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Reasoning System for Computer Aided Diagnosis with explanations aware computing for medical applications

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Résumé

Les systèmes de raisonnement artificiels sont maintenant très puissants pour résoudre maints problèmes complexes dans tous les domaines des sciences de la santé. Il y a aussi de nombreuses investigations dans ce domaine qui se concentrent sur la modélisation, la combinaison, la mise en œuvre des méthodes intelligentes pour explorer les connaissances utiles extraites automatiquement à partir d'un entrepôt de données ou modélisé des expertises de l'expert humain, qui représentent les résultats de plusieurs années d'observations manuelles. Dans cette thèse, nous avons étudié dans de nombreux aspects théoriques pour servir le domaine médical qui protègent la vie humaine via le diagnostic le soin et la protection de la santé.

En tant qu'application crucial dans la science de santé les systèmes d'aide au diagnostic ou les systèmes d'aident à la décision, prennent une place importante dans le marché des logiciels ainsi que dans la société. Une diversité de systèmes mis au point apparaît pour assister aux défis médicaux et les besoins pour assurer un niveau élevé de prise en charge de la santé humaine en assurant le soutien et les installations pour les déférents acteurs médicaux.

EXACT : (Explanation aware computing) Informatique avec l'explication consciente avec beaucoup de buts d'utilisation et de nombreuses sortes d'explications est une tendance convient à tous les type d'utilisateurs, y compris les docteurs médecins, les patients et même les développeurs. Pour établir une relation solide basée sur la confiance entre les applications médicales complexes et les utilisateurs.

Cette thèse est composé de deux parties, la première est une description des aspects théorique du raisonnement artificiel: le raisonnement à partir de cas, le raisonnement distribué et le raisonnement sous incertitude avec les systèmes flous. La deuxième partie, nous décrivons nos contributions dans les domaines de la médecine: la première contribution concerne un système d'aide au diagnostic médical appliquées dans la détection des arythmies cardiaques et de cancer du sein à partir des signaux et des images par l'utilisation d'une combinaison d'approches intelligentes cité dans la première partie. La deuxième contribution, qui représente un complément du processus de diagnostique cité dans la première partie, décrit les explications dans le système de raisonnement développé et la réutilisation de ces explications pour la recommandation des documents via les technologies participatives du web2.0.

Abstract

The artificial reasoning systems are now very powerful for resolving much kind of complex problems in all health science domains. Also there are many investigations in this area which focus on modeling combining implementing some intelligent methods for exploring the useful knowledge extracted automatically from a data warehouses or modeling from the human experts expertise's' which represent the results of many year of manual observations. In this thesis we have investigated in many theoretical aspects for serving the medical domain which protect the life of human beings by detecting caring and protecting the health.

As a crucial application in the health science the computer aided diagnosis or decision support systems, take an important place in the market of software as well as in the society. A diversity of developed systems appears for attending the medical challenges and needs for ensuring a high level of caring the human health by ensuring the support and facilities for deferent medical actors.

ExACt: Explanation Aware Computing with many goals and many kinds of explanations is a suitable trend for all Medical IT users including doctors, developers and patients. For developing a strong relationship based on the trust and believes between the complex medical applications and users.

This thesis focus on two parts the first one is an horizontal description of many theoretical aspect in the domain of artificial reasoning as well as case based reasoning, distributed reasoning and reasoning under uncertainty with fuzzy systems. In the second part we describe our contributions in the medical domains the first contribution concerns an original computer aided diagnosis applied in the detection of cardiac arrhythmias and breast cancer from signal and image pattern by using a combination of intelligent approaches. The second contribution, which is a complement of the first part, describes the EXACT in the developed reasoning system and the reuse of explanations for documents recommendation via the participative technologies of web2.0.

Contents

Part 3 publications

Introduction

Reasoning is a mental operation in which, with predefined judgments, we generate a new judgment. The artificial reasoning systems are now very powerful for resolving much kind of complex problems in all health science domains. Also there are many investigations in this area which focus on modeling combining implementing and integrating some intelligent methods for exploring the useful knowledge extracted automatically from a data warehouses or modeling from the human experts expertise's which represent the results of many year of manual observations. These investigations are developed for responding to the challenges of health science applications as accuracy transparency flexibility and other optional needs as adaptability…etc.

The case based reasoning is a successful paradigm for resolving a variety of complex problems as diagnosis, classification, information retrieval, strategic games and others. This approach consists of reusing the most similar resolved problems for resolving the new problems.

The distributed reasoning is widely applied in much kind of reasoning systems due to the existing systems architectures and the distributed resources and to improving the systems performances. The multi-agents systems which implement the distribution of reasoning comprise a group of intelligent agents working towards a set of common global goals or separate individual goals that may interact. An agent may have to communicate and negotiate with other agents to resolve any uncertainties (arising out of the partial or imperfect views of the global problem-solving context) to the extent that it can make positive contributions to the ongoing problem solving process.

The reasoning environment and also the reasoning contain many sources of uncertainty. This uncertainty can be due to the applied method of measuring or due the approximate knowledge used. This uncertainty increases the risk of errors and faults which can't be accepted in some critical domains as health sciences where the human life is concerned. Reasoning under uncertainty is widely discussed and focused by researchers; the fuzzy systems based on the fuzzy sets theory introduce a new variant which enrich the classical sets by a membership function defined between 0 and 1. This enrichment gives the opportunity to many researchers to optimize their reasoning systems as the case of our system.

The Explanation Aware Computing EXACT, which is hardly and widely developed by the research community, with many goals and many kinds is a suitable trend for all Medical IT users including doctors, developers and patients. For developing a strong relationship based on the trust and believes between the existing complex application and users. The EXACT become not an option but indispensable criteria of the newest complex smart applications for medical purpose where the life of the human is the first preoccupation.

The web 2.0 centered applications give more accessibility for a variety of actors who collaborate via the existing sophisticated applications as blogs social networks wikis etc. These kinds of applications have the specificity of mass and participative uses in the other side the opportunity of knowledge sharing.

In this area some indispensable criteria will considered as the information quality, the privacy and others. A newest sub-types of these applications the health 2.0 applications which focus on putting these opportunities for the services of health sciences by adapting the resources for users.
Our thesis focus on two trends the first one is to develop a strong Case based reasoning system for medical computer aided diagnosis and explanation aware computing for this we have combined many theoretical aspect in the domain of artificial reasoning as well as case based reasoning, distributed reasoning and reasoning under uncertainty. The second trends is to develop a web centered application which reuses the generated explanations from the CBR system for prevention, home health caring and document recommendation system. This system should ensure an adapted interaction between the reasoning system and all kind of users by using the Web 2.0 (social network, wiki…etc) technologies.

1 Research plan

1.1 CBR classifier for computer aided diagnosis

The case based reasoning is a successful paradigm in the health science applications many realized system was cited in [15] but each one of them is specialized in some diseases and need more accuracy for responding to the uncertainty of medical information. This paradigm has a large use in many domains; also there are many developed variants [13] which give the possibility to solve many kinds of problem as the classification.
The first step on our thesis is to develop an accurate CBR system for medical computer aided diagnosis, by integrating the distributed CBR [17], IK-CBR [16], fuzzy sets [14] and data mining approaches [18]. The developed system should be evaluated and compared with the performance of related works.

1.2 Explanation aware computing

In human to human interaction, the ability to explain its own behavior and course of action is a prerequisite for a meaningful interchange; therefore a truly intelligent system has to provide comparable capacities. [3] But on the case of human machine interaction where there are a complex recorded knowledge and a mass application users with a different goals and kinds and in sometime a critical kind of application as health science applications an adaptive explanations become a necessity not just an option.
These explanations could be divided into four types [Swartout and Smoliar, 1987; Chandrasekaran et al., 1989; Gregor and Benbasat, 1999]:

• Reasoning Trace: Producing an explanation from the trace of the reasoning process used by the system to find the solution. Examples are MYCIN’s how and why explanations [Clancey, 1983].

• Justification: Providing justification for a reasoning step by referring to deeper background knowledge. This type of explanation was first offered by the XPLAIN system [Swartout, 1983].

• Strategic: Explaining the reasoning strategy of the system. The NEOMYCIN system first provided this kind of explanation [Clancey, 1983].

• Terminological: Defining and explaining terms and concepts in the domain. This type of explanation was identified in [Swartout and Smoliar, 1987].

Also five goals a user can have with explanations are introduced, namely 1. Transparency (explain how the system reached the answer), 2. Justification (explain why the answer is a good answer), 3. Relevance (explain why a question asked is relevant), 4. Conceptualization (clarify the meaning of concepts), and 5. Learning (teach the user about the domain). [1, 2]

A cognitive agent for explanation is proposed which ensure all kinds of explanation by reusing the log files generated by the developed classifier and by inferring from a knowledge base which contains the needed knowledge for ensuring an adapted explanation for each kind of users by considering some levels of abstractions.

