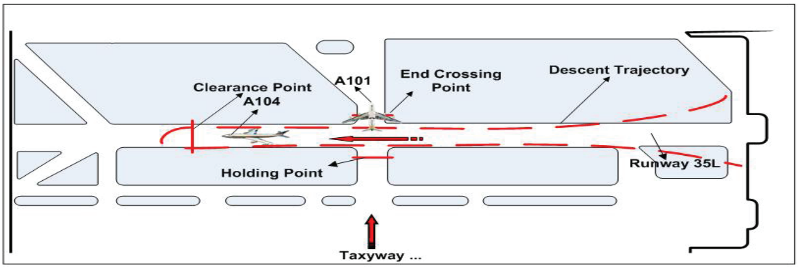


Figure 43. Phase showing a regular (not critical) crossing situation.

6.4 Experimental Results

In this section the author talks about experimental results obtained by the execution of a multi-agent system based on the architectural model presented in the previous sections and addressing the problem of supporting situation awareness in the domain of airport security. Specifically, simulations have focused on the evaluation of a real recording log concerning with the Milan (Malpensa) airport, lasting about 2 hours and 30, split into seven distinct test cases. In each log, anomalous traces, aimed at creating situations of danger (even potential) for airport security, have been introduced. These logs were made to evaluate (sight) by a human operator who has identified possible safety/security violations in the airside, reporting the instants of identification of the anomalies. In this way it was possible to define an evaluation oracle consisting of the set of facts identified (by human operator) in the observed scenario (ground truth) to be compared with the results of the automatic evaluation performed by the multi-agent system.

The following table summarizes the structure of test cases for the evaluation and validation of the system.

Table 1. Summary Table of Test Cases.

Ground Truth				
Test Case	**No. Sweep Radar**	**Duration (min.)**	**Max No. Traces**	**No. Anomalies and Conflicts**
1	356	12	21	8
2	498	17	21	5
3	604	21	16	5
4	576	20	16	6

5	583	20	18	5
6	505	17	19	8
7	645	22	17	7

In particular, the author has considered the evaluation of the following performance measures:

- fairness (or precision): ratio between the number of relevant alarm situations retrieved by the system and the total number of the alarm situations retrieved by the system;
- completeness (or recall): ratio between the number of relevant alarm situations retrieved by the system and the total number of the relevant alarm situations;
- timeliness: amount of time needed to inferential processes aimed at the derivation of relationships between entities in the scenario (infons' elaboration process) and the evaluation times of the situations related to them (reasoning aimed to infer conflict or anomalous situations).

Table 2. Performance Measures Definition.

Measure	**Definition**
fairness (or precision)	$\frac{\lvert\{relevant\ situations\} \cap \{retrieved\ situations\}\rvert}{\lvert\{retrieved\ situations\}\rvert}$
completeness (or recall)	$\frac{\lvert\{relevant\ situations\} \cap \{retrieved\ situations\}\rvert}{\lvert\{total\ relevant\ situations\}\rvert}$
timeliness	$Medium\ Time(First\ Inferential\ Process) + Medium\ Time(Second\ Inferential\ Process)$

Furthermore in the following sections a comparative analysis according to the measures defined in Table 2, will concern with two variants of the implemented multi-agent system, namely, a variant only based on description logic (that will be referred as Airport Security Agents System or ASAS) and another one based on a combination between description logic and fuzzy logic (that will be referred as Fuzzy Airport Security Agents System or FASAS).

6.4.1 Fairness (or precision)

In Figure 44 are shown fairness evaluation results according to previously defined test setting. In general, the obtained results may be considered quite good since both variants of the multi-agent system, for each test, provide values greater than or equal to 0,66.

In particular, FASAS exhibits better results than ASAS, almost in all the tests. Only in three test cases they obtain the same result.

As result, we can observe that the introduction of uncertainty in situations modeling enhances the precision of detection.

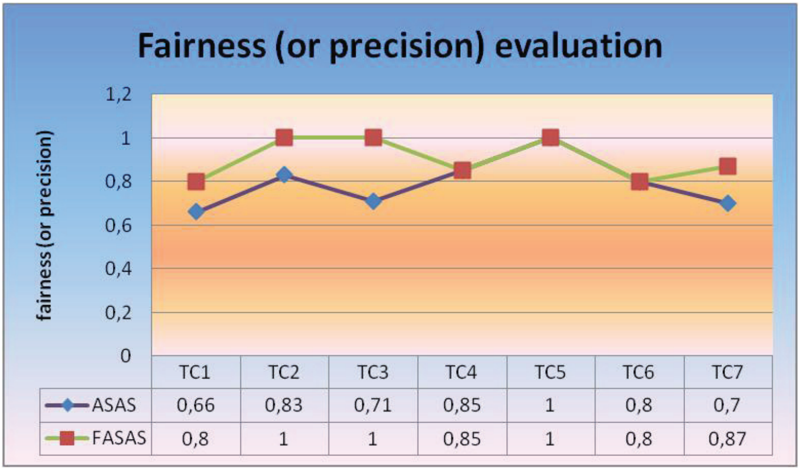


Figure 44. ASAS and FASAS fairness (or precision) evaluation.

6.4.2 Completness (or recall)

In terms of completeness (or recall), the results obtained by considering the previous test setting and the two variants of the multi agent system may be considered good. In this case, the plot in Figure 45 is not very meaningful since completeness evaluation, for each test and for both variants, provides value 1. In conclusion, we can assert that the system implemented, in each case, is able to detect all relevant situations.

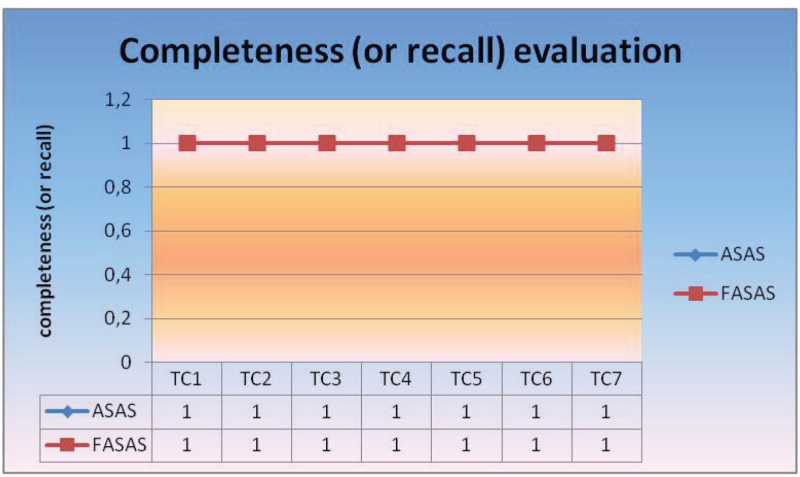


Figure 45. ASAS and FASAS completeness (or recall) evaluation.

6.4.3 Timeliness

The evaluation of the timeliness required in-depth analysis regarding the significance of indicators that could highlight the good performance exhibited by the system in terms of "real-time response". In particular, by considering the previously given definition for timeliness, it was possible to identify the average delay introduced by the detection process at each radar sweep.

In this profiling particularly relevant are data relating to mean and standard deviation both for the time of inference (first inferential process) and for the time of reasoning (second inferential process). By the sum of the averages times (inference mean + reasoning mean) it is possible to get the average processing times, while by the sum of the averages and standard deviations (inference mean + inference standard deviation + reasoning mean + reasoning standard deviation) it is possible to obtain the upper bound (or worst case) of the system for each test case.

Specifically, as shown in Figure 46, both variants of the system, in the best case, exhibit significantly high performance since they complete the combined process of inference and reasoning in less than 0,5 sec.

In addition, Figure 46 highlights that both variants of the system exhibit quite good results also in the worst case. In fact, only in two cases the combined inferential process takes more than 0,5 sec, but these cases coincide with a greater load of relevant situations and traces, that is, a greater number of sweeps for which the reasoning times are greater than 100 milliseconds.

Finally, the author observes that the fuzzy variant of the system exhibits slightly lower performance in terms of timeliness due to a greater complexity of the whole inferential process.

In summary, the system identifies the relevant situations in times less than or equal to 0.5 sec, except in special load conditions, due to the number of tracks to be processed, the number of inferred infons, the number of detected conflict or anomalous situations, etc.

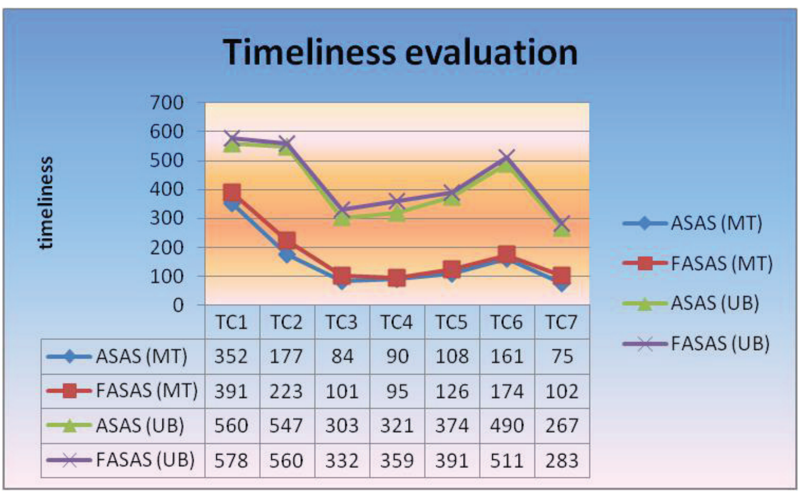


Figure 46. ASAS and FASAS timeliness evaluation.

However, in general the times are improvable since the hardware used for the tests is not particularly powerful.

6.5 Conclusions

Nowadays an inappropriate SA is the main factor of accidents in sensible domains, therefore, supporting SA is particularly important in environments where the information flow can become very high and wrong decisions can cause serious effects (i.e. piloting an Aircraft, etc.) [115][116].

Lately, the trend is to use cognitive approach for modeling of environments, objects and situations by moving the focus increasingly towards the knowledge modeling.

Furthermore, SA stresses native requirements of the agent paradigm: real-time responsiveness, continuous working for a long time, pro-activeness and predicibility of highly dynamic contexts.

After drawing this scenario, it is possible to say that the main contribution of this work is to support and improve SA introducing a distributed agent approach, based on ontology and soft computing components and applying it to the Airport Security field.

In order to achieve this goal, the author has showed a layered ontological modeling of SA in the specific application domain and the possibility to introduce fuzziness [117][118] in a situation awareness ontological meta-model [114]. In particular, it was presented a feasible modeling tool for situation awareness in the Airport domain based on a fuzzy interpretation of situation theory ontology. Then, the author also depicted an agent-based architecture to support Airport Security Operators decisions with several roles involved.

The preliminary experimental results were also discussed and it was emphasized their goodness through a comparative analysis considering two variants of an implemented multi agent system with respect to some meaningful measures.

In conclusion, the author highlighted the benefits deriving from the application of CoMSA approach (discussed in Section 5.1) in the domain of Airport Security. In particular, the instantiation of the aforementioned approach showed in this chapter, is based on merging an agent-based distributed architecture and a fuzzy cognitive awareness based on meta-ontologies. It should be clear from the discussion as this approach involves the achievement of two aforementioned research objectives (dealt in Section 5.4), that is, knowledge representation and semantic reasoning.

Finally, expected future works are related to:

- extending the Airport Security scenario including more complexity. In particular, the aim is to monitor risky situations deriving from several threats (i.e. terrorism, organized crime, etc.);
- applying this approach in other interesting fields (i.e. military, diagnostic and so on);
- evaluating the goodness of situation awareness by means of analysis, measurements and error estimation [119][103].

Chapter 7

Situation Awareness and Traffic Jam

The rapid development and deployment of sensor technology involves several types of sensors (e.g., thermostats, pressure gauges, pollution detectors, cameras, microphones, glucose sensors, etc.) that enable us to monitor cities, atmosphere, our body, and so on. Recently sensor technology offers cheap and energy-efficient hardware for data sensing. Deployment of (wireless) sensor and actuator networks makes it possible to monitor physical phenomena and reason on obtained information. It is possible to use sensor networks to detect and identify a multitude of observations, from simple phenomena to complex events and situations. For instance, sensor technology has been applied in several domains, such as meteorology, for weather forecasting and wildfire detection, civic planning for traffic management, satellite imaging for earth and space observation, medical sciences for patient care using biometric sensors and homeland security for radiation and biochemical detection at ports. Nevertheless, the lack of integration and communication between sensor networks often isolates important data streams and intensifies the existing problem of too much data and not enough knowledge. Specifically, quality and efficiency of reasoning on sensor data is closely related to the representation, sharing and management of observations. To realize the vision of a global (wireless) sensor network and service environment, there is a need to guarantee interoperability and universal access to sensor observations and measurements. Over the past few years, many research works address developing of large scale sensor networks, such as SensorWeb[8]. Open Geospatial Consortium (OGC) has proposed Sensor Model Language (SensorML) that is an XML-based standard that lacks of semantic model. Recently many research works address this problem by encouraging development of sensor and actuator data representation using semantic technologies [119], such as: Semantic Sensor Web [87], OntoSensor [121], etc. Semantic web technologies enable to enrich sensor data with semantic annotations. In particular, semantic formalisms enable to acquire machine understandable contextual information. As highlighted in [122], emerging challenge is related to perform reasoning over the sensor observation and measurement and linked data[9] to detect emerging situation.