1.3 Health 2.0

The health 2.0 and homecare systems based on the web 2.0 technologies realize a tie between the health care actors (doctors, patients and the other users) for explanation and prevention. For example the Facebook web site is an interactive social network with a mass uses (880.5 million users in Dec 2012 on the world) launched in February 2004 contains an important API for developers with an ubiquitous ability for relevant applications in health sciences. But the problem of online information is that this information can be inaccurate, incomplete, controversial, misleading, and alarming for individuals with health questions [4, 5].

The developed reasoning system will realize the connection between all these capacities for a newest and original healthcare application. This system will contains a set of cognitive agents each one will be specialized for resolving some sub-problems. The system will be divided on two parts: 1-a CBR system for online computer aided diagnosis discussed in section 2.1. 2- An explanation agent which reuse the traces on the log files and a sets of documents.

The second step of our thesis will focus on developing an explanation agent which can ensure an adaptive explanations for a mass uses with categorization of these users. Also the agent will enrich the explanation by a document recommendation system centered on the web2.0 technology (social networks, wikis and blogs) for health caring and prevention by avoiding the problems of online information which can be inaccurate, incomplete, controversial, misleading, and alarming for individuals with health questions. The risk of these problems can be decreased by considering the recommender category and the rate of recommendation.

2 Contributions

A case based reasoning system is developed for medical diagnosis and classification [1] through some measures taken from the patient the system can generate the disease of this patient. We have also evaluated this system by a benchmark with two international medical data sets cardiac arrhythmias and breast cancer, the results and the comparison with the related works exist in [8,10,11,12] and [6,7]. Also we have applied and compared between deferent strategies and algorithms in [8,9,10,11,12]. Many problems was discussed and resolved in the published works as transparency, distributed reasoning, case base learning, features selection, intensive-knowledge CBR, data mining with CBR, Uncertainty measures and Fuzzy CBR. A novel similarity measures was developed and evaluated in the classifier for enriching the retrieving process by merging the fuzzy sets and the traditional global-local similarity measures presented and evaluated in [7,8,9] and an uncertainty measures function is proposed in [6].
As cited above the researchers distinguish four kinds of explanation also five user's goals. In the developed explanation agent just one kind of explanation is published in this moment which is the reasoning trace by visualizing the recorded traces situated in the log files in [8]. An interface for explanation is developed which ensure the justification, terminological and strategic explanation. The terminological explanations will be reused for the document recommendation system. User goals for explanation will be integrated for the categorization of users with the social profile and contacts offered by Facebook API. The design of a health 2.0 application for explanation and prevention will be presented.

3 Thesis Outline

The thesis contains two parts the first one entitled "fundament in reasoning system" contains three chapters:
Chapter 1 Case Based Reasoning Systems -State of the art and applications-
Chapter 2 Distributed reasoning with multi agents integration
Chapter 3 Fuzzy Systems theory and application for Reasoning under uncertainty
The second part of our dissertation entitled " Contributions" contains three chapters which describe our original research works:
Chapter1 KI-DCBRC: Knowledge-intensive case based classification system for medical computer aided diagnosis
Chapter II: Explanation aware computing for medical applications: Explanation agent for a medical decision support system
Chapter III: Web centered participative reasoning system for computer aided diagnosis and prevention
The third part contains all published works in the referee conferences

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Part1 Fundaments in reasoning systems

Reasoning is a mental operation in which, with predefined judgments, we generate a new judgment. The artificial reasoning systems are any software application, hardware device or combination of software and hardware whose computational function is to generate conclusions from available knowledge using logical techniques of deduction, induction or other forms of reasoning. Reasoning systems are a subset of a broader category of intelligent systems. They play an important role in the practical implementation knowledge engineering and artificial intelligence.

A reasoning system manipulates previously acquired knowledge in order to generate new knowledge and judgments. Knowledge is typically represented symbolically as informational facts and propositional statements that capture assertions, assumptions, beliefs and other premises. Sub-symbolic (connectionist) knowledge representations may also be used (e.g., trained neural nets). Reasoning systems automate the process of inferring or otherwise deriving new knowledge via the application of logic. In a concrete implementation, reasoning systems may support procedural attachments and built-in actions to process or apply knowledge within some given domain or situation.

In this part we will investigate in some aspects cited on the state of the art in some indispensable and popular approaches and techniques used in the engineering of reasoning systems. First of all we will present an important approach of reasoning: case based reasoning which is a problem solving paradigm in which the reasoning is a process of reusing an existing expertise or knowledge structured cases for resolving the novel problems. Flowing that we will present the distributed reasoning via multi agent systems where the reasoning is distributed through a set of autonomic cognitive agents which collaborate for attending the global goals. Finally we will describe an important kind of knowledge modeling for approximate knowledge where the measures or the inputs are very uncertain and contains conflicts: fuzzy systems.

Chapter 1 Case Based Reasoning Systems
-State of the art and applications-

Abstract: The case based reasoning consists of using similarity for producing the solutions of different kind of problems. It has a large uses in many domains as the planning, diagnosis, information retrieval, decision support systems, data mining and other important domains. It consists of reusing stored cases memorised from the prior resolved problems for solving new problems. In this chapter we will explain this paradigm by citing the essential aspects in the area such as CBR life cycle, case representation, similarity measures, learning, adaptation, variants of CBR and others crucial aspects for realizing reasoning systems. Finally we will present some popular software systems in the domain of CBR.

1. CBR origin

The origin of CBR is referenced to The Roger Schank and Robert Abelson works that formalised the human problems solving by introducing the notion of **script** and **the dynamic memory model.** A script is a set of expectations about what will happen next in a well-understood situation. It is defined as a structure used in the conceptual memory that holds information about stereotypical situations. The general human knowledge about situations is organised in the form of scripts, based on which humans found their expectations and draw conclusions. **[26]** Later Schank and his students at Yale University (1994) proposed a **dynamic memory** model in which reminding has a significant role in problem solving and learning. It has been noted that people analyse the problems and create solutions in the context of prior experiences. Instead of dealing with the problem in an isolate manner, people rather place a new problem in a similar context previously experienced and construct the solution based both on the current problem specification and useful information extracted from prior experiences that can facilitate finding a solution to the new problem.

After, the Interest in CBR is grown in the international community. Many schools have invested in this field after YALE University in Europe and America. This preoccupation have generated, In 1990s, by the establishment of an European Conference on Case-Based Reasoning ECCBR which became an international one ICCBR and it is established in many place on the world, as well as Germany, Italia , USA, Ireland, UK, France and other countries.

2. Definitions

Many researchers have proposed or participated in the Case Based Reasoning definition. In this section we will present some definitions for proposing a general one which contains the majority concepts and which explain the principle of this approach.

1. *Case based reasoning is to solve a new problem by remembering a previous similar situation and by reusing information and knowledge of that situation. Aamodt & Plaza, 1994*
2. *Case-based reasoning is [...] reasoning by remembering. D.Leake, 1996*
3. *A case-based reasoner solves new problems by adapting solutions that were used to solve old problems. Riesbeck & Schank, 1989*
4. *Case-based reasoning is a recent approach to problem solving and learning [...] Aamodt & Plaza, 1994*
5. *Case-based reasoning is both [...] the ways people use cases to solve problems and the ways we can make machines use them. Kolodner, 1993*

From these definitions we can define the CBR as:

An intelligent approach inspirited from the human reasoning. It consists to use the prior expertise to resolve a new problem. This expertise or knowledge is constructed as a set or collection of cases. Each case represent problem associated with its solution. The idea is that two similar problems have the same solution. Then to resolve a new problem we will pass by the similarity measures between this problem and all problems in the case base. The expert can add a new knowledge (adapted cases) then we can considerate the CBR as a machine learning techniques.

We can also describe the CBR systems as a memory which contain the prior experience drown as a collection of problems description associated with their solution. This collection is called **case base**. The input of this system is a new problem description called also **query** and the output is the solution of this problem. When the users write or give a query to the system, this last uses some similarity measures techniques to retrieve the most similar cases to this problem from the case base. After this step the system adapt one solution to the problem from retrieved cases (Fig1).

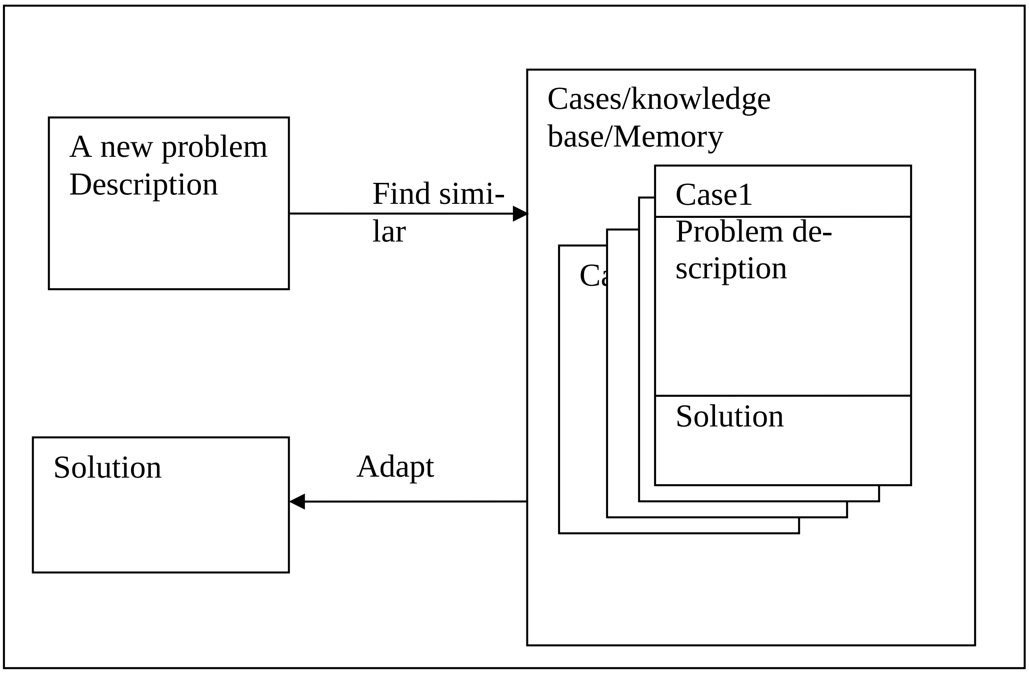

Fig1.21 Case-Based Reasoning System.

3. The CBR models

To explain the CBR paradigm there are two models proposed in the literature which describe the CBRS. The first one proposed by Plaza and Amodt in 1994 which describe the processes cycle of the CBRS, the second one proposed by Richer in 1995 describe the knowledge containers in the CBRS. Another one is described in this section about tasks and subtasks of the CBR processes proposed by Plaza and Amodt.

1. The CBR process model

In CBR research a generic process model introduced by Aamodt and Plaza (1994) is commonly accepted. This process model describes the basic steps of problem-solving when applying CBR. This model describe the CBR life cycle as four process summarized below.

-The first process consists to retrieve from the case base the similar case or cases which can be useful to solve the current problem. In this step

-In the Second process, reuse, all solutions (cases) retrieved by the retrieve process are reused to find the potential solution.

-The Third one called revise process; which revise and check the solution to fit the specifics of the current problem.

- Finally, the retain process, which update the memory by adding the resolved problem as a new case to the case base.

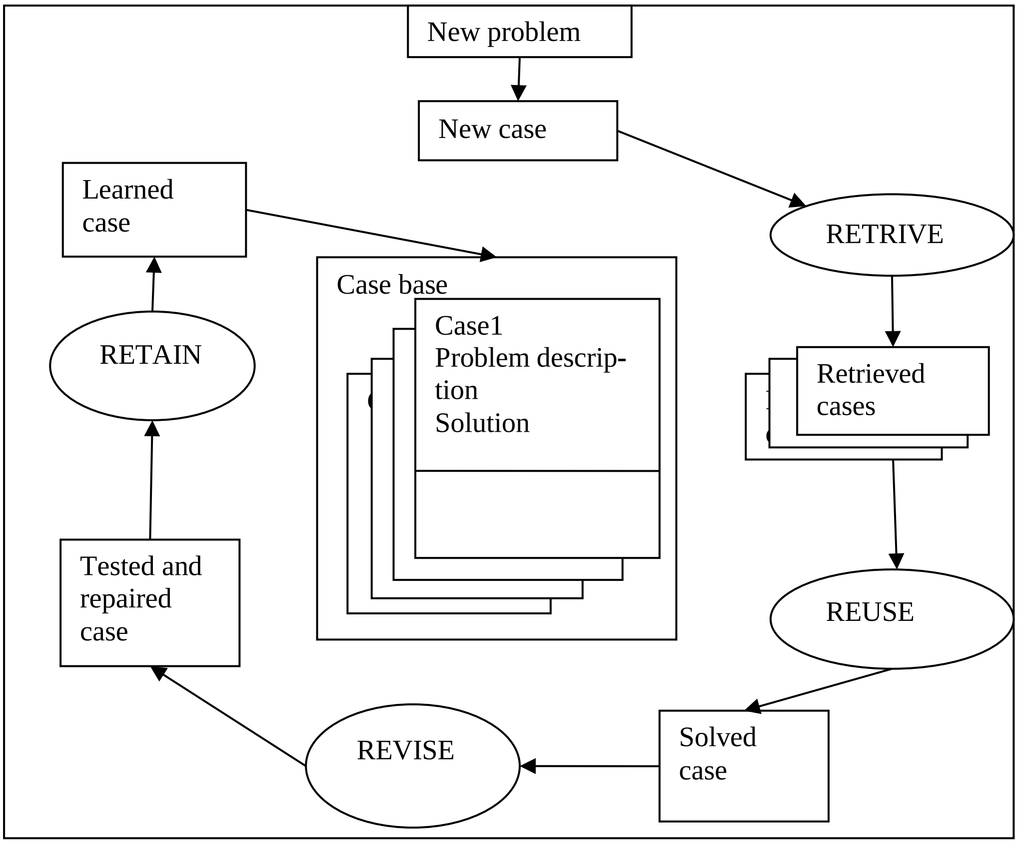

Fig1.1 case-based reasoning process model (Aamodt and Plaza 1994)

2. *Knowledge containers Model*

The knowledge container is a collection of knowledge that is relevant to many tasks. According to Richter (1995) in the CBR system we can distinguish four different knowledge containers (vocabulary, case knowledge, adaptation knowledge, and similarity measure).

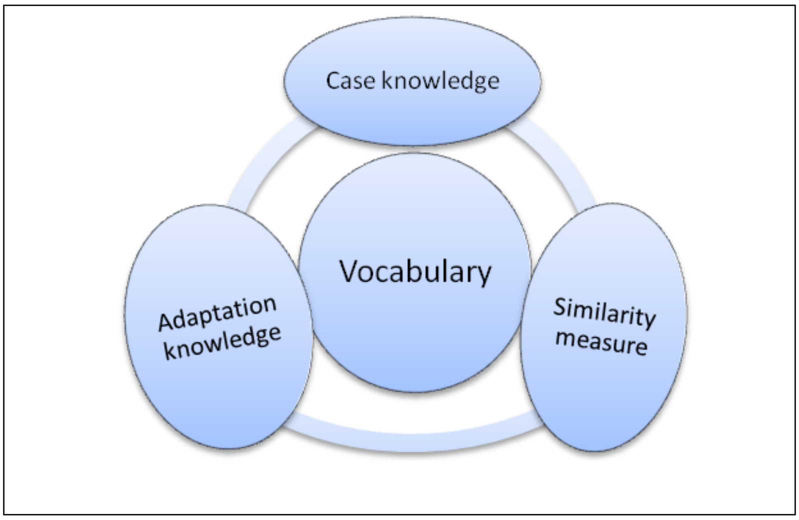

Fig1.2 Knowledge containers (Richter 1995)

1. **Vocabulary container** the set of attribute, entities and structures used to represents the cases (problems and solution). It can be characterized as the language words used to talk about the domain.

2. **Case knowledge containers** the past structured experience which will be exploited by the system. In other words it is situation-specific knowledge obtained from the past situations in problem solving.

3. **Similarity measure** General knowledge required to select or to retrieve the similar cases to be reused in a particular problem situation.

4. **Adaptation knowledge** General knowledge needed to allow an efficient reuse of retrieved cases. It takes a form of Heuristics and algorithms used to modify the solution and to evaluate their usability for the new situations.

These four knowledge containers should not be seen as completely independent. Generally, it is possible to shift knowledge between the separate containers in order to adapt CBR systems to the specific conditions of the addressed application domain.

3. A hierarchy of CBR tasks

Another model describing the tasks of CBR systems is introduced by Plaza 94 see fig1.3. This model describes the hierarchy of sub-tasks of the process model described in 3.1.