The approach discussed in this chapter is mostly based on SbESA approach (see Section 5.2), so it exploits some of the research objectives described in Section (see Section 5.4) such as knowledge representation, semantic and fuzzy reasoning. Indeed, the proposed approach doesn’t considering data analysis and consequently the automatic design of classification rules.

Furthermore, the proposed architectural overview concerning with the definition of a framework able to use distributed semantic sensor data sources in order to identify relevant

[8] http://research.microsoft.com/en-us/projects/senseweb/

[9] http://www.w3.org/DesignIssues/LinkedData.html

situations in the domain of traffic management. Specifically, this work focuses on the problem of reasoning on distributed semantic data sources and enhances description logic reasoner by exploiting fuzzy theory in order to approximate relevant situations. In [123] the authors emphasize the role of upper ontology OWL-FC to exploit Fuzzy Logic in OWL in order to model vagueness and uncertainty of the real world. On the other hand, the proposed application scenario stresses the evaluation of fuzzy controls on distributed semantic sensor data in order to forecast emerging situations.

Let us assume that sensor data are represented according to Semantic Sensor Web [87]. The main contribution of this work, complying with SbESA approach previously described, is the application of a synergic approach based on swarm intelligence and fuzzy control theory in order to reason on distributed semantic sensor data and to push out emerging situation (i.e. traffic jam situations) before they happen. In particular, we provide a swarm based fuzzy logic control (FLC) algorithm that integrates groups of simple agents (swarm entities), which are equipped with limited-range communication ability. Each agent acts as a node in the sensor network. The control algorithm is implemented on each individual node, and each node decides its action. Each node's action is regulated by swarm behavior [124], a computational metaphor inspired by social insects.

The chapter is organized as follows: Section 7.1 presents some related works available in literature; Section 7.2 defines the swarm-based framework and workflow for supporting fuzzy classification of distributed semantic sensor data. Then, Section 7.3describes an illustrative scenario aimed to approximate knowledge about road and traffic in order to identify traffic jam situations. In Section 7.3 the author also presents an implementation of a prototype system for traffic jam situation awareness and analyzes some preliminary experimental results. Finally, in Section 7.4 conclusions and future works close the chapter.

7.1 Related works

The work proposed in this chapter concerns with the approximate reasoning on distributed semantic sensor data. As highlighted above, in literature there are many approaches that address sensor data annotation to increase interoperability and provide contextual information essential for situational awareness. A semantic sensor network uses declarative descriptions of sensors, networks and domain concepts to support searching, querying and managing the network and data. Architectures for semantic sensor networks [125][126][127][128][129], use multiple layers of semantics and technology to provide infrastructure and services. In particular, in [87] is presented an approach that annotates sensor data with spatial, temporal, and thematic semantic metadata. This technique builds on current standardization efforts within the W3C and Open Geospatial Consortium (OGC) and extends them with semantic Web technologies to provide enhanced descriptions and access to sensor data.

Since semantic models are often unable to deal with many cases of real world, where information is vague in meaning, in order to deal with this issue, in literature there are some researches whose main logical infrastructures are Fuzzy Description Logics (briefly Fuzzy DLs) in order to approximate data uncertainty. Straccia proposed a fuzzy extension of DL ALC called F ALC in [130] and in [131] a fuzzy extension of SHOIN(D). Stoilos et al. [132] discuss Fuzzy OWL and uncertainty representation with rules. They present a fuzzy reasoning engine that implements a reasoning algorithm for a fuzzy DL language fKD-SHIN. Moreover, in [123] the authors introduced OWL-FC in order to to represent fuzzy controllers and enable their discovery and execution by means of Description Logic constructs. This work exploits OWL-FC in order to semantically specify controllers.

In literatures other approaches that combine fuzzy logic theory and Semantic Technologies are defined. Specifically, Ciaramella et al. in [133] propose a situation-aware framework in which inference is carried out by semantic rules which embody fuzzy logic to take the assessment of real-world inaccurate information into account.

Furthermore, to obtain better performance and have higher fault tolerance in sensor observation errors, swarming agents in sensor networks may be used for data acquisition, data fusion and control applications. The swarm intelligence design approach adapts robust, self-organizing coordination mechanisms observed in distributed natural systems (e.g., social insect colonies) to engineered systems. Swarm intelligent agent systems for command and control and for data acquisition and transmission are defined in [134]. Specifically, [135] presents a swarming agent architecture for distributed pattern-detection and classification. Again, [136] describes a swarm-based fuzzy logic control mobile sensor network for collaboratively locating the hazardous contaminants in an unknown large-scale area.

Finally, with reference to the application domain, namely the traffic management, there are not many contributions in the literature that apply hybrid approaches such as that proposed by the author. However, in [137] the authors illustrate scenarios with examples from the field of road traffic management and argue that an ontology-driven Situation Awareness system does not replace but may actually enhance traditional probabilistic approaches to it. On the contrary, in [138] the authors presents an ontology for representing road traffic situations in a traffic management center, involving representation and reasoning for qualitative spatio-temporal patterns. In particular, the applicability of the developed ontology to the recognition of road traffic management scenarios is demonstrated.

Analogously with [135], in this chapter the author proposes a framework that applies swarm intelligence techniques to globally coordinate local data processing. In particular, the approach proposed here exploit fuzzy control in order to classify data streams. Specifically, swarm intelligence and fuzzy control are exploited to make reasoning on semantic sensor data in order to push out knowledge and forecast emerging situation in the domain of traffic management.

7.2 The proposed framework

From the architectural point of view, the work addresses the problem of pattern detection by defining swarming architecture and by applying fuzzy control based classification of semantic sensor data. Figure 47 shows an overview of the architectural components, on the left side, and of the workflow, on the right side. In the considered sensor network large populations of mobile agents coordinate their activities by stigmergetic interactions. Using artificial pheromones the agents dynamically organize themselves around patterns observed in the data streams. The agents in the proposed framework coordinate their activity and communicate their results through markers in a shared dynamic environment. Marker-based stigmergy in social insect colonies uses chemical markers (pheromones) that the insects deposit on the ground in specific situations (e.g., food found). The spatial structure of the pheromone infrastructure is captured in a network of places. A place is a location where agents may deposit or sense pheromones and where the infrastructure manipulates local concentrations. So, the intended swarm intelligence behavior in the proposed work foresees the ability for agents to migrate from place to place in the sensor infrastructure. As a result, this behavior introduces advantages in terms of parallel processing, dynamic adaptation, tolerance to network faults and so on, with respect to conventional agent-based approaches. Specifically, the architecture involves different task oriented agents populations that are based on following kinds of agent:

- *Place Agent*, which provides infrastructure services in order to manage pheromone properties (i.e., concentration, propagation and evaporation) on each geographic location (i.e., the place). These agents perform activity of semantic data sensing, implement the local pheromone dynamics, provide topological information and manage the local interactions among neighbor agents [139].

- *Fuzzy Classifier Agent*, which faces the problem of finding global patterns across distributed heterogeneous sensor data sources by performing local data classification. These agents identify patterns according to their classification schema (i.e., fuzzy control). So, they influence: a) where to focus the search; and b) what to declare part of a pattern. Furthermore, population of Fuzzy Classifier Agent could be deployed at any time, for instance to add more classification schemes.

- *Notifier Agent*, migrates on each place and acquires classification by detecting pheromone released by Fuzzy Classifier Agents. These agents provide notifications about patterns identified and spatio-temporal information. In particular, specific threshold could be configured in order to choose which classified pattern should be notified.

On the other hand, from a methodological point of view, the workflow of the proposed approach is essentially composed of three main phases: Semantic Data Sensing, Swarm-based Fuzzy Classification and Relevant Pattern notification. On the right side of Figure 47 is sketched execution of this workflow. Next subsections detail each activity.

7.2.1 Semantic Data Sensing

Extracting useful knowledge from raw sensor data is not a trivial task. Conventional data analysis tools might not be suitable for handling the massive quantity, high dimensionality, and distributed nature of the data. The goal of this phase of the workflow is therefore to provide sensor data with knowledge useful for their interpretation and make this knowledge available for further processing aimed to infer new information. The activity of Semantic Data Sensing concerns with the acquisition of data from different data sources (e.g. thermostats, cameras, microphones, position sensors, etc). Data acquisition begins with the physical phenomenon or physical property to be measured. Examples of this include temperature, light intensity, gas pressure, fluid flow, location and force.

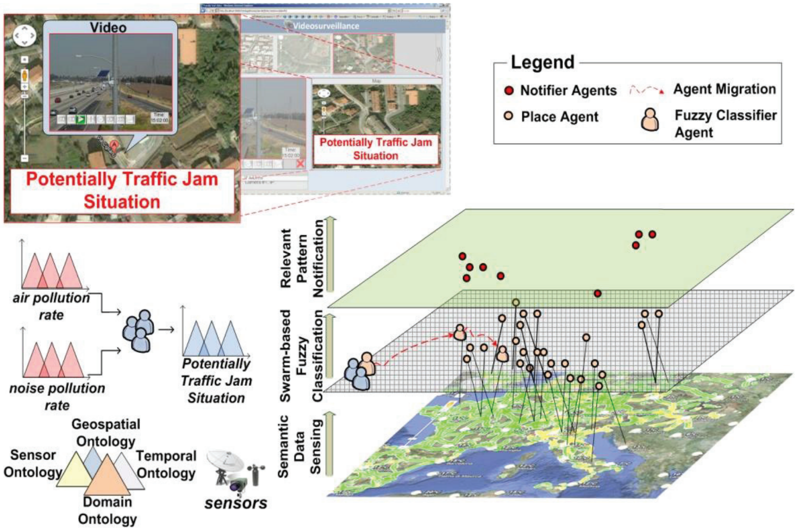


Figure 47. Architectural components (left side) and phases of the workflow (right side).

Regardless of the type of physical property to be measured, sensors transform the physical state to be measured into a unified form that can be sampled by a data acquisition system. The ability of this activity to measure differing properties depends on having sensors that are suited to detect the various properties to be measured. In this approach the authors assume that each measurement provided by sensor is semantically annotated. In particular, each measurement is supposed to have spatial, temporal and thematic dimensions. This assumption leverages on the efforts of OGC and Semantic Web Activity of W3C aimed to achievement sensor Web, that is, a special type of Web-centric information infrastructure for modeling, collecting, storing, reasoning and visualizing sensor observations of phenomena [87]. The OGC recently established Sensor Web Enablement (SWE) to address semantic annotation aim by developing a suite of specifications related to sensors, sensor data models, and sensor Web services that will enable sensors to be accessible and controllable via the Web. The result of efforts is Semantic Sensor Web framework, which is able to provide enhanced meaning of sensor observations. It enhances meaning by adding semantic annotations to existing standard sensor languages of the SWE.

These annotations provide more meaningful descriptions and enhanced access to sensor data than SWE alone, and they act as a linking mechanism to bridge the gap between the primarily syntactic XML-based metadata standards of the SWE and the RDF/OWL-based metadata standards of the Semantic Web. Many languages can be used for annotating sensor data, such as RDFa, XLink, and SAWSDL (Semantic Annotations for WSDL and XML Schema). Figure 48 shows an example of semantic modeling of sensor measurement. Specifically, example in Figure 48 is annotated by exploiting OGC SWE approach. OWL-Time upper ontology and pollution domain ontology are used to annotate the observation.

```
<swe:component name="time">
        <swe:Time definition="urn:ogc:def:phenomenon:time" uom="urn:ogc:def:unit:date-time">
                <sa:swe rdfa:about="?time" rdfa:instanceof="time:Instant">
                        <sa:sml rdfa:property="xs:date-time"/>
                </sa:swe>
        </swe:Time>
</swe:component>
<swe:component name="air_pollution_rate">
        <swe:Quantity definition="urn:ogc:def:phenomenon:airPollutionRate"
        uom="urn:ogc:def:unit:percentage">
                <sa:swe rdfa:about="?air_pollution_rate"
        rdfa:instanceof="senso:airPollutionRateObservation">
                        <sa:swe rdfa:property="pollution:percentage"/>
                        <sa:swe rdfa:rel="senso:occurred_when" resource="?time"/>
                        <sa:swe rdfa:rel="senso:observed_by" resource="senso:buckeye_sensor"/>
                </sa:swe>
        </swe:Quantity>
</swe:component>

<swe:value name="air-pollution-data">
        2008-03-08T05:00:00,62.1
</swe:value>
```

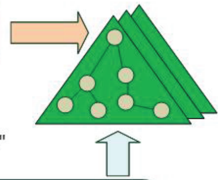


Figure 48. Semantic annotation of sensor data by RDFa.