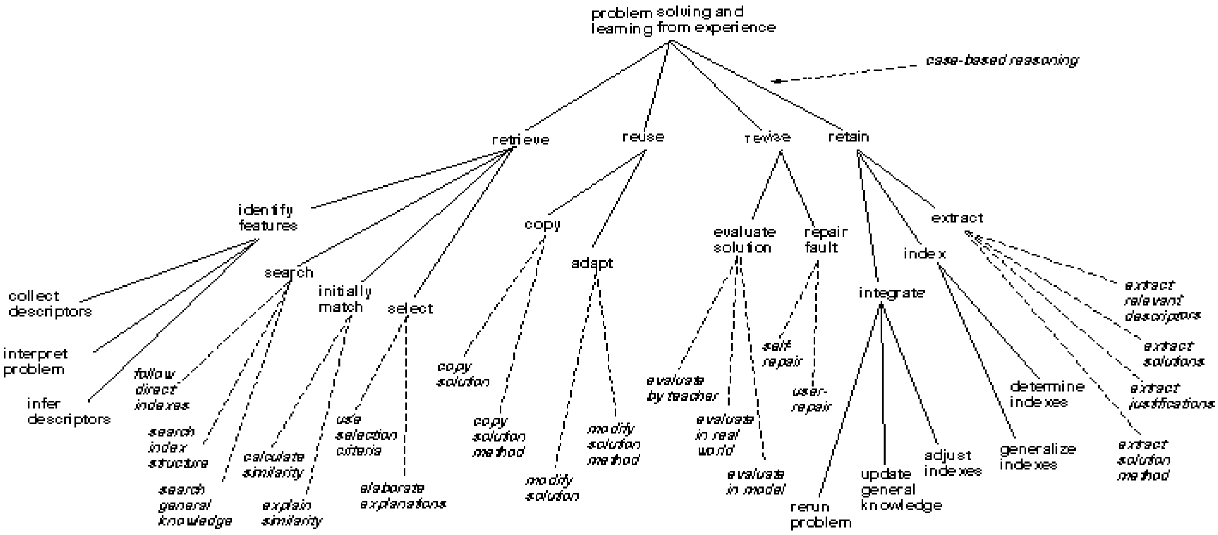

Fig1.3 Hierarchy of CBR tasks

To further decompose and describe the four top-level steps, we switch to a task-oriented view, where each step, or sub-process, is viewed as a task that the CBR reasoning system has to achieve.[Plaza. al 94] The relation between tasks and methods (stippled lines) identify alternative methods applicable for solving a task. A method specifies the algorithm that identifies and controls the execution of subtasks, and accesses and utilizes the knowledge and information needed to do this.

4. CBR approaches

In CBR there are three main approaches that differ in the sources, materials, and knowledge they use [Bergmann99].

- ***The textual CBR*** approach is similar to traditional information retrieval in that it works directly on the text documents. There is no a-priori domain model, but similarity measures can be introduced between the words occurring in the documents. Therefore, retrieval is very similar to keyword matching, but considers the similarity for document scoring.

- ***Conversational CBR*** captures the knowledge contained in customer/agent conversations. A case is represented through a list of questions that varies from one case to the other. There is no domain model and no standardized structure for all the cases. This approach is very useful for domains where a high volume of simple problems must be solved again and again.
- ***The structural CBR*** approach is the third approach and relies on cases that are described with attributes and values that are predefined. In different SCBR systems, attributes may be organized as flat tables or as sets of tables with relations, or they may be structured in an object-oriented manner. The SCBR approach is useful in domains where additional knowledge, beside cases, must be used in order to produce good results.

5. The case structure

A case is a contextualized piece of knowledge representing an experience that teaches a lesson fundamental to achieving the goals of the reasoning system. [Kolodner1993]. There are two viewpoints proposed for the case structure:

1. **The traditional or basic CBR approach:** Which assumes that a case consists of two major parts:

- **Problem Part**: This part of a case contains information characterizing the problem situation occurred in the past. Due to the basic assumption of CBR, it is crucial that this description in particular includes information relevant to decide whether two problems are similar or not.

- **Solution Part:** This part contains information used to reproduce the solution applied successfully in the past when being confronted with new problem situations.

Although, the solution part can also include additional information that might improve or simplify the reuse of the experience, for example, information about

- The way how the solution was obtained,
- The solution's quality,
- Constraints restricting the solution's application,
- Alternative solutions.

2. **The approach proposed by Bergmann:** Contrary to the case structure of the traditional CBR approach that distinguishes between a problem and a solution part, Bergmann (2002) distinguish between the following two components of cases:

- **Characterization Part:** The case characterization part contains all information required to decide whether a case can be reused in a certain situation. That means this part of the case can be seen as an index used to estimate the utility of cases.
- **Lesson Part:** The lesson part describes all additional information that might be useful for the actual reuse of the case. Note that the lesson part may also be empty. In this situation, the information contained in the case characterization part is already sufficient to reuse the case.

The representation problem in CBR is primarily the problem of deciding what to store in a case, finding an appropriate structure for describing case contents, and deciding how the case memory should be organized and indexed for effective retrieval and reuse. There are two relevant proposals for the CBR memory organization: The dynamic memory model of Schank and Kolodner in CYRUS system, and the category-exemplar model of Porter and Bareiss in The PROTOS system. These works are more described in Plaza 94.

6. Cases representation

The cases representation is the most important part to construct a case based reasoning system. There is several knowledge representation formalisms used to represent the cases. We present here some one of them.

1-Attribute-Value Based Representation

The basic element of this representation formalism is the attribute which is defined as:

An attribute, called also feature, A is a pair (A_{name}, A_{range}) where A_{name} is a unique label out of some name space and A_{range} is the set of valid values that can be assigned to the attribute, also called value range. Further, $a_{name} \in A_{range}$ U {undefined} indicate the current value of a given attribute A identified by the label A_{name}. The special attribute value undefined may be used, if an attribute value is unknown or irrelevant. In principle, the range value of an attribute may contain an arbitrary (possibly infinite) collection of elements of a basic value type. Examples of basic value types are

- The numeric type Integer
- The numeric type Real
- Symbolic types
- Temporal types like Date and Time
- Etc.

Usually, the range of allowed values is not defined directly within the attribute declaration but by the declaration of a specialized value type. This approach simplifies the definition of identical value ranges for several attributes by assigning type names to attributes. To describe the set of allowed attribute values efficiently, three possibilities to define attribute ranges can be used:

1. By specifying only the basic value type all values of this type are allowed to be assigned to the attribute (e.g., all Integer values).

2. When using numeric types, a set of allowed values can easily be defined by the specification of an interval (e.g., Real values of the Interval [0, 1]).

3. The most flexible way, which is also the only feasible way for the definition of symbolic types, is an explicit enumeration of all allowed values (e.g., an enumeration of colors {red, yellow, green}).

As already mentioned above, we assume that cases consist of a case characterization and a lesson part then we can define:

The case characterization model or pattern is a finite, ordered list of attributes D = (A1, A2... An) with n > 0. The symbol D denotes the space of case characterization models.

The lesson model is a finite, ordered list of attributes L = (A1, A2.. An) With n ≥ 0. The symbol L denotes the space of lesson models.

Then we can now introduce the basic definitions for a formal description of cases using an attribute-value based representation:

A case model is a pair C = (D, L) = ((A1, A2, . . ., An), (An+1, An+2, . . ., Am)) $\in$ D×L with m ≥ n. The symbol C denotes the space of case models. Note that we assume a non-empty case characterization part in opposite to the lesson part of cases that might contain no information at all.

A case c is a pair c = (d, l) where d = (a1, a2… an) with n > 0 and l = (an+1, an+2… am) with m ≥ n are vectors of attribute values and ai $\in Ai_{range}$ U {undefined} is the value of the attribute Ai. Further, the vector d is called the case characterization and the vector l is called the lesson of c.

The Case space C_C of *C* is the set of all valid cases according to a given case model $C \in Cc$. Moreover, the symbol D_D denotes the *case char-*

acterization space according to a case characterization model $D \in \hat{D}$, and the symbol L_L denotes the *lesson space* according to a lesson model $L \in \hat{L}$.

The query is a special case $q = (d, l) \in C_C$ with an empty lesson part l, i.e., for all attributes $Ai \in l$ holds $q.ai$ = *undefined*.

A case base CB for a given case model C is a finite set of cases {c1, c2… cm} with ci $\in C_C$.

There are many CBR applications and frameworks which use the attribute-value based representation such as CBR-Work, ISOR…

Example

In the car repair field we can represent the case as shown in the following Figure (Fig4). The case has eight attributes, two for describing the solution part or the lessen part and the rest to represent the solution or characterization part.

Case 1
Symptoms: • **Front-light = doesn't work** • **Car-type = Golf II, 1.6** • **Year = 1993** • **Batteries = 13.6V**
Solution: Diagnosis: Front-lights-safeguard = broken **Help measures: "Replace front lights safeguard"**

Fig 1.6 Case represented by an Attribute based representation

2-Object-based representation

Object-oriented case representations can be seen as an extension of the attribute-value representation. They make use of the data modeling approach of the object-oriented paradigm including "is-a", "is-a-kind-of", "is-a-part-of" and other arbitrary binary relations as well as the inheritance principle. Such representations are particularly suitable for complex domains in which cases with different structures occur.

The structure of an object is described by an object class that defines the set of attributes together with a type (set of possible values or sub-objects) for each attribute. Object classes are arranged in a class hierarchy that is usually an n-ary tree in which sub-classes inherit attributes as well as their definition from the parent class.

Also, we distinguish between *simple attributes*, which have a simple type like Integer or Symbol, and so-called *relational attributes*. Relational attributes hold complete objects of some (arbitrary) class from the class hierarchy. They represent a directed binary relation, e.g., a part-of relation, between the object that defines the relational attribute and the object to which it refers. Relational attributes are used to represent complex case structures. The ability to relate an object to another object of an arbitrary class (or an arbitrary sub-class from a specified parent class) enables the representation of cases with different structures in an appropriate way [Bergman 2003].

- Advantages:
  - Structured and natural in many domains
  - Relations between objects are explicitly represented
  - More compact storage as with attribute-values
  - Structured relations can be used to define similarity
- Disadvantages:
  - Similarity computation and retrieval can be time costly

Example The following diagram explain the hierarchy

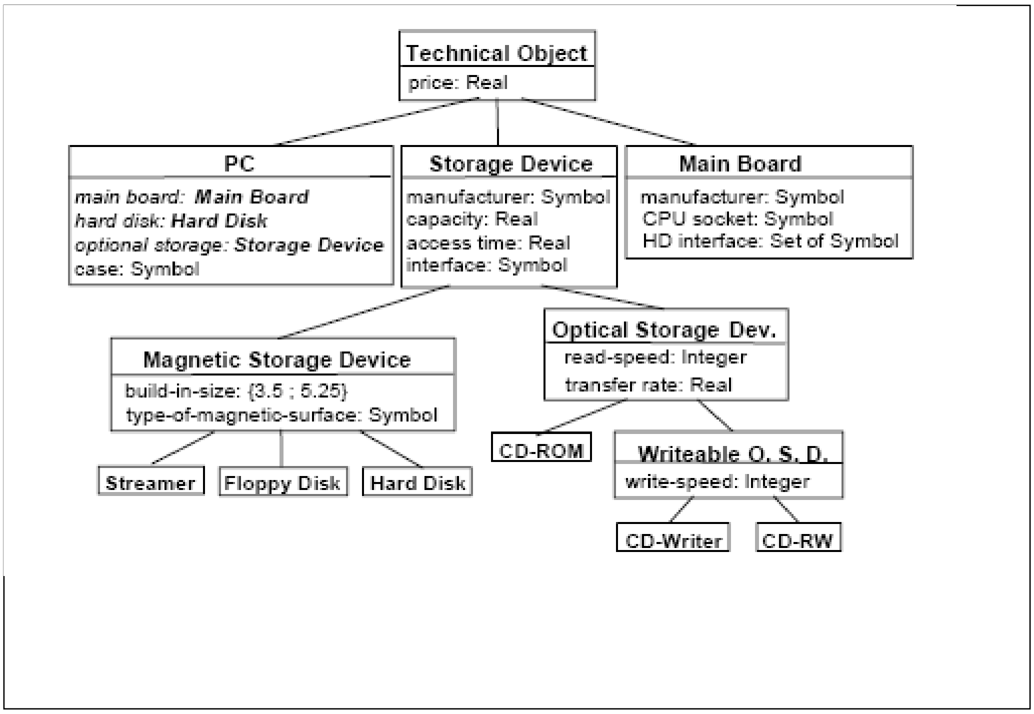

Fig1.7 cases oriented object representation sample

3- First-order logic representation

First-order logic (FOL) is a language in symbolic science. It goes by many names, including: first-order predicate calculus (FOPC), the lower predicate calculus, the language of first-order logic or predicate logic. FOL is a system of deduction extending propositional logic by the ability to express relations between individuals (e.g. people, numbers, and "things") more generally.

The FOL vocabulary is composed of:

1. A set of **predicate variables** (or **relations**) each with some **valence** (or **arity**) ≥1, which are often denoted by uppercase letters *P*, *Q*, *R* ...
2. A set of **constants**, often denoted by lowercase letters at the beginning of the alphabet *a*, *b*, *c* ...
3. A set of **functions**, each of some valence ≥ 1, which are often denoted by lowercase letters *f*, *g*, *h*,... .

4. An infinite set of **variables**, often denoted by lowercase letters at the end of the alphabet *x*, *y*, *z* ...
5. Symbols denoting **logical operators** (or **connectives**): $\neg$ (logical not), $\wedge$ (logical and), $\vee$(logical or), $\rightarrow$ (logical conditional), $\leftrightarrow$ (logical biconditional).
6. Symbols denoting **quantifiers**: $\forall$ (universal quantification), $\exists$(existential quantification).
7. Left and right parenthesis.
8. An identity or equality symbol = is sometimes but not always included in the vocabulary.

The cases representations based on first order logic are commonly used in planning domains. The Problem part and the Solution part are represented through a set of predicates.

Advantages:

- As flexible as it gets
- Complex structural relations can be represented
- Can take advantage of inference mechanism (i.e., prolog)

Disadvantages:

- Computing similarity can be very complicated
- Inference procedures are frequently very time costly

Example

We can represent the case represented by the attribute-based value cited in fig 2.4 with the FOL as:

Case (symptoms(frontLight(dw), carType(GolfII_1.6), year(1993), batteries(13.6))
Diagnosis (broken(fls), measures(rfls)))

Where Case is a predicate and frontLight() is a term.

4-Graph representation

The Graphs G mathematical representations consist of vertexes V(nodes) and edges E(arcs), which offer a number of advantages over traditional feature vector approaches G= (V, E). In case-based reasoning (CBR), graph-structured representations are desirable for complex application domains such as Data flow, Query answer, planning and design. Graph is a powerful data structure and allows knowledge to be encoded completely and expressively. However, the advantages come with a computational overhead for case retrieval, which presently prevents the usage of graph-structured representation for large-scale problems.

Example:

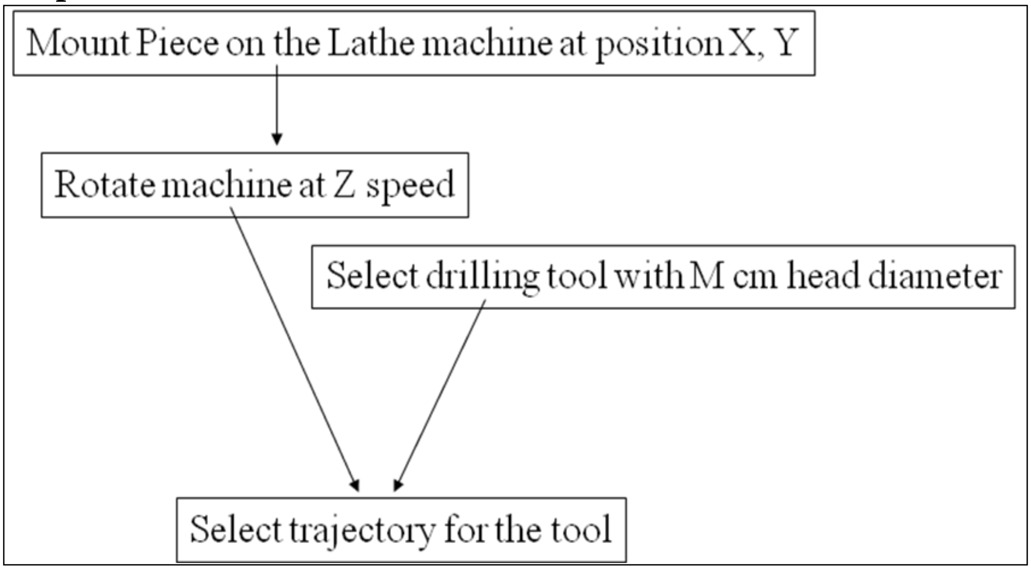

Fig1.7: a case represented by a graph

5. Ontological representation

Ontology knowledge representation is widely used for different purposes and in different fields within AI systems. The most quoted definition of ontology in literature, by Gruber [9], states that an ”ontology is an explicit specification of a conceptualization” , but other relevant definitions suggest important contributions such as: sharing, modeling, logics...etc. the Ontologies can be described from very informal to highly descriptive way. The ontology community distinguishes between lightweight and heavyweight ontologies [8]. Lightweight ontologies include concept taxonomies, properties, and relationships, as distinguished from heavyweight ontologies that entail a deeply detailed description of terms, and adding axioms, needing the use of a knowledge formal representation paradigm.