7.2.2 Swarm-based Fuzzy Classification

Fuzzy Classification of Semantic Sensor Data represents a fundamental phase of the workflow. Specifically, the main aim is related to classify acquired semantic sensor data according to a specific goal. The sensor data classification performed is exploited in order to notify, in the next activity, specific detected pattern, such as alerts or warning in emergency situations, traffic jam, etc. In order to manage uncertainty and distributed semantic sensor data classification is based on Fuzzy Control and Swarm Intelligence techniques. Swarm-based Fuzzy Classification activity involves a multi agent swarm behavior where the swarm entities are distributed among the several sensors scattered in a wide area. To address these questions the idea of the proposed work is to integrate Fuzzy Control in each Classifier agent, firstly in order to guide research focus and secondly to classify relevant pattern or part of them. Let's suppose that Place Agents also perform semantic sensor data fuzzification, that is, semantic annotation of sensor data is exploited to design fuzzy controls according to OWL-FC [123]. So, each sensor observation corresponds to an ontological concept represented by a fuzzy set, defined by two or more membership functions that qualitatively represent the acquired sensor data, for instance by linguistic variables such as low, medium, high and so on. The inference step is carried out by the evaluation of a fuzzy rule base where each rule is in the form of Takagi-Sugeno model [140] and is described as follows:

$$R_i : \boldsymbol{if}\ x_1\ is\ A_{i1}\ AND\ x_2\ is\ A_{i2}\ AND\ \dots AND\ x_n\ is\ A_{in}$$
$$\boldsymbol{then}\ y_i = a_{i1}x_1 + a_{i2}x_2 + \cdots + a_{in}x_n + b_i$$
$$with\ weight\ [w_i]$$

where R_i is the i-th rule, $x_1, x_2, \dots, x_n$ are fuzzy sets representing the input variables resulting from sensor data detections, $A_{i1,}A_{i2}, \dots, A_{in}$ are membership functions assigned to corresponding input variables, variable y_i represents the value of the i-th rule output, and $a_i = [a_{i1}, a_{i2}, \dots, a_{in}]$ and b_i are parameters of the consequent function.

In the proposed work, each Classifier Agent evaluates a pre-defined rule base whose evaluation refers to degree of truth (or certainty) of a pattern. We observe that the defuzzified value deriving from the evaluation of fuzzy rule base in each Classifier Agent may be interpreted as pheromone concentration of a specific flavor. Each Classifier Agent population research the maximum concentration of pheromone for one flavor. In this way, the pheromone infrastructure is achieved where the property of concentration is obtained by the just described approach and the property of evaporation is determined by the temporal change of sensor detections. Therefore, Fuzzy Classifier Agents moving as well as their pattern identification task are determined by pheromone concentration deriving from fuzzy control evaluation. Figure 49 introduces the application scenario described in more details in the following section, where sensor data detections refer to air pollution rate and noise pollution rate and relevant pattern refer to the identification of potentially traffic jam situations. Moreover, in Figure 49 are highlighted the existing relations between fuzzy control and swarm intelligence theories.

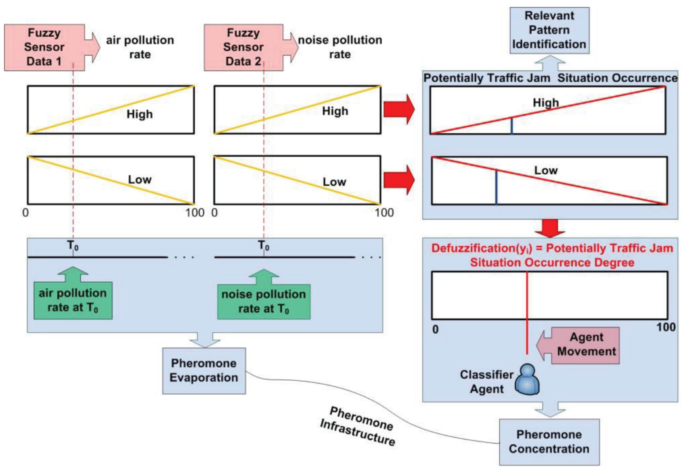


Figure 49. Swarm-based Fuzzy Classification.

7.2.3 Relevant Pattern Notification

Relevant Pattern Notification activity concerns with the elicitation of relevant patterns identified in the previous activity. In particular, this task is performed by Notifier Agents which provide notifications in push-out mode. Specifically, in our approach the activity of pattern notification consist of filtering identified pattern according to a specific pheromone threshold.

The general framework discussed in this section has been applied to notify traffic and road information in order to identify traffic jam situations. The notification could be used to leverage decision makers through a user friendly front end.

7.3 Simulation prototype and experimental results

In this section the author discusses a real application of the proposed approach in in the domain of traffic management with emphasis on the identification of traffic jam situations. The case study is particularly aimed to prove the goodness of the proposed approach in terms of classification performance. Specifically, to the discussion about the simulation environment will follow the description of the simulation prototype and the section will end with some observations about simulation results.

7.3.1 Simulation environment

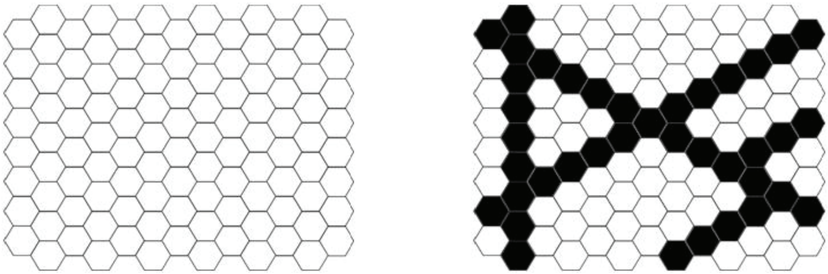
Traffic jam situations detection concerns with the notification of traffic events (i.e. traffic information) to operations center. In this section the author tries to highlight as the proposed framework could be able to support an operator to the dissemination of information on traffic jam. As aforementioned, in the framework, Fuzzy Classifier Agents try to identify congested road points in the monitoring area, that is, they perform local classification. On the other hand, Fuzzy Classifier Agents try to identify congested road section, thus their aim is to perform distributed classification of patterns. Let us suppose that we are able to detect traffic jam situations starting from sensor measurements relative to the following magnitudes:

- number of transited vehicles;
- rate of noise pollution;
- rate of air pollution.

In other words, we are assuming that if in a place there is a high rate of air pollution as well as a high rate of noise pollution and, at the same time, few vehicles have passed in that place, then we can infer that with high probability in that place there is a traffic jam. So, these sensor observations are semantically annotated and subsequently fuzzy classification rules are designed. These rules enable agents populations to determine, for each place, the membership degree of each observation to several traffic situations, such as flowing, jam and so on. In particular, as previously described, Notifier Agents follow the pheromone trails released by Fuzzy Classifier Agents and try to infer if the discovered local pattern is a false positive or a real traffic jam situation. In further detail, Notifier Agents, after a pheromone detection, attempt to verify the goodness of the discovery by carrying out movements that are no longer random, but follow the pattern of road. Therefore, if a Classifier Agent senses pheromone concentrations along a road, then it will enhance its believe to have found a distributed pattern (that is a traffic road) by dropping a high concentration of pheromone along its path. Finally, pheromone released by Notifier Agents concentrations represent the output of the swarm based framework and thanks to them it will be possible to identify traffic roads on a map. This map in the simulation environment is represented by double layered grid, where the first layer consists of a hexagonal cell matrix with a Place Agent in each cell (see Figure 50a); on the other hand, the second layer consists of road layer and is overlaid to the previous layer (see Figure 50b).

7.3.2 Traffic Jam Simulator

This subsection briefly describes a traffic jam simulator implemented by the author in order to analyze the performances of the proposed framework in the road traffic domain.



(a) Sensor layer (b) Road layer

Figure 50. Simulation environment double layered grid.

Therefore, the goal of this simulator is to identify traffic jam situations according to the proposed swarm-based framework. In particular it is based on World Wind Java SDK[10], a software development kit enabling developers to embed World Wind technology in their own applications. In the specific of the proposed application, this software is used in order to have a graphical feedback about the areas in which traffic jams were detected. Furthermore to Nasa World Wind globe it was added a road layer, namely Open Street Map[11]. This software creates and provides free geographic data such as street maps to anyone who wants them. Finally, multi-agent stigmergic behavior as well as agents schedulation and synchronization has been implemented by using MASON[12] simulation environment, a multi-purpose simulation library for the Java programming language. In Figure 51 is shown the user interface that allows users to interact with the simulator.

The traffic jam simulator interface pratically presents two section, that is, a control section (on the left side of Figure 51) and an output section (on the right side of Figure 51), where the output results are graphically shown. Among the main features of the simulator there is the capability for users to deploy sensors (that is, Place Agents), in an interactive mode, on the road layer (as shown in Figure 52). Specifically, on red nodes take place sensor measurements and they are placed on road layer, whereas yellow nodes are only auxiliary nodes; therefore, these nodes do not perform sensor detections but are only used in order to achieve a fair distribution of agents on the network.

To clarify, nodes, agents and pheromones in traffic jam simulator are represented by markers and they are distinguished by color. Finally, in Figure 53 a graphical output of a traffic jam pattern and the related informations are depicted.

7.3.3 Simulations results

The last subsection of the proposed application scenario concerns with the evaluation of simulations results.

[10] http://worldwind.arc.nasa.gov/java/
[11] http://www.worldwindcentral.com/wiki/Add-on:OpenStreetMap
[12] http://cs.gmu.edu/ eclab/projects/mason/

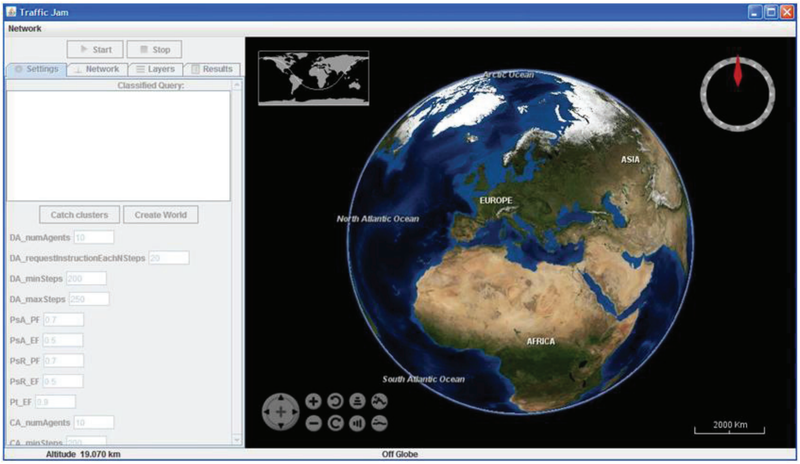


Figure 51. Traffic Jam Simulator graphical user interface.

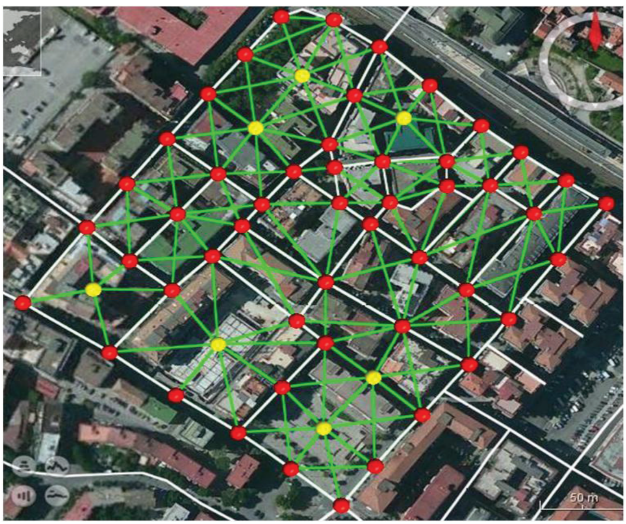


Figure 52. Traffic Jam Simulator sensor nodes deployment.

Since the proposed framework is based on a distributed algorithm whose aim is to optimize the emergent traffic situations detection by exploiting swarm intelligence theory and fuzzy theory, the idea here is to evaluate performances both in terms of convergence and in terms of classification. To this end, we analyze the results of three simulations.

Figure 53. Traffic Jam Simulator graphical output.

In particular:

- *simulation 1*, where sensor nodes are scattered on a small regular area;
- *simulation 2*, where sensor nodes are scattered on an irregular but slightly wider area;

In the simulations, the deployment of sensors and the creation of ground truth took place according to Monthly Traffic Forecast data provided by "autostrade per l'Italia" [13]. In Figure 54a and Figure 54b the different distributions of sensor nodes for the simulations 1 and 2 are highlighted. Once we have obtained the ground truth for simulation 1 and 2 the second step was the running of tests, aimed at a comparative analysis resulting from the comparison between truth on the field and system response. Specifically, for each test run we show a table and a plot with results related to the evaluation of F-measure (i.e. the weighted harmonic mean of precision and recall measures) in specific steps during the algorithm execution.

7.3.3.1 Simulation 1

The Simulation 1 considers the sensor network setting shown in Figure 54a and the performances of the framework have been evaluated by considering the number of steps for convergence and classification results in reference to an increasing number of situations of traffic jam. Specifically, four simulations have been run with an increasing number of traffic jam situations, namely from two to five.

[13] http://www.autostrade.it/

(a) Simulation 1 (b) Simulation 2

Figure 54. Sensor network settings for simulations.

In particular, the F-measure evaluation for Simularion 1 is depicted in Figure 55. Let us observe as the convergence rate decreases with increasing number of traffic jam situations, however, it is still limited since it goes from forty to seventy steps.

7.3.3.2 Simulation 2

The Simulation 2 considers the sensor network setting shown in Figure 54b and the performances of the framework have been evaluated in the same way that in Simulation 1. So, Simulation 2 also consists of four executions with a number of traffic jam situations ranging from two to five.

The F-measure evaluation plot for each test in Simulation 2 is showed in Figure 56. Let us observe as in a similar way to the Simulation 1, also in this case the convergence rate decreases with increasing number of traffic jam situations. However, the number of step for the convergence is slightly higher than the Simulation 1 because of increased complexity of the sensor network.

7.3.3.3 Observations about simulations

The previous description of the performed simulations highlights that, for both areas, after about sixty step the algorithm converges to the desired solution. In fact, the presented graphs show that after just ten step some patterns are identified. However, this is not a result to be considered as in the first steps of the simulations the agents don't have the appropriate instructions and they may incorrectly release pheromone. On the one hand this leads to highlight actually anomalous pattern, on the other hand it will generate several output false positives.

The oscillation which is sometimes observable after many step is instead due to the distribution of the *Fuzzy Classifier Agents*, which attracted by high concentrations of attractive pheromone will tend to move toward long stretches of road traffic, rather than on isolated segments.

However, these problems can be partly solved by acting on the parameters of the algorithm.

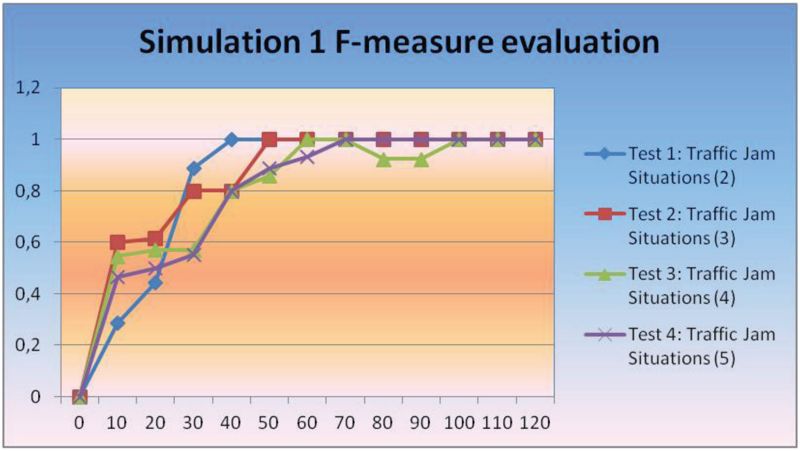


Figure 55. Evaluation of F-measure for Simulation 1.

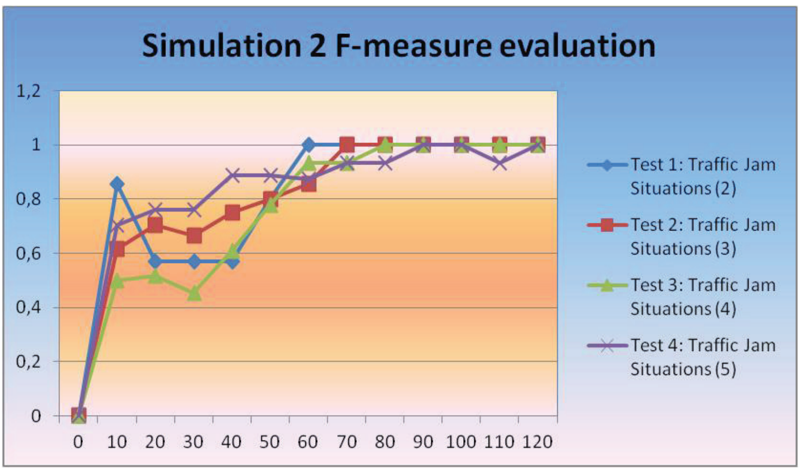


Figure 56. Evaluation of F-measure for Simulation 2.

In addition, the framework is thought to be distributed, that is to say that the processing will not be performed on a central unit, but the swarm algorithm will be distributed on each node of the network; this means that every node in the network will have to manage a few agents at a time, therefore each step of the algorithm is extremely fast.

7.4 Conclusions

In this chapter, the author presents an architectural overview concerning with the instantiation of the previosly discussed SbESA approach and an application scenario refers tothe domain of traffic management. In particular, in order to support the identification and detection of traffic jam situations the work discussed in this chapter proposes a swarm-based approach to fuzzy classification of distributed semantic sensor data.

In terms of research objectives, this work relies on the knowledge representation, semantic and fuzzy reasoning. If knowledge representation is achieved by exploiting the semantic annotation of heterogeneous sensors data according to Sensor Web infrastructure, fuzzy control evaluation supports reasoning on distributed semantic sensor data in order to forecast emerging situations in traffic management.

So the main aim of the author is related to propose a framework able to autonomously push out emerging situation (in the domain of traffic management) by processing large and dynamic knowledge bases.

The preliminary experimental results highlight the goodness of the proposed framework (based on this combined approach) both in terms of convergence and classification. Nevertheless, as well as classification performances further experimentations are in progress addressing communication issues in the proposed approach.

A future extension of this approach foresees automatic fuzzy control design [141]. In particular, a fuzzy classifier to support relevant pattern notification could be automatically trained according to historical data. Further works concerns with the refinement of fuzzy based swarm behavior, the migration towards semantic fuzzy reasoning and tests running in different scenarios.

Chapter 8

Situation Awareness and Smart Grids

Power systems monitoring is assuming a major role in the context of Smart Grids, where a malfunctioning power network could be responsible for serious damages to a large number of system operators having access to the shared energy resources. At the same time the constant growth of the market participants and the number of Energy Management Systems operating on the Smart Grids will raise the interdependency between the operation of the electric networks and the electric markets and, consequently, the intrinsic complexity of Smart Grid monitoring. The main difficulties arising in developing an effective, Smart Grid monitoring is mainly due to the upgrade and interoperability of existing EMS/DMS that are typically based on client server based paradigms characterized by different information technologies. In these systems a large volume of raw data is collected by distributed sensors and sent to central servers for post processing activities [142]. The large scale deployment of this hierarchical paradigm in a Smart Grid is causing designers of high performance monitoring systems to revisit numerous design issues and assumptions pertaining to scale, reliability, heterogeneity, manageability, and system evolution over time [143][144]. Power sensors heterogeneity, a non-issue in traditional electricity distribution systems, must now be addressed since measurement systems that grow over time are unlikely to scale with the same hardware and software base. Manageability also becomes of paramount importance, since Smart Grids could integrate hundreds or even thousands of power nodes. Finally, as Smart Grids evolve to accommodate growth, monitoring system configurations inevitably need to adapt [145][146]. In this connection situation awareness supported by the deployment of distributed classification techniques in the context of multi-agents systems could play a strategic role. This is mainly due to the successful application of these paradigms in processing massive and heterogeneous information aimed at detecting anomalous situations and incoherencies [147][148][149][150][151]. Armed with such a vision in this chapter the author proposes an instantiation of the previously described SbESA approach involving a distributed approach aimed at exploiting the semantic representation of power system measurements and a collaborative architecture aimed at detecting anomaly in power sensors data. With refers to research objectives the proposed approach achieves knowledge representation by means of semantic annotation of power sensors data; on the other hand pattern recognition is achieved whose peculiarity is represented by the application of clustering based anomaly detection.

In particular, the semantic annotation of sensor data has been addressed by the semantic web research community in recent years. Specifically, through the W3C SSN-XG[14] group, the semantic web and sensor network communities have made an effort to provide a

[14] http://www.w3.org/2005/Incubator/ssn/

domain independent ontology able to adapt to different use-cases, and compatible with the OGC standards. These ontologies have also been used to define and specify complex events and actions that run on an event processing engine [152]. Approaches providing search and query frameworks that leverage semantic annotations and metadata, have been presented in several past works. The architectures described in [153] and [154], rely on bulk-import operations that transform the sensor data into an rdf representation that can be queried using sparql in memory, lacking scalability and the real-time querying capabilities. Some works suggest the use of logic-based reasoners over RDF streams [155] but challenges such as performance and handling of uncertainty exist with such approaches in real-world scenarios [156].

Furthermore, the proposed work stresses the aspects related to swarm based architectures and collaborative behaviors in order to enable a more efficient management of large distributed sensor data sets. In literature swarm based architectures for command and control and for data acquisition and transmission are defined in [157]. Furthermore, in [158] the authors presents a swarming agent architecture for distributed pattern-detection and classification. Whereas in [136], a swarm-based fuzzy logic control mobile sensor network for collaboratively locating the hazardous contaminants in an unknown large-scale area has been described. Similarly to [158] and [136], in [159] the authors propose a framework that applies swarm intelligence techniques to globally coordinate local data processing. In particular, swarm intelligence and fuzzy control are exploited to make reasoning on semantic sensor data in order to push out knowledge and forecast emerging situations.

Finally, the proposed paper also deal with the topic of clustering anomaly detection. In particular in the proposed work the authors propose an approach based on fuzzy clustering able to identify anomalous situations during grid monitoring. Anomaly detection in sensor networks poses a set of unique challenges. Clustering is one of the most used technique for anomaly detection. Clustering based anomaly detection techniques can be grouped in several categories. One of these is based on the assumption that normal data instances belong to large and dense clusters, while anomalies either belong to small or sparse clusters. Techniques based on the above assumption declare instances belonging to clusters whose size and/or density is below a threshold as anomalous. Several variations of the third category of techniques have been proposed [160][161][162][163]. The technique proposed by [163], called *FindCBLOF*, assigns an anomaly score known as Cluster-Based Local Outlier Factor (CBLOF) for each data instance. The CBLOF score captures the size of the cluster to which the data instance belongs, as well as the distance of the data instance to its cluster centroid. Analogously with [159], the present chapter, from an architectural point of view, proposes a framework that exploits on one side a swarm based architecture in order to coordinate the elaboration of distributed semantic sensor data and on the other side fuzzy clustering and classification to detect anomalies in customers load profiling according to the aforementioned assumption.

8.1 Proposed approach

The present work proposes a framework based on swarm intelligence and fuzzy data analysis for decentralized smart grids monitoring. The challenging idea is to adopt the swarm intelligence theory to efficiently distribute computation among heterogeneous power sensors scattered over a wide geographic area, and to employ the fuzzy cluster analysis to perform anomaly pattern recognition. In further detail, in the proposed approach each sensor detection in each node is classified as belonging to a cluster with a certain degree;

therefore the framework is able to identify anomaly ontological individuals (i.e. semantically annotated sensor observations) as belonging to the less dense cluster with a high degree. In other words, there is a fundamental assumption in this work, that is, the more a cluster represents a standard phenomenon, the more it is populous. The following subsections provide an architectural overview and a detailed description of the workflow with reference to the overall proposed framework.

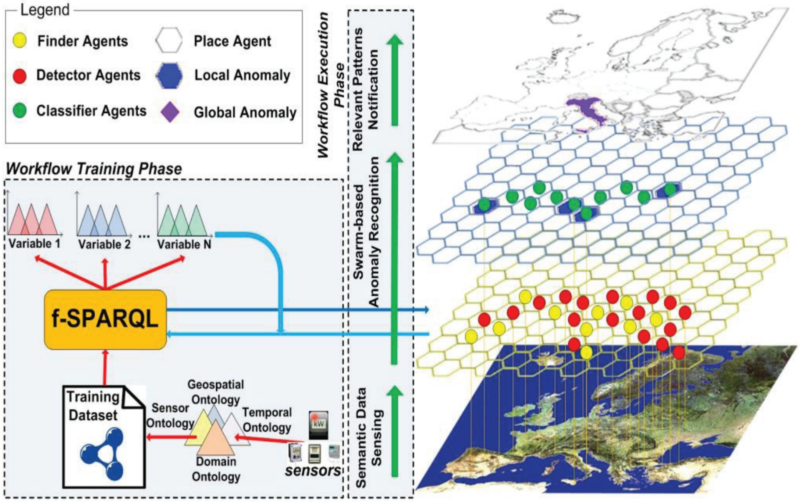


Figure 57. Architectural components and workflow phases.