In practice many languages was defined for accomplishing this representation of knowledge for example in semantic web we find the DAML-oil, RDF, RDFs, OWL and OWL-DL which are based on XML syntax. And they have a large uses for the representation of ontology in semantic web applications and many other domains.

There are some works in the CBR research area where they used the ontology for representing the cases or for representing the vocabulary knowledge, in particular those based in DL, provides an effective formalism for conceptual description and inferential capabilities. For instance, in [7] these reasoning properties are used for the selection of the most suitable CBR design, and in [6] an ontological framework is described for CBR systems integration. Therefore, previous experiences in CBR systems and other ontological approaches in medicine point out the suitability of using heavyweight ontologies for the representation and integration of cases. Another work [8] In order to describe the case representation ontology, they use the OWL-DL (Ontology Web Language) advantageous, an ontology language based on Description Logic (DL)[13] which is flexible enough to describe any kind of concepts and relations (classes and properties in OWL terminology) and also a formal base that allows reasoning engines (such as Racer) to produce inferences from the described ontological model. We can cite here another works [24,25,26,27]:

7. Similarity measures

1-Utility and similarity functions:

The first task realised by the CBR system when they are a given query to solve is the finding of the useful cases to provide the solution. To do this process there are an additional general knowledge which have a serious importance called similarity measures. The task of these measures is to estimate the *utility* of cases with respect to the current problem-solving task.

Unfortunately, the actual utility of cases cannot be determined until problem-solving is finished, or in other words, utility is an *a-posteriori* criterion. The reason for this is the general problem that the underlying utility functions are usually only partially known. In order to be able to approximate the utility of cases before the actual problem solving process, CBR systems rely on specific similarity knowledge encoded in form of similarity measures. Hence, similarity measures can be characterized as an *a-priori criterion* or a *heuristics* used to approximate the unknown utility functions.

In other words we can define the utility as:

The Utility Function is a function u: $D_D \times C_C \rightarrow R$ on the case space C_C. Which assigns a value from the set of Real numbers to a case c and a case characterization d (the query). This value represents the utility of c with respect to d. Of course, a utility function depends on the underlying case model C. However, for one case model C there might exist an arbitrary number of different utility functions $u_1, u_2 \dots u_n$.

Generally, the utility of cases and so the underlying utility function may be influenced by several different aspects, for example, by

• The underlying domain and the application scenario addressed,

• The provided problem-solving functionality of the CBR system employed,

• The knowledge contained in the different knowledge containers of the CBR system,

• The preferences of all users, individual users, or groups of users,

• The point of time of the problem-solving situation, etc.

A utility function induces the following preference relation:

Preference Relation Induced by Utility Function: Given a case characterization d, a utility function u induces a preference relation $\succeq_d^u$ on the case space C_C by ci $\succeq_d^u$ cj if u(d, ci) $\geq$ u(d, cj).

To estimate the utility of a given case *c and* a given query *q*, the case characterizations of *c* and *q* have to be compared by a similarity measure generally defined as follows:

Similarity Measure, General Definition: A *similarity measure* is a function $Sim : D_D \times D_D \rightarrow [0, 1]$.

To find the similar cases for a given query *q* we should firstly compute the similarity between *q* an the case characterizations of the cases contained in the *Case Base*, the retrieval mechanism has to identify a list of cases, called *retrieval result*, ordered by the computed similarity values. The number of cases to be retrieved may be specified by one of the following parameters:

• An integer value specifying the *maximal number of cases* to be retrieved.

• A real value specifying a *similarity threshold*. This threshold defines the least similarity value required for some case *c* to appear in the retrieval result.

Like utility functions, which induce the preference relation the similarity function also induces a preference relation:

Preference Relation Induced by Similarity Measure Given a case characterization *d*, a similarity measure *Sim* induces a *preference relation* $\sqsubseteq_d^{Sim}$ on the case space C_C by $c_i = (d_i \sqsubseteq_d^{Sim}$ $c_j = (d_j, l_j)$ if $Sim(d, d_i) \leq Sim(d, d_j)$. These preference relations can now be used as a foundation to define correctness criteria for similarity measures.

According to Bergmann (2002), the soundness of a similarity measure *Sim* can be defined on different levels of generality:

1. Total soundness w.r.t. the complete domain, if *Sim* orders all possible cases correctly according to a given utility preference relation.

2. Total soundness w.r.t. a given case base *CB*, if *Sim* orders all cases contained in *CB* correctly according to a given utility preference relation.

3. Partial soundness w.r.t. a given case base *CB*, if *Sim* orders the "most useful" cases of *CB* correctly according to a given utility preference relation.

Basically, in a CBR system we are interested in retrieving the most useful cases regarding to some utility function *u*. However, depending on the concrete application scenario, minor retrieval errors can be tolerated. This leads to the following definitions:

The Best-*n* List: Suppose a list of cases $CL = (c1, c2 \ldots cn, \ldots, cm)$ partially ordered according to some preference relation $\succeq$, i.e. $\forall i, j \; ci \succeq cj$ holds. The list $CL_{best-n} = (c1, c2, \ldots, cn, \ldots, cr)$ so that $\forall ci \in CL_{best-n}$, $\forall cj \in CL \setminus_{CLbest-n} \; ci \succ cj$ holds, is called *best-n list* of *CL* where *n* is a parameter to be determined. Further, $\forall n \leq i, j \leq r$ it holds: $ci \not\succ cr$ and $ci \not\prec cr$.

This definition states that the best-*n* list for some list of cases *CL* consists of the *n* most preferred cases ($c1$, $c2$, . . . , cn) of *CL* extended by all cases of *CL* being indistinguishable from c_n w.r.t. the underlying preference relation $\succ$. Figure2.7 illustrates this exemplarily for a best-4 list. Here, the best-4 list consists of the 4 cases $c1$, $c2$, $c3$, $c4$ preferred mostly, and three additional cases $c5$, $c6$, $c7$, since these cases are indistinguishable from $c4$.

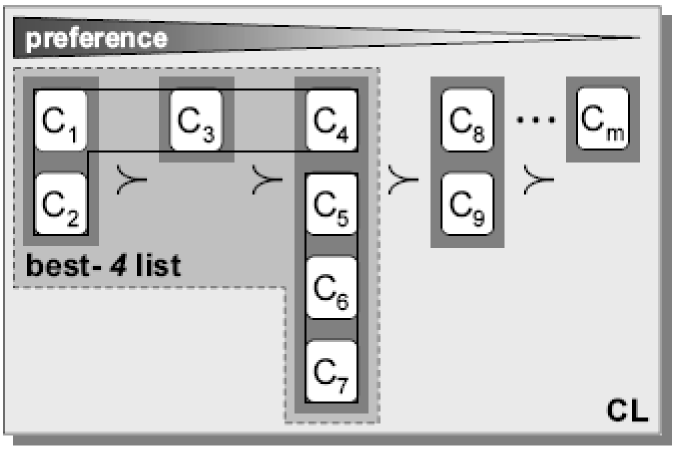

Fig 1.8. The best-n List

2-Similarity Measures Properties

We describe here just some basic properties of the similarity measures (reflexivity, symmetry, Triangle inequality and Monotony).

1. **The Reflexivity:** A similarity measure is called *reflexive* if:
   $Sim(x, x) = 1$ holds for all x.
   If it additionally holds $Sim(x, y) = 1 \rightarrow x = y$, Sim is called *strong reflexive*. Reflexivity is a very common property of similarity measures. It states that a case characterization is maximal similar to itself. From the utility point of view, this means, a case is maximal useful with respect to its own case characterization. Therefore, similarity measures might violate the reflexivity condition, if a case base contains sub-optimal cases. Similarity measures are usually not strong reflexive, i.e. different cases may be maximal useful regarding identical queries. For example, different solution alternatives contained in different cases might be equally accurate to solve a given problem.
2. **The Symmetry:** A similarity measure is called symmetric, if it holds Sim(x, y) = Sim(y, x) for all x, y. Otherwise it is called asymmetric. Symmetry is a property often assumed in traditional interpretations of similarity. However, in many application domains it has been emerged that an accurate utility approximation can only be achieved with asymmetric similarity measures. The reason for this is the assignment of different roles to the case characterizations to be compared during utility assessment. Usually, the case characterization representing the query has another meaning than the case characterization of the case to be rated.
3. **Triangle inequality:** A similarity measure fulfills the triangle inequality, if $Sim(x, y) + Sim(y, z) \leq 1 + Sim(y, z)$ holds for all x, y, z. The triangle inequality is usually demanded for distance measures only and is required to ensure the property of a metric. However, due to the dualism of similarity and distance measures it can also be formulated for similarity measures by applying an accurate transformation.