8.1.1 Architectural overview

In this subsection are discussed architectural components involved in the proposed framework. In particular, the main components involved in the different layer of the proposed architecture are depicted in the Figure 57 (left side). To clarify, the lower layer is represented by sensor network upon which acts a large population of very simple agents according to a swarm behavior. Namely, artificial pheromones (i.e. space-time variables) are used by agents in order to dynamically organize themselves around relevant patterns observed in the sensor data stream. On the other hand, the middle layer of the framework is represented by pheromone infrastructure, that is, a component emulating the pheromone dynamics (i.e. aggregation, evaporation, dispersion) in the real world. In practice, the aforementioned infrastructure consists of a network of places where each place is connected to each other by means of spatial or social connections. In more detail, a place is a location where agents can deposit or sense pheromone and where the pheromone infrastructure manipulates local concentrations of pheromone. Therefore, the proposed intelligent swarm behavior provides the ability for agents to migrate from one place to another in the infrastructure of sensors. In particular, the architecture involves different tasks depending on the type of agents, that is:

- *Place Agents*: provide infrastructure services in order to manage the pheromone properties (such as concentration, evaporation, and propagation) on each node of the network. These agents implement pheromone's logics as well as operations of data sensing; moreover, they provide topological information and manage the interactions between neighboring agents.

- *Finder Agents*: move in the environment in a totally random way, trying to estimate clusters density, which can be translated as a measure of not anomaly for clusters.
- *Detector Agents*: cooperate according to artificial stigmergy, that is, by dropping pheromone in the environment. Their main aim is to locally classify sensor measurements in order to recognize anomalies in semantic sensor data sensed on a node of the network.
- *Classifier Agents*: classify the anomalies detected by Detector Agents, highlighting the most meaningful for the specific domain.

Finally, a layer of higher level can be considered in the proposed framework, that is, an application layer where analysis applications could be receive notifications from agents in the middle layer and show detected results by means of graphical user interfaces.

8.1.2 Workflow

The application environment of the proposed framework may be viewed as a network of interconnected nodes where each node is equipped with sensors able to observe physical phenomena. In particular, let us assume that each sensor observation will be described according to ontologies able to define the capabilities of sensors as well as sensor systems and networks. As a result, each sensor dataset referred in this work is represented by a semantically annotated dataset comply with W3C SSN specifications.

Figure 57 depicts the workflow of the framework, too. In particular, it consists of two main phases: the training phase and the execution phase.

1) *Workflow Training Phase*: the training phase of the workflow involves two subphases:
   a) *Training Data Set Building*: this first phase refers to sensor data pre-processing aimed to filter data and prepare a semantically annotated training data set that will be given in input to clustering algorithm.
   b) *Clustering of Sensor Observations*: in this phase the selected clustering algorithm is carried out on previously collected sensor observations. Therefore, in this phase it is possible to obtain for each cluster a centroid (the most representative element). Specifically, the search for centroids can be performed using f-SPARQL (see Section 4.6.1.1), a framework able to perform approximate querying, fuzzy clustering and classification on semantic datasets. The algorithm exploited by f-SPARQL for clustering is Fuzzy C-Means [99]. Furthermore, f-SPARQL framework also allows the automatic extraction of fuzzy sets, fuzzy terms and fuzzy classification rules from clustering. In particular, in this phase of the workflow, the fuzzy clustering algorithm is run on the semantic training dataset and classification rules are automatically extracted.
2) *Workflow Execution Phase*: this phase of the workflow can be divided into three subphases. Specifically, the first sub-phase is represented by Semantic Data Sensing and

is achieved in order to acquire distributed sensor data and semantically annotate them; the second sub-phase is related to Swarm-based Anomaly Recognition and its goal is to exploit classification rules (resulting from training phase of the workflow) in order to classify sensor data anomalies; finally, the third sub-phase of the workflow refers to the notification of classification results to decision makers (e.g. analysts, operators, etc.) or systems.

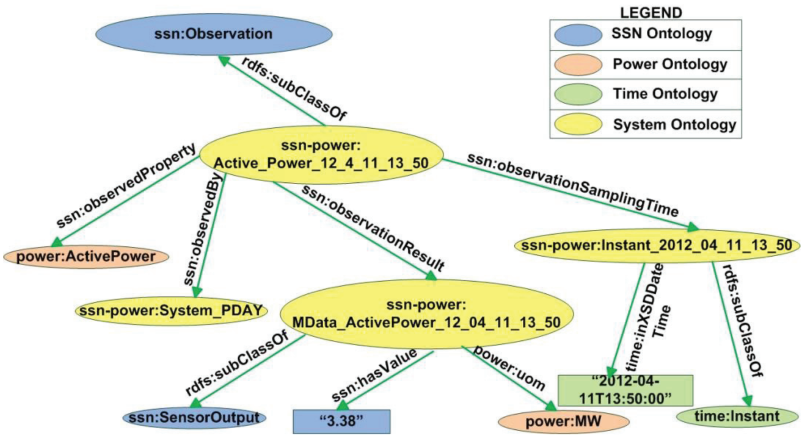


Figure 58. SSN Semantic annotation of a sensor observation.

a) *Semantic Data Sensing*: in this sub-phase of the workflow ontologies and other semantic technologies are key enabling technologies for sensor networks because they can improve semantic interoperability and integration, as well as facilitate reasoning, classification and other types of assurance and automation not addressed in the OGC standards. A semantic sensor network will allow the network, its sensors and the resulting data to be organized, installed and managed, queried, understood and controlled through high-level specifications. Further, when reasoning about sensors, complex physical constraints such as limited power availability, limited memory, variable data quality, and loose connectivity need to be taken into account. When these constraints are formally represented in an ontology, inference techniques are more readily applied [164]. For all this reasons, the author has chosen to focus on W3C Semantic Sensor Network Ontology in our works. Hence, in this work all sensor observations are semantically annotated as described in Figure 58, where the concept of Active Power is modeled according to semantic sensor network specifications.

b) *Swarm-based Anomaly Recognition*: this sub-phase of the workflow concerns with the recognition and classification of anomalies in geographically distributed sensor data. In particular, the execution of a swarm distributed algorithm in this phase foresees the deployment of the agents populations previously described. Therefore, these populations coordinate their activities according to a stigmergic behavior and their goal is to highlight anomaly patterns in sensor data stream. In more detail, there is a Place Agent for each processing node. These agents realize sensor detections acquisition and storing according to Semantic Sensor Network Ontology. Then they make acquired data available to the other entities of the swarm. Furthermore, these agents also provide pheromone management, topological and directory services to the other swarm entities. In other words, Place Agents act as facilitators, providing the agents populations with information about other agents on the same node. Consequently, all interactions between agents are located, the attention of the system is focused on limited fractions of space, thus reducing the need for large bandwidths for communication, a critical feature for real-time applications. On the other hand, each Finder Agent maintains a vector with as many cells as clusters: when it moves over a cell makes a f-SPARQL query requesting the fuzzy classification of the last sensor acquisition, so it adds the belonging degree to each cluster to the value in the corresponding cell of the vector. Then, Finder Agents on the same cell will periodically exchange among themselves the information contained in their arrays, with the aim to refine the search. Moreover, these agents update the cells of their vectors with the mean value resulting from the information exchange with the other agents of population. In this way, Finder Agents converge in a short time towards the same results, estimating thus the density of individuals for each cluster. Detector Agents, on their side, firstly contact a Finder Agent present in the same place in order to get the density vector. Secondly, after the normalization of the density value for each cluster according to (8.1.1),

$$densitydegree_{cluster_i} = \frac{density_{cluster\,i}}{\sum_{j=1}^{n} density_{cluster\,j}} \qquad (8.1.1)$$

they calculate the anomaly vector according to (8.1.2),

$$\begin{aligned} &anomalydegree_{cluster_i} \\ &= max_{0\leq j\leq n}\left\{densitydegree_{cluster_j}\right\} - \\ &\left\{densitydegree_{cluster_i}\right\} \end{aligned} \qquad (8.1.2)$$

with n equals to clusters number. This value represents how much a cluster is far from the densest cluster. As aforementioned, Detector Agents coordinate their operations through the release of pheromone, which depends on the previously calculated anomaly vector. In particular, an Agent Detector will drop three types of pheromone:

- *Attractive Research Pheromone (ARP):* Detector Agents are attracted by this type of pheromone. It is calculated as

$$ARP = \sum_{i=1}^{n} belongingdegree_{cluster_i} * anomalydegree_{cluster_i}. \qquad (8.1.3)$$

However, this concentration of pheromone will actually be issued if, and only if, it will be grater than or equal to the average concentration in the system, that is,

$$concentration \geq system\_average\_concentration. \qquad (8.1.4)$$

This cut is necessary in order to avoid that on a node is released pheromone only because it is close to an anomaly node. Furthermore, when a Detector Agent arrives on a cell, there remains a minimum number of steps equal to:

$$\#step = released\_concentration * y \qquad (8.1.5)$$

with y constant value, for instance equal to 10. This allows to emphasize the discovery.

- *Repulsive Research Pheromone (RRP):* since the anomaly "zones" could be more than one, to avoid that detectors converge towards a single solution, they will also release repulsive pheromone (with a certain factor of propagation and evaporation) adversed by Detector Agents. In particular, each agent will release a concentration of repulsive pheromone equal to:

$$RRP = system\_average\_concentration \qquad (8.1.6)$$

- *Found Pheromone (FP):* it is used to emphasize discoveries, that is, the anomaly observations. In fact, unlike the pheromone research attractive, it does not propagate and evaporates more slowly. FP is released together with ARP and in the same quantity. The movements of Detector Agent are random, but the randomness factor is weighted according to the concentrations of pheromone in the neighboring cells.

Last entities of the swarm are represented by Classifier Agents. They classify anomaly sensor observations detected in the previous phase highlighting the most important ones. Classifier Agents release Classification Pheromone (CP), which spreads and evaporates slowly. The population of Classifier Agents moves into the environment following FP trails released by Detector Agents and according to their classification scheme, which can be local or distributed. The concentration of CP, released on the nodes, will depend on both the concentration of FP and the confidence that the Classifier Agents have in having found a pattern; confidence that increases as its classification scheme proves to be exact. Classifier Agents, however, to limit the problem of false positives, do not consider any concentration of pheromone found, but only those that exceed a certain threshold, globally calculated in the system.

c) *Relevant Patterns Notifications*: the last step of the proposed swarm approach refers to the reporting of classification results to analysts. For instance, Place Agents regularly monitor the concentration of CP on their node and if it is greater than zero, they will send location-aware sensor acquisition together with classification information to analysts that, through a graphic user interface (GUI), are able to understand what is happening in the monitored area at a given time.

8.2 Simulations results

This section discusses the application of the proposed approach of situation awareness in the task of grid monitoring for the IEEE 57-bus test system. The adopted sensor network is composed by 57 cooperative sensors distributed along the power system (one for each node). In order to perform power grid simulations the author has implemented a java simulator whose graphic user interface is shown in Figure 59.

Each sensor senses the following bus variables: voltage magnitude, active and reactive power demand. The data adopted in this study refers to an operating scenario of 96 hours with a sample period of 1 hour. These data has been organized in two data set, namely the training and the validation data set. The first one includes the operation data corresponding to the first 30 hours while the validation data set, reported in Figure 60, is composed by the remaining data samples. The results obtained by applying the proposed monitoring framework on the validation set are depicted in Figure 61. This figure reports the time evolution of the classification pheromone computed by each sensor. Analyzing these profiles it is worth noting as the sensors network detects a network anomaly during the first 22 hours of operations.

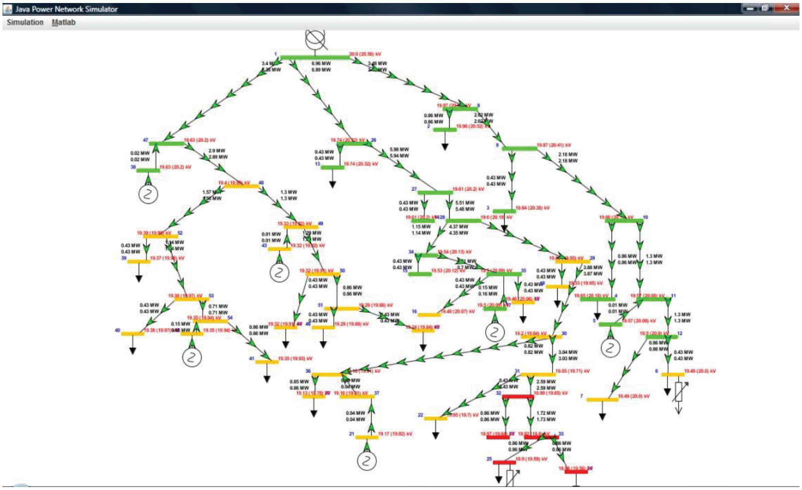
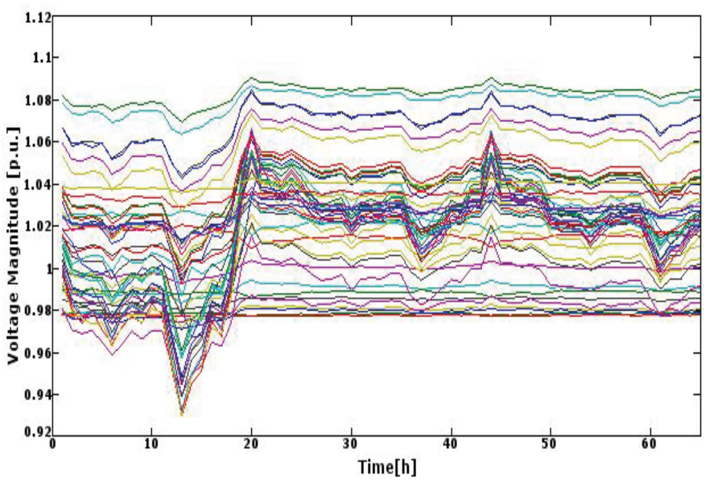
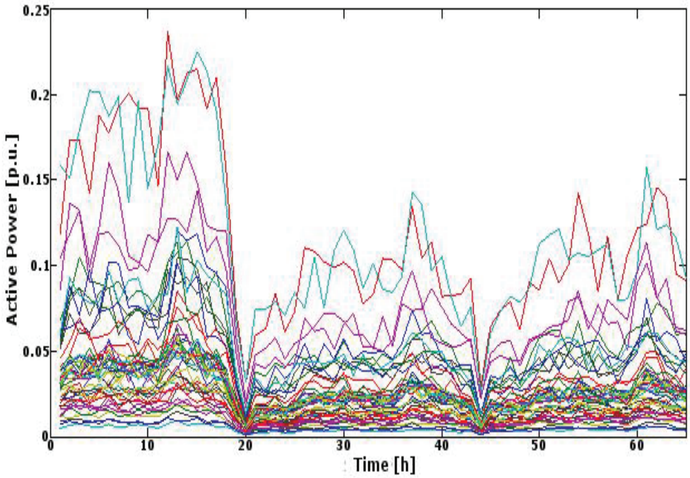


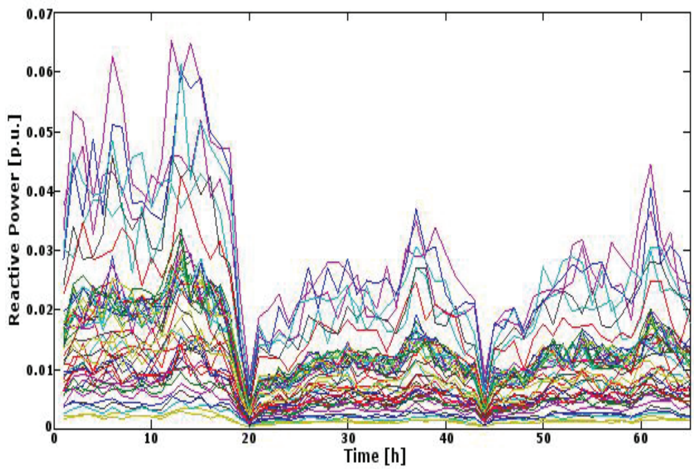
Figure 59. Power Grid Simulator.



(a)



(b)



(c)

Figure 60. Validation data set: (a) Bus voltage Magnitude; (b) Bus active power demand; (c) Bus reactive power demand.

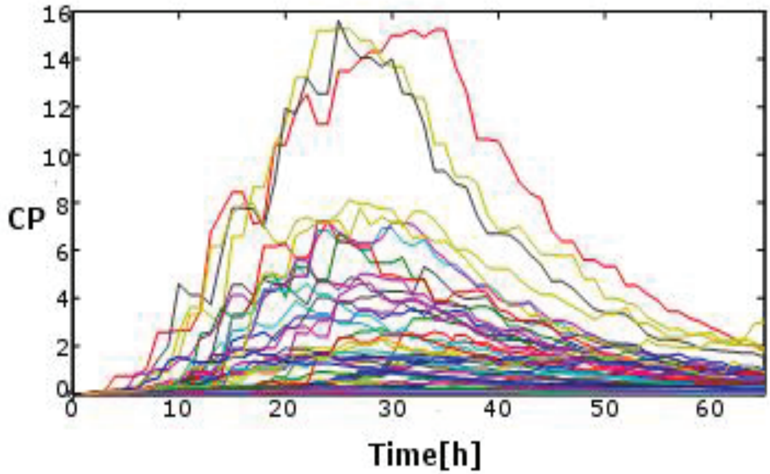


Figure 61. Classification Pheromone concentration on each sensor.

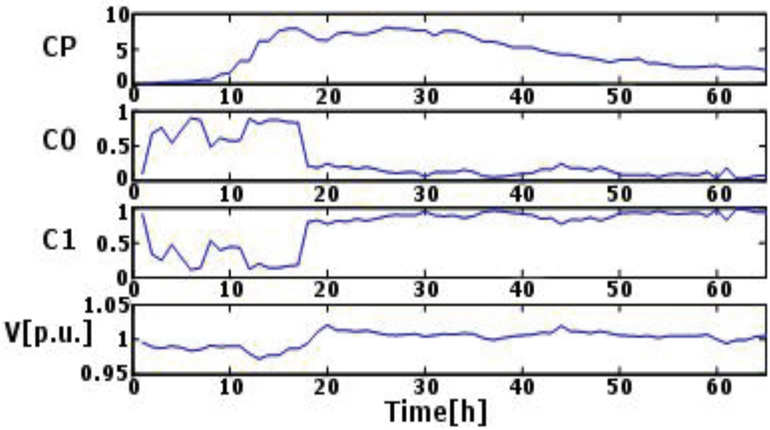


Figure 62. Classification Pheromone, degree of belonging to the anomalous cluster (C0) and regular cluster (C1) corresponding to the reported voltage magnitude profile.

8.3 Conclusions

Modern trends in Smart Grids are oriented toward the employment of advanced monitoring architectures that move away from the older centralized paradigm to a system distributed in the field with an increasing pervasion of smart sensors where central controllers play a smaller role. In supporting this complex task, this paper proposes the concept of a decentralized non-hierarchal monitoring architecture based on intelligent and cooperative smart entities. The hybrid approach proposed in this work aims to highlight as the synergic application of computational intelligence as well as soft computing techniques and semantic technologies can bring benefits from several point of views. Specifically, in the proposed framework the collaborative and self-organizing architecture based on swarm intelligence paradigm (compared to traditional approaches) takes advantages in terms of parallel processing, dynamic adaptation, fault tolerance of the network and so on. On the other hand, fuzzy data analysis enable synthesis, understanding and classification of a huge quantity of sensor data.

Finally, semantic annotation of sensor data enhances information retrieval enabling querying and reasoning to make inferences about data and improve interoperability by creating a common knowledge base.

So with the proposed application scenario the author aims to point out as the instantiation of the previously discussed SbESA approach can take advantages, in a complex domain (i.e. power system domain), on one side in terms of knowledge representation and pattern recognition and on the other side in terms of decentralized monitoring.

The goodness of the proposed approach is also supported by the results obtained on a test power grid showing as this situation awareness approach gives rise to a monitoring paradigm allowing smart sensors to assess the main variables characterizing the actual grid operation without the need of a central server acquiring and processing all the sensors data. This makes the proposed approach an ideal candidate for a decentralized Smart Grid monitoring.

Chapter 9

Context Awareness and Healthcare

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, 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.

In 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 chapter, the author proposes a feasible instantiation of the previously described CAPSD approach in the field of healthcare. Specifically, the aim of the author is to propose 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. Furthermore, the work presents an integrated environment aimed at providing personalized healthcare services which appropriately meet the user's context. In other words, the main 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. The proposed 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 an 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 the proposed approach, the author proposes an application scenario in the domain of healthcare, useful tooutline that a personalized system, based on context-aware service discovery, can improve the quality and efficiency in the user context management. In particular, the author priority is to highlight as the instantiation of CAPSD approach in the field of healthcare allows to meet research objectives such as knowledge representation and information retrieval.

The chapter is organized as follows: Section 9.1 presents an overview of works in the literature related to both context-awareness and computational intelligence approaches that deal with healthcare; Section 9.2 introduces overall architecture which attains the proposed aims and emphasizes the roles played by all the system components; Section 9.3 describes the complete working flow and details theoretical approach on which relies the application scenario; then, Section 9.4 describes the process model applied to healthcare domain. Conclusions and future works close the chapter.

9.1 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 an 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, the author focuses 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, the author focuses 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.

9.1.1 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. [165]and [166] present an OSGi based service infrastructure for context-aware service in smart homes.

A few projects, including Context Toolkit [167], Semantic Space [168], UC Berkeley's open infrastructure [169], and the European Smart-Its project [170], 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 [171][172] or keyword-based [173] service matching process. Context information are also represented by key-value pairs and may be supplemented by simple if-then-rules. An exception is the COSS approach [174] 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 [175] 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 [171][172][173] 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 [172] none of the matching algorithms takes user preferences into account. The approach of [174] also allows to integrate user-defined attributes like 'nearby' into an service request. Advanced concepts for context-aware request modification come from the field of database systems, 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 [176][171][172] or on inquiry [177], but isn't coupled to the matching process, where we actually need it. Merely [171][172] utilize dynamic service attributes within the matching process.

9.1.2 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 [178]. 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 [179], collaborative [180], and hybrid methods [181].

There has been some work done in the area of personalized healthcare. Koutkias et al. [182] 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. [183] introduce an intelligent Personalised 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 a HTML-based personalized health information package on the basis of an individual's current health profile. Takeshi et al. [184] 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.

9.1.3 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 [185], 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 [186]) include depth of anesthesia [187], muscle relaxation [188][189], hypertension during anesthesia [190], arterial pressure control [191], mechanical ventilation during anesthesia [192] and post-operative control of blood pressure [193]. Fuzzy Logic has been applied to computerized clinical guidelines [194], as well as in risk assessment in a healthcare institution [195]. Similarly, knowledge management techniques have been applied to structuring clinical and patient information [196][197].

9.2 Architectural overview

The approach, proposed in this chapter, 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, Figure 63 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 Figure 63, 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.

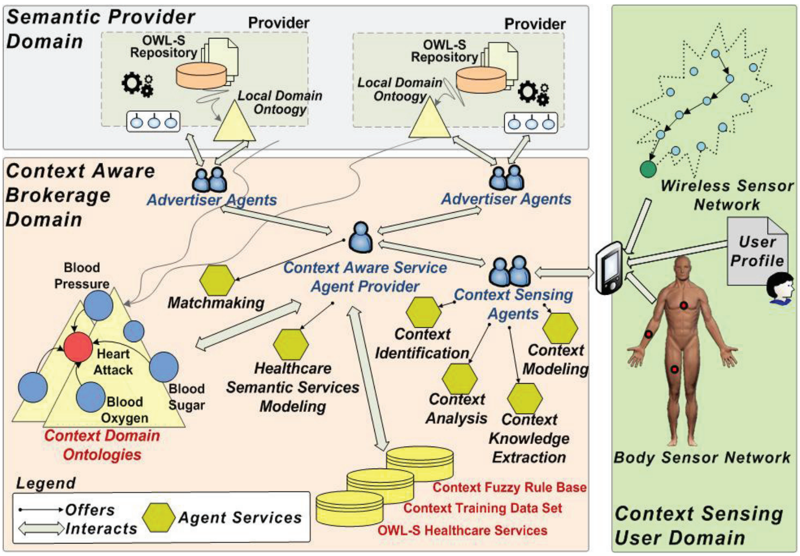


Figure 63. Architectural overview.

9.2.1 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.

In particular, Zigbee compliant Wireless Body Sensor Network (BSN) is used in the architecture for health care 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 oxy-meters 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)[15].

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.

9.2.2 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 [99][198][199]. This work assumes that there exist semantic web services providers. So, in the architecture Semantic Provider Domain as shown in Figure 63 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.

9.2.3 Context aware brokerage domain

In this architectural domain brokerage, mediation and matchmaking activities take place. In particular, as shown in Figure 63 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[16] 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[17] 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

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

[16] JADE, Java Agent DEvelopment Framework, URL: <http://jade.tilab.com/>.

[17] FIPA, Foundation for intelligent physical agents, URL: <http://www.fipa.org/>.

by agents will be achieved through SPARQL[18] queries and description logic reasoner. Next subsections details the agents' individual goals.

9.2.3.1 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 multisensory 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 Modelling*, *Context Analysis*, *Context Knowledge Extraction*, *Context Identification*. More specifically, the *Context Modelling* 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.

9.2.3.2 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*.

18 SPARQL, RDF query language, URL: http://www.w3.org/TR/rdf-sparql-query/

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.

9.2.3.3 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.

9.3 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.

9.3.1 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.

Figure 64 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 Figure 64, 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.