4. **The Monotony:** Let $C = (D,L) \in Cc$ be a given case model and *Sim* be a similarity measure. Further, assume the existence of an order relation $<D_D$ defined over D_D. *Sim* is called monotonic, if it holds $Sim(x, y) \geq Sim(x, z)$ for $x <D_D y <D_D z$ or $z <D_D y <D_D x$.
   The monotony property can be characterized as a kind of compatibility to the ordering on D*D* (if existing). It is also an important aspect when modeling similarity measures in practice.

3-Similarity computing techniques

To compute the similarity there are many techniques we can divide it to two approaches: 1) the traditional one and 2) the global-local similarity measures one.

a) The traditional approaches: The similarity measures employed in many traditional CBR systems are often quite simple. They have not been developed especially for the purpose to be used in the scope of CBR, but they are founded on common mathematical principles and distance measures as well as Hamming Distance, Simple Matching Coefficient SMC, weighted SMC, non linear SMC, Tversky contrast Model, city block metric, Euclidean Distance, Maximum norm…etc. (See the Annex A for more detail).

b) Global-local similarity measures

When we have a complex case representations consisting of attributes with various different value types, the previously described traditional similarity and distance measures are not appropriate. Instead one needs a more flexible similarity measure that can be adapted on a particular attribute-value based case representation.

The foundation of such a similarity representation is the so-called local-global principle. According to this principle it is possible to decompose the entire similarity computation in a local part only considering local similarities between single attribute values, and a global part computing the global similarity for whole case based on the local similarity assessments. Such decomposition simplifies the modeling of similarity measures significantly and allows defining well-structured measures even for very complex case representations consisting of numerous attributes with different value types. In the following we will detail the different elements required to define similarity measures according to the local-global principle.

1-Local similarity

The local similarity consists to compute the Measure similarity on the attribute or feature level. We can define the local similarity as:

Definition A local similarity measure for an attribute A is a function $sim_A : A_{range} \times A_{range} \rightarrow [0, 1]$, where A_{range} is the value range of the attribute A.

In the practice the local similarity functions representation strongly depends on the basic value type of the attribute. We can divide the attributes type on two kinds 1) The Discrete or symbolic Value Types and 2) The Numeric or continue Value Types. In the following we will introduce some representation formalism for both value types used commonly.

Local Similarity Measures for Discrete Value Types

The only feasible way to represent local similarities is an explicit enumeration in form of a lookup table called similarity table which defined as:

Definition Let A be a symbolic attribute with the value range A_{range} = ($v1$, $v2$, . . . , vn). A $n \times n$-matrix with entries $si,j \in [0, 1]$ representing the similarity between the query value $q = vi$ and the case value $c = vj$ is called a *similarity table* for A_{range}.

A similarity table represents a reflexive measure, if the main diagonal consists of similarity values $sii = 1$ only. Further, we call a similarity table symmetric if the upper triangle matrix is equal to the lower triangle matrix, i.e. if for all *i, j sij* = *sji* holds.

Example:

q \ c	laptop	mini-tower	midi-tower	big-tower
laptop	1.0	0.2	0.1	0.0
mini-tower	0.3	1.0	**0.9**	0.5
midi-tower	0.2	**0.7**	1.0	0.7
big-tower	0.1	0.4	0.6	1.0

Fig1.9: Similarity table

This example show a similarity table for the attribute casing of the personal computer example domain. This table represents the similarities between different kinds of computer casings, for example, it expresses that a mini- and a midi-tower are quite similar. However, the degree of similarity between these casings also depends on which value occurs as query, i.e. the similarity table is asymmetric. The semantics here is, that customers will probably be less satisfied with a minitwoer when demanding a midi-twoer (sim(midi-twoer, mini-twoer) = 0.7), than in the opposite case (sim(mini-twoer, midi-twoer) = 0.9). The underlying assumption is that bigger casings would be tolerated due to the advantage of the greater number of extension slots.

A similarity table represents a very powerful representation because of the possibility to define separate similarity values for all possible value combinations. Nevertheless, the effort required to define such a measure increases quadratic ally with the number of values to be considered.

Local Similarity Measures for Numeric Value Types

The numeric attributes contains an infinity number of values, for this the similarity tables are not suitable for this kind of attribute. In order to reduce the modeling effort, one can profit from the implicit ordering of numbers. A commonly used method is to reduce the dimension of the similarity measure by defining it on the difference between the two values to be compared. In contrast to the general 2- dimensional similarity functions, this approach results in a 1-dimensional function only:

Definition (Difference-Based Similarity Function) Let "*A*" a numeric attribute with the corresponding value range A_{range}. The local similarity function is defined as: $simA : \mathbb{R} \rightarrow [0, 1]$ that computes a similarity value $simA(\delta(q, c)) = s$ based on some *difference function* $\delta : A_{range} \times A_{range} \rightarrow \mathbb{R}$.

Typical the difference functions are:

- A linear difference $\delta(q, c) = c - q$,
- Or a logarithm deference:

$$\delta\,(q, c) = \begin{cases} \mathrm{Ln}(c) - \ln(q) & \text{for } q,c > 0 \\ -\mathrm{Ln}(-c) - \ln(q) & \text{for } q,c < 0 \\ \text{Undefined} & \text{else} \end{cases}$$

The foundation of such difference-based similarity functions is the assumption that the decrease of similarity stands in some relation with increasing difference of the values to be compared. The identification of this relation and its formalization by choosing an appropriate similarity function is the crucial task when modeling local similarity measures for numeric attributes. Typically, as shown in fig9 an accurate similarity function can be defined by combining some base functions *f*1, *f*2 for negative and positive values.

$$sim_A(q, c) = \begin{cases} f_1(\delta(q, c)) & : c < q \\ 1 & : c = q \\ f_2(\delta(q, c)) & : c > q \end{cases}$$

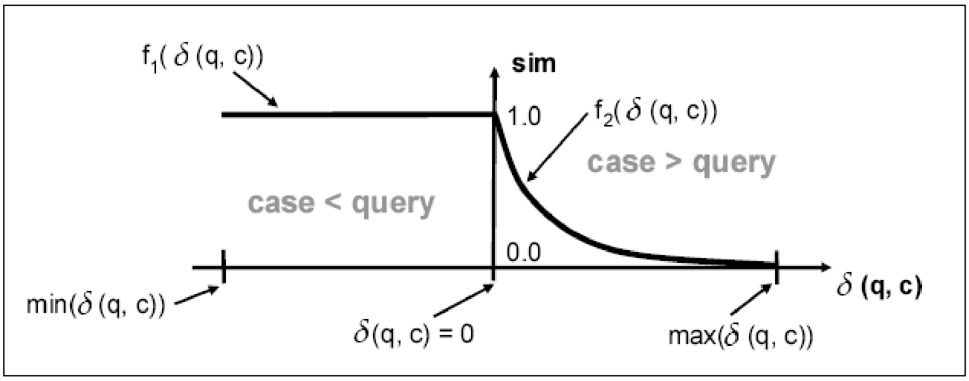

Fig1.10. Difference-Based Similarity Function

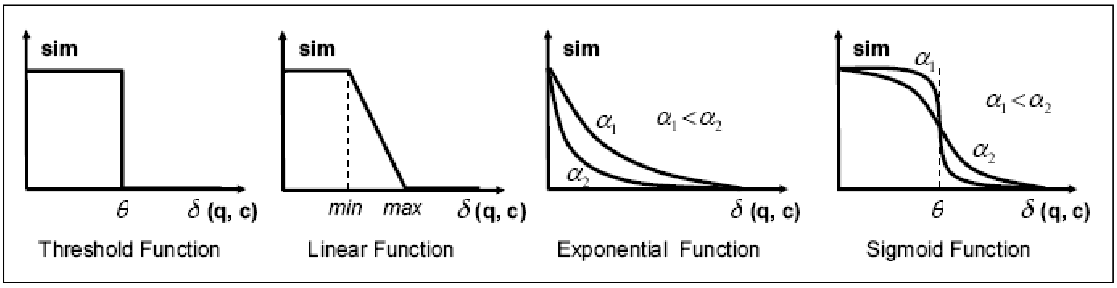

Figure 1.11. Base function (f1, f2) for the Difference-Based Similarity Function

The Base function (f1, f2) can be one from the functions shown in Fig10. (Threshold, linear, exponential and sigmoid … functions) for more detail see Annex B.

When modeling local similarity measures in that way, the utility approximation can be influenced by the following parameters that have to be defined during the similarity assessment process:

- The difference function δ
- The base functions $f1$ and $f2$
- The parameters required by the chosen base functions (*α, θ, min, max)*

2-Global similarity

The global similarity consists of computing the similarity on the case or object level. Before talking about this concept we will introduce the weight concept which is used to express the different importance of individual attributes for the entire utility approximation. And we define the weight vector as:

Definition Let $D = (A1, A2, \ldots, An)$ be a case characterization model. The vector $w = (w1, w2, \ldots, w$ $\sum_{i=1}^{n} w_i = 1$ 1] and is called *weight vector* for *D*, where each element *wi* is called *attribute weight* for *Ai*.