9.3.1.1 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 modelling by the use of context domain ontologies and the actual mapping to a suitable model, based on a well-defined mathematical formalism. Homogenous data representation is often required to guarantee a right data processing.

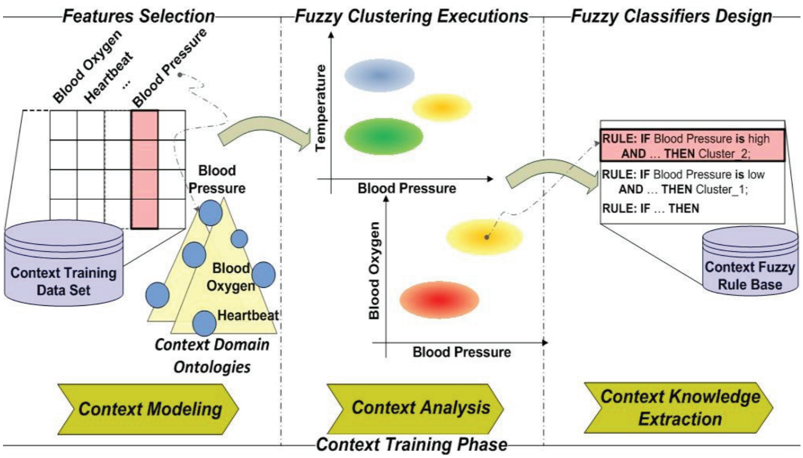


Figure 64. Main phases of the workflow during Context Training Phase.

In the 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 [200]. 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 [201], 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 [202]. 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 [203]. 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) [204], DAML+OIL[19], and OWL [205]. 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) [206].

The overview of Context Modeling is shown in Figure 64. 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 modelling 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.

9.3.1.2 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 [207][208] and clustering techniques [209][210] are widely employed in the extraction of knowledge automatically from clinical data. Moreover, combined approaches between fuzzy clustering and GA-optimization [211], fuzzy mining medical rules [212] are demonstrated the responsiveness at this kind of activity.

In the proposed application scenario, this phase is accomplished by fuzzy clustering approach. More specifically, the main tasks foreseen in this phase are listed as follows:

[19] http://www.daml.org

- *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 the proposed 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 [99] (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 [213][214][215][216]. 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 the proposed application scenario 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:

$$V(U) = \sum_{i=1}^{c} \sum_{j=1}^{n} u_{ij}^{m} \left\| x_j - v_i \right\|^2 \tag{9.3.1}$$

where $c \geq 2$ is the number of clusters, $u_{i,j} \in [0,1]$ 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 $m = 2$).

In this approach, each row of data matrix is a vector representing the context parameters measures (viz. eight characteristics identified before) of each user $x = (x_1, x_2, x_3, x_4, x_5, x_6, x_7, x_8)$. 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, hearthbeat. 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.

9.3.1.3 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 [217] 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 [218][219].

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 [220] (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 Figure 65, in the proposed application scenario the author foresees a mapping between sensing and context concepts of domain ontologies and a FCL/FIS file input and output parameters respectively.

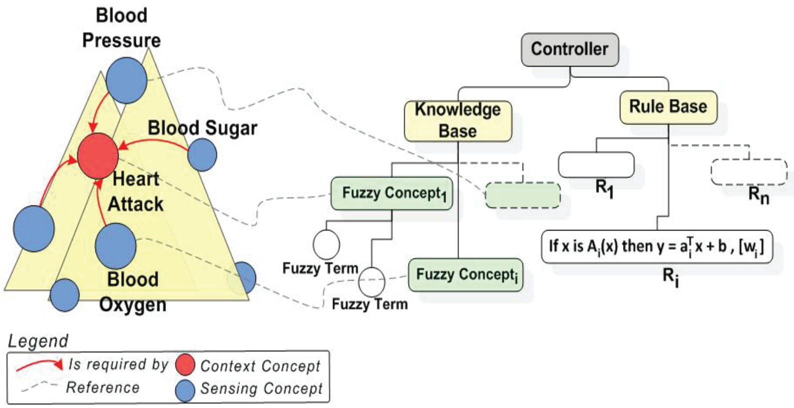


Figure 65. A mapping between sensing and context concepts and a FIS/FCL files structure.

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 [140] is described as follows:

$$R_i\colon if\ x_1\ is\ A_{i1}\ AND\ x_2\ is\ A_{i2}\ AND\ \ldots AND\ x_n is\ A_{in}\ then$$
$$y_i = a_{i1}x_1 + a_{i2}x_2 + \cdots + a_{in}x_n + b_i,$$
$$with\ weight[w_i]\ i = 1, \ldots, c$$

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 [221]; indeed the uniform structure of bell-shaped function is suitable for identification, analysis and optimisation. 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:

$$A_{ij}(z) = exp\left\{-\frac{1}{2}\left(\frac{z-\alpha_{iq}}{\beta_{iq}}\right)^2\right\} \tag{9.3.2}$$

where

$$\alpha_{iq} = \frac{\sum_{j=1}^{n} u_{ij}x_{qj}}{\sum_{j=1}^{n} u_{ij}} \quad and \ \beta_{ij} = \sqrt{\frac{\sum_{j=1}^{n} u_{ij}\left(x_{qj}-\alpha_{iq}\right)^2}{\sum_{j=1}^{n} u_{ij}}} \tag{9.3.3}$$

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

On the other hand, the computation of parameters $a_i = [a_{i1}, a_{i2}, \dots, a_{in}]^T$ 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 [222].

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 [222]:

$$\hat{y}_k = \sum_{i=1}^{c} [w_i(x_k)(x_k a_i + b_i)] \tag{9.3.4}$$

with $k = 1, 2, 3, \dots, n$ 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 $\hat{Y} = X'\left[a_i^T, b_i\right] + \varepsilon$ is evaluated: herein ε is the approximation error, X' assumes the form: $X' = \left[w_{1,}x_k^T, 1,\ w_{2,}x_k^T, 1, \dots, w_{c,}x_k^T, 1\right]$. The vectors $[a_i^T, b_i]$ are determined using the least-squares method [222].

9.3.2 Context Aware Services Discovery Phase

Context Aware Service Discovery Phase represents the runtime process. This section outlines main tasks: context identification, healthcare services modelling and matchmaking. As shown in Figure 66, on the left side the context identification activity take place, here by means the results of the previous phase (see Section 9.3.1). In particular, degree of fulfilment of rules set is evaluated in order to recruit context identified features. On the right side of the Figure 66, characterization of healthcare services based on OWL-S formalism (mainly Input-Output-Precondition-Result) is depicted. Then, in the middle of Figure 66, the activities of context identification and healthcare services modeling converge in the matchmaking task. Next subsections give more details about these tasks.

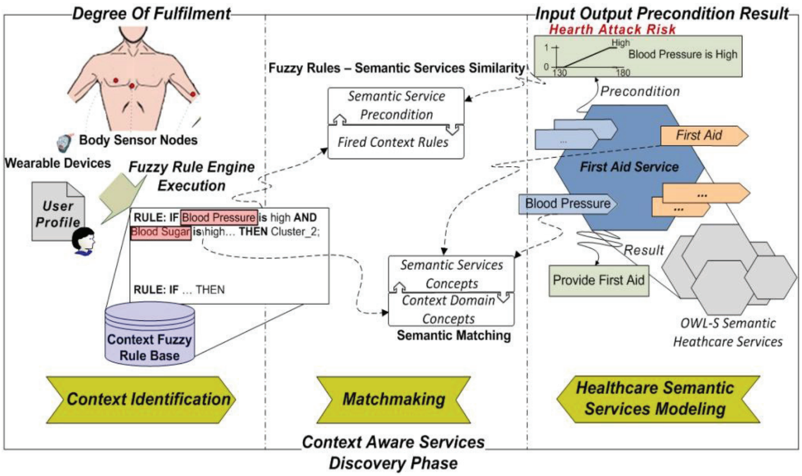


Figure 66. Main phases of the workflow during Context Aware Services Discovery Phase.

9.3.2.1 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 Figure 63); and Context Fuzzy Rule Bases carried out from previous Context Traing Phase.

Now, context identification is performed by means of the evaluation of degree of fulfilment among all fuzzy rules available in Context Fuzzy Rule Base. Since terms in the rules previously extracted (see Section 9.3.1.3) 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 9.3.2.3).

9.3.2.2 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 [223], 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;
- 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 Figure 67, IOPR components in the Service Profile refer context domain ontologies (as well as the identified context see Section 9.3.2.1). In particular, Figure 67 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 Figure 67 dispatch user rescue to the Assistence. 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 Figure 67. 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.

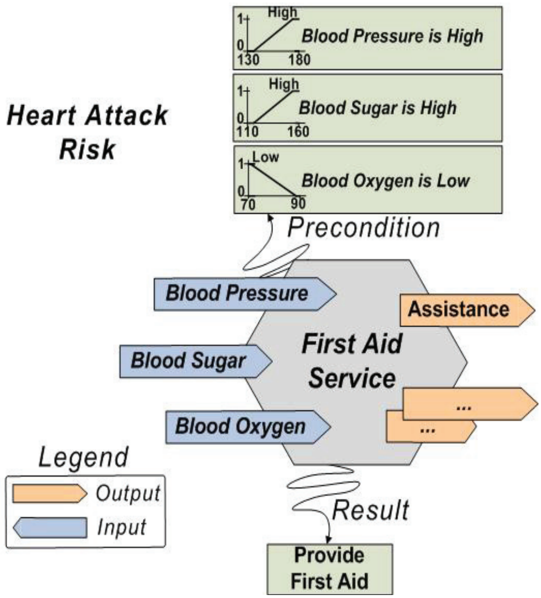


Figure 67. An illustrative example of healthcare semantic service IOPR specifications.

9.3.2.3 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 [224] 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:

$$S(A,B) = \frac{|A \cap B|}{|A \cup B|} \tag{9.3.5}$$

where $|\quad|$ 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:

$$if\,(x_1\ is\ A_{i1})\ and\ (x_2\ is\ A_{i2})\ and\ \dots and\ (x_n\ is\ A_{in})\ then\ x\ is\ \mu_i$$

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 fullfillment 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:

$$deg_{MATCH}(SWS_f) = \max_i \left\{ \frac{\sum_{j=1}^{n} S(A_j, B_j)}{n} \cdot \mu_i(x) \right\} \tag{9.3.6}$$

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 (9.3.5) and $\mu_i(x)$ is the membership degree to the i-th cluster (i.e. rule).

In the following section, the author will show the benefits in terms of qualitative matchmaking deriving by the application of (9.3.6).

9.4 Experimental results

The aim of this section is to show the experimental results obtained by the application of the proposed approach on simulated sensor data. In particular, the test environment of the proposed simulation relies on a Framework for the development of Body Sensor Network (BSN) applications, that is, SPINE (Signal Processing in Node Environment) [225]. Particularly, sensors used in the simulation are pulse monitors for heart rate, pulse oxymeters for blood oxygen level, spirometers for the amount of air inspired and expired by the lungs and a blood pressure sphygmomanometer. Furthermore, the author has also considered the problem of missing data related to the information provided by sensors. In this regard, some modifications to clustering algorithm have been applied in order to cope the problem of incomplete data, as suggested in [226].

Figure 68 shows a high-level view of a typical semantic web service processed by the system. In particular, the aim of the author is to highlight as the definition of service have been enriched by *Precondition Fuzzy Set*.

The analysis proposed in this section is aimed to evaluate the results by exploiting Precondition Fuzzy Set and instances of concepts in the context domain ontologies.

On the other hand, other matchmaking approach based on semantic similarity between context domain ontologies general concepts are taken into account.

Before going on with the presentation of experimental results, the author will try to clear the difference between the two aforementioned approaches through the example in Figure 69. In particular, thanks to this example the author wants to point out the qualitative representation of context by exploiting of Fuzzy Set Preconditions and admissibility ranges of under observation healthcare parameters.

In more details, Figure 69 show three services *S1*, *S2*, *S3* with input Blood Pressure and an Assistance operation as output and a request *R* with Blood Pressure as input concept. A semantic matchmaking purely based on logic will match all three services (as shown in Figure 69a), whereas the proposed hybrid matchmaking will even match all three services but with different matching degrees (as shown in Figure 69b), therefore a threshold can cause the triggering of context services (e.g. a 0,7 threshold).

9.4.1 Matchmaking evaluation

In order to highlight the goodness of the proposed approach in terms of matchmaking performances, the author has chosen to apply the precision and recall measures. This choice is justified by the fact that in this approach, the context characterization represents the query and the selected services stand for the answer, that is to say, we are doing query answering.

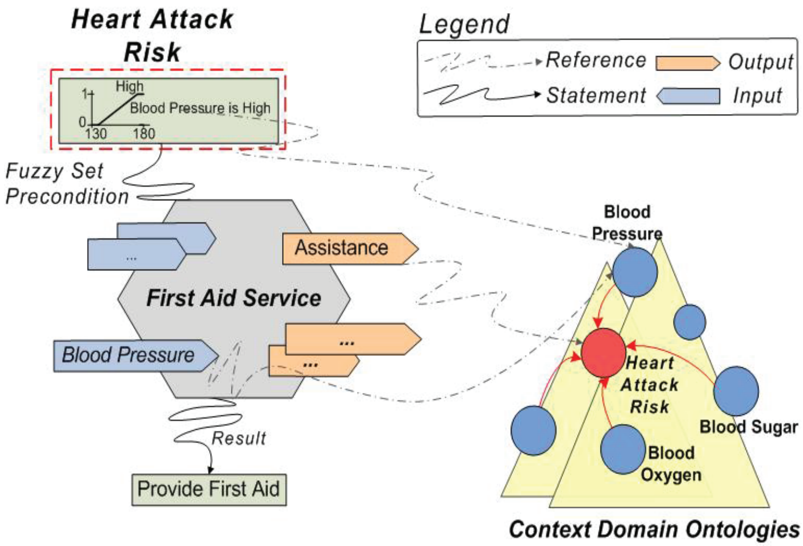


Figure 68. An example of healthcare semantic web service with the possible application of Precondition Fuzzy Set.

Specifically, our simulation exploits the relevance data set summarized in Table 3, that is to say, part of service retrieval test collection Owls-TC v2[20] with the addition of a suitable block of healthcare services. Notably, Table 3 shows the total number of services and relevant services, the identifier of each query with the related context and number of steps.

In order to get an adequate comparison we have used the OWLS-MX experimentation, and therefore we have tried to set up a similar starting configuration. This test case has been executed on the OWLS Profile description of semantic web services, by considering only the terms declared in the specifications of OWLS IOPRs. Indeed, OWL-S MX doesn't consider the pre-condition. On the contrary, our approach use pre-condition that represents the context aware modeling embed into a web service. Specifically, the retrieval performance of the proposed system is assessed in terms of precision and recall measures. Like in OWLS-MX approach we consider the evaluation of micro-average of the individual precision-recall curves, exploiting a number $\lambda = 15$ of steps up to reach the highest recall value.

Thus, let Q be the set of service requests, D all the relevant service OWLS descriptions of all requests in Q. According to [227] the micro-averaging of recall and precision (at step λ) overall requests, is defined as in (9.4.1):

$$Rec_\lambda = \sum_{R \in Q} \frac{|A_R \cap B_{\lambda,R}|}{|A|} \quad Prec_\lambda = \sum_{R \in Q} \frac{|A_R \cap B_{\lambda,R}|}{|B_\lambda|} \qquad (9.4.1)$$

[20] http://projects.semwebcentral.org/projects/owls-tc/

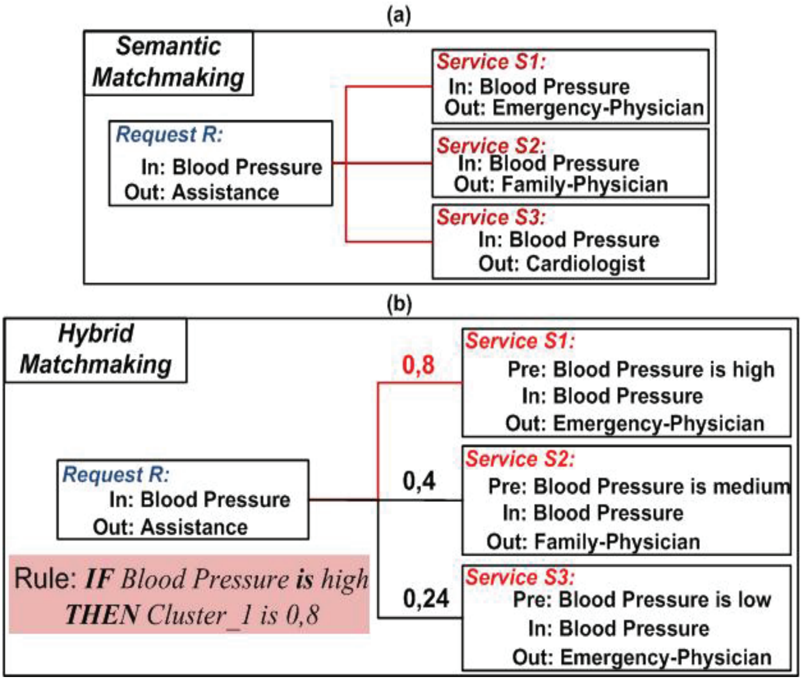


Figure 69. Different matchmaking approaches: (a) semantic matchmaking; (b) hybrid matchmaking.

Table 3. Precision and Recall Relevance Data Set.

Medical Care Services Data Set			
No. Total Services		**No. Total Relevant Services**	
670		**300**	
Query	**Context**	**No. Relevant Services**	**No. Steps**
1	Heart Attack	28	15
2	Fainting	37	15
3	Flu	45	15
4	Ictus	56	15
5	Tachycardia	64	15
6	Renal Insufficiency	70	15

where A_R is the answer set of relevant services (service advertisements) for given request R, B_λ is the set of retrieved OWLS descriptions at the step λ and $B_{\lambda,R}$ is the set of all relevant OWLS descriptions, retrieved at the step λ.

In particular, in the experimentation the curve obtained by the proposed approach (hybrid matchmaking) is compared with the results computed on the same queries, by exploiting the OWLS-MX algorithm [228]. In fact, the experimentation performed on the OWLS-MX approach is based on different variants of their matchmaker: they range over a purely logic based approach, named OWLS-M0, to (four) more hybrid variants, called OWLS-M1 to OWLS-M4. Conversely, the proposed matchmaker exploits Precondition Fuzzy Set, Context Domain Ontologies instances and context parameters admissibility ranges. In

Figure 70 the author compares the obtained results, with refers to the proposed approach, with the OWLS-M0 and OWLS-M4 variants that represent the two extremities, that is to say, the first one exploits only logic-based filters (EXACT, PLUG-IN, etc.) whereas the second one is a hybrid approach based on Information Retrieval techniques, using syntactic similarities. In particular,

Figure 70 shows the tendency of the micro-average of recall/precision curve evaluated on the whole collection set. Let us observe that the performances of the proposed approach are mainly better in term of precision. This happens because the service matching takes into account context awareness embedded in the pre-condition of the service. So, the performance curve seems to show best results, overcoming all OWLS MX variants in terms of precision. On the other hand, while both the proposed approach and OWLS-M4 curve reach a maximum value for recall, OWLS-M0 can't reach a value 1 for recall. The main reason for this is that the additional IR based similarity check of the nearest-neighbor filter and the qualitative representation of context by exploiting of Fuzzy Set Preconditions allows to OWLS-M4 and the proposed approach, respectively, to find relevant services that OWLS-M0 would fail to retrieve.

Finally, let us highlight that the query/answering time of the proposed approach is insignificant, and no optimization techniques have been adopted. In this sense the approach presents performance that are very similar to a traditional web search engine.

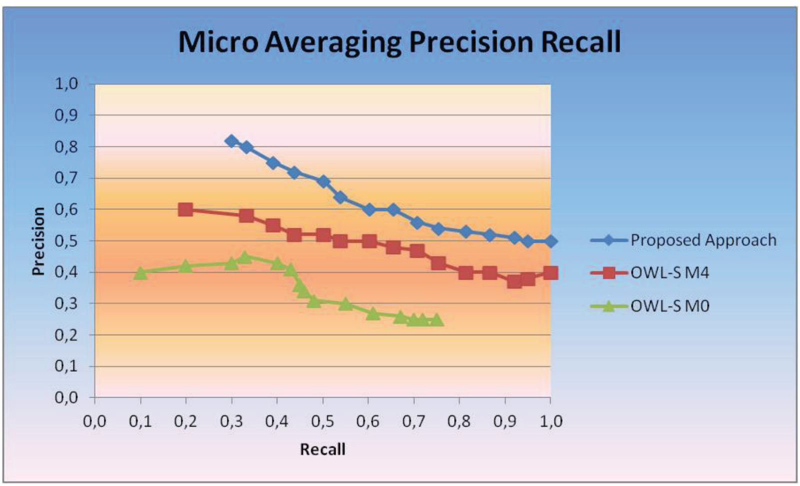


Figure 70. Comparison between Context Aware Service Matchmaking and OWLS-MX in terms of Precision/Recall.

9.5 Conclusions

This chapter presents an architectural overview of a framework in the domain of healthcare based on the instantiation of CAPSD approach. This instantiation results in a context aware architecture whose main aim is related to support proactive context identification and context-aware healthcare services discovery. Through a sequence of phases the system trains itself by means of unsupervised context data analysis aimed at profiling the user's context.

It is important to point out as for the proposed approach is fundamental the knowledge representation, since ontologies are very important to provide usability and interoperability. In other words, ontologies enable the semantic description of data and the interrelationships among concepts.

Always in terms of research objectives, it is important to highlight the enhanced performances of the proposed approach in terms of information retrieval. In particular, experimental results, prove the goodness of the proposed approach with respect to OWLS-MX variants. From the obtained experimental results it is possible to address the conclusion that in order to support context aware services discovery there is a need to model and identify the context requirements. In particular, context awareness should be used during services matchmaking evaluation.

A future extension of this approach foresees two aspects; in particular, the first one is related to the introduction of time entity in the modelling 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.

Finally the application scenario carried forward in this chapter, 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.

Chapter 10

Conclusion and Future Work

This chapter closes the thesis work by describing a short summary. Furthermore, Section 10.1 concludes the dissertation with considerations about the contributions resulting from the present work whereas Section 10.3 describes future challenges.

10.1 Summary

This research work aims to define general frameworks to support Situation\Context Awareness in several complex and dynamic application scenarios. In particular, the main idea of this research refers to the integration of general approaches for Situation and Context Awareness in these frameworks.

So, the author proposes two general approaches for SA (i.e. CoMSA and SbESA) and one general approach for CA (i.e. CAPSD). Each approach is characterized by the synergic combination of Semantic Web technologies and Computational Intelligence techniques to enhance the representation and elaboration of knowledge intended as distributed sensor data.

Specifically, CoMSA approach for SA is based on the exploitation of an upper ontology based on situation theory and the distribution of reasoning about situation among several task oriented agents.

On the other hand, SbESA approach represents an evolution of CoMSA approach since it foresees a sensor data analysis phase for the automatic extraction of relevant patterns from sensor data (i.e. relevant situations). Furthermore, SbESA approach takes advantage of Swarm Intelligence theory for the distribution of sensor data processing among different populations of simple agents whose interactions are minimized.

Instead, CAPSD approach exploits ontologies and fuzzy data analysis in order to support proactive context identification and context-aware services discovery.

All these approaches have been extended and applied to achieveseveral research objectives such as knowledge representation, semantic reasoning, pattern recognition and information retrieval as well as several scenarios in the following application domains: *Airport Security*, *Traffic Management*, *Smart Grids* and *Healthcare*.

Finally, in these application scenarios experimental results highlight that hybrid approaches, complying with the proposed general approaches, may improve the reasoning and retrieval performances.

10.2 Conclusions and contributions

This research work analyzes and addresses the main issues in the fields of Situation and Context Awareness. Specifically, one of the most important issues in these fields concern with the availability of too much data and not enough knowledge. Moreover, the data is very often uncertain and geographically distributed leading to difficulties in their management and processing. As result, this work proposes to combine technologies deriving from Semantic Web and techniques of Computational Intelligence in order to overcome these challenges and meet research objectives such as Knowledge Representation, Semantic Reasoning, Pattern Recognition and Information Retrieval.

So the main contributions of this research work refer to:

- the exploitation of sensor ontologies to support the acquisition and aggregation of dynamic environmental information from the field (i.e. sensors, cameras, etc.)
- the definition of formal approaches to knowledge representation (i.e. situations, contexts, concepts, relations, etc.);
- the definition of formal approaches to knowledge processing (i.e. reasoning, classification, extraction, retrieval, recognition, discovery, etc.);
- the definition of multi-agents architectures capable to efficiently support the modeling and processing of a large amount of knowledge.

10.3 Future Work

Some of the future challenges go in the following directions:

- *Semantic Modeling of Fuzzy Control*. Study, definition and development of an upper ontology for semantic modeling of Fuzzy Control. The main contribution will consist in the exploitation of Fuzzy Logic in RDF/OWL to model vagueness and uncertainty of the real world. Moreover, the aim of this future work is to support automatic discovery and execution of fuzzy controllers, by enabling context aware parameterization of them, that is to say, one or more appropriate controllers will be activated, depending on the parameters identified in the environment.

- *Temporal Issues.* Address temporal issues such as the semantic modeling of time entity as well as temporal reasoning.

- *Automatically Ontology Elicitation*. Exploiting Fuzzy Data Analysis in order to elicit implicit conceptualization in the data and translate that in the ontology knowledge.

- *Extension to other Application Domains*. Applying this approach in other interesting fields (i.e. military, diagnostic and so on).

- *More Experiments*. The author also plans to do more experiments in the near future against available data sources to further test the performance and the scalability of the prototype systems.

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