And we can define the Global Similarity Measure as:

Definition Let $D = (A1, A2, \ldots, An)$ be a case characterization model, *w* be a weight vector, and *simi* be a local similarity measure for the attribute *Ai*. A *global similarity measure* for *D* is a function $Sim : \mathrm{D}_D \times \mathrm{D}_D \rightarrow [0, 1]$, of the following form:

$Sim(q, c) = \pi(sim1(q.a1, c.a1), \ldots, simn(q.an, c.an), w)$

where $\pi : [0, 1]^{2n} \rightarrow [0, 1]$ is called *aggregation function* that must fulfill the following properties:

- $\forall \vec{w} : \pi(0, \ldots, 0, \vec{w}) = 0$
- π is increasing monotonously in the arguments representing local similarity values.

The aggregation function π can be arbitrarily complex. However, in practice usually quite simple functions are used, for example:

$\pi(sim_1, .., sim_n, \vec{w}) = \sum_{i=1}^{n} w.sim_i$ (Weighted Average Aggregation) (1)

$\pi(sim_1, .., sim_n, \vec{w}) = (\sum_{i=1}^{n} w.sim_i^p)^{1/p}$ (Minkowski Aggregation) (2)

$\pi(sim_1, .., sim_n, \vec{w}) = max_{i=1}^{n} w.sim_i$ (Maximum Aggregation) (3)

$\pi(sim_1, .., sim_n, \vec{w}) = min_{i=1}^{n} w.sim_i$ (Minimum Aggregation) (4)

To define the attributes weights or the weight vector we present the following approaches:

1. **Global Weights:** This is the most general weight model where the importance of attributes is defined globally, i.e. the defined weights are valid for the entire application domain. Here, the influence of attributes on the utility approximation is constant for all cases and queries that may occur.

2. **Case Specific Weights:** This is a more fine-grained weight model that allows the definition of different attribute weights for different cases. This means, when comparing a query with a given case, a specific weight vector for this particular case is used to perform the similarity computation. A special form of this weight model is class specific weights used for classification tasks. Here, the weight vector to be used is determined by the class membership of the particular case.
3. **User Weights:** Another approach is the use of specific weights for each new retrieval task, i.e. the weights are acquired together with the query. Such a weight model is in particular useful in domains where the users might have individual preferences with respect to the utility of cases. For example, a product recommendation system in e-Commerce might allow customers to input attribute weights in order to express the importance of particular product properties for her/his buying decision.

Different weight models can also be combined. For example, user weights are often not used exclusively, but they are combined with a global weight vector defining the general importance of attributes from the application domain point of view.

4- Object similarity measures

Current similarity modeling approaches are tightly integrated with object-oriented vocabulary representations [Bergmann 02]. The goal is to determine the similarity between two objects, i.e., one object representing the characterization (or a part of it) and one object representing the query. We call this object similarity. It is determined recursively in a bottom up fashion, i.e., for each simple attribute, a local similarity measure determines the similarity between the two attribute values, and for each relational attribute an object similarity measure recursively compares the two related sub-objects. Then, the similarity values from the local similarity measures and the object similarity measures, respectively, are aggregated by an aggregation function to the object similarity between the objects being compared.

The similarity measures depend of the case representation formalism. For example when we use the graph representation the similarity measures the Sub Graph isomorphism is used, if the FOL is used to represent the cases the similarity is computed by the logical inferences.

5. Similarity between textually represented cases

Some of the pioneer work in TCBR demonstrated how CBR techniques can be applied to retrieval tasks. These approaches do not rely on a symbolic representation of cases but compare these cases as text tokens using a variety of techniques adapted from information retrieval (IR). They achieve a richer notion of case similarity by supplementing the textual comparisons with basic linguistic techniques and methods that take the meaning of words into account.

Burke et al. (1997) developed FAQ-Finder, a question–answering system. Given as input a typed question, it retrieves textual answers from Usenet FAQ files, which contain frequently asked questions with answers. Conceptually, each of the question–answer pairs is treated as problem and solution in a CBR framework. FAQ-Finder uses techniques that combine statistical and semantic knowledge. It starts with a standard IR approach based on the vector space model, where cases are compared as term vectors with weights based on a term’s frequency in the case versus in the corpus. In addition, FAQ-Finder includes a semantic definition of similarity between words, which is based on the concept hierarchy in WordNet (Fellbaum, 1998). An evaluation showed that adding semantic information led to performance improvements. FAQ-Finder was one of the first TCBR implementations that demonstrated the benefits from incorporating background knowledge. Lenz & Burkhard (1997) took a different approach in FAQ, another question-answering system that compares textual cases through the meanings of terms. Cases consist of a question text, a list of attributes, and the answer text. The program processed the free text components to identify Information Entities (IE), which are indexing concepts that may occur in text in different forms. This approach requires some domain-specific knowledge engineering to identify task-specific terms, which may include product names or physical units. FAQ's similarity assessment checks word similarity using two lexical sources: a manually constructed domain-specific ontology and a generic thesaurus. Case Retrieval Nets, which support FAQ's retrieval strategy, represent the case base as a network of IE nodes where similarity arcs connect nodes with similar meaning. Retrieval is performed by propagating activation through this network.

Wilson & Bradshaw (2000) investigated cases that required mixed representations including both textual and non-textual features. They used the IR term vector space model to assess individual similarities between the textual features and integrated them into case similarity assessment techniques for the non-textual features. [23]

8. Adaptation techniques

After retrieving the most similar cases represented in the best-*n* List the next step is to adopt or reuse their solution to the new problem. To ensure this process we need a general knowledge called knowledge adaptation.

To adapt a solution to a new problem there is three possible strategies. The first one and the most simple are just to copy the solution of the retrieved case to the query with any modification. In the second one the adaptation is ensured by the user or the expert through an interactive interface, it is also called the manual or interactive approach. The last one and the most complex is the Automatic solution adaptation. The adaptation depends of the context and the case representation too.

In the last scenario (Automatic solution adaptation) we can distinguish between two basic approaches to perform solution adaptation:

Transformational Adaptation: Here, the cases' solution part represents a concrete solution generated in the past. During adaptation the retrieved solution has to be transformed to a new solution fulfilling the current situation's requirements by adding, modifying or deleting solution parts.

Generative Adaptation: Instead of storing the actual solution it is also possible to store the process by which the solution was generated in the past. This information can be reused to generate an accurate solution in a similar situation efficiently. Therefore, a generative problem-solver tries to replay the known solution way as far as possible. If some solution steps cannot be replayed, alternative solution steps have to be generated from scratch. This strategy is also denoted as **derivational analogy** (Cunningham et al., 1993).

The major difference between these two basic approaches is the way how adaptation knowledge has to be provided and how it is employed. One the one hand, generative adaptation requires a generative problem-solver that is, in principle, able to solve a given problem without the use of cases. Hence, this problem-solver requires a complete and consistent domain theory. This general domain knowledge is also used to perform adaptation of retrieved cases. Some approaches realise case adaptation by using constraint satisfaction techniques (Purvis and Pu, 1995). On the other hand, transformational adaptation is performed without a generative problem-solver. Thus, it requires another formalism to represent and to apply adaptation knowledge within the CBR system. Which concrete representation formalism is appropriate depends on the application domain. A common approach is adaptation rules (Bergmann et al., 1996; Leake et al., 1995; Hanney and Keane, 1996) or adaptation operators (Schmitt and Bergmann, 1999b). Another approach for describing adaptation knowledge within the case representation is generalised cases (Bergmann et al., 1999b; Bergmann and Vollrath, 1999; Mougouie and Bergmann, 2002). Artificial Neuronal Network is also used in some particular application as classification and selection of pedagogical scenarios for e-learning application (M.a CHIKH and al 2007) for a generative adaptation of online courses other intelligent technics can be used for achieving this aim.

9. Some CBR variants

- **Distributed CBR**

A *Distributed Case Based Reasoning system* DCBR is one that is composed of separate modules (called *agents*[1]) and a set of communication paths between them. Each agent usually has some behaviors to reach a local goal and it cooperates with the other agents to achieve the global goal. Plaza and McGinty 2006 said:"The research efforts in the area of distributed CBR concentrate on the distribution of resources with the intent of improving the performance of CBR systems. Although the phrase distributed CBR can be used in a number of different contexts".

Enric Plaza and Lorraine McGinty (2006) have classified the realized CBR systems in four classes (see Fig11) by using two key criteria: (1) how knowledge is organized/managed within the system (i.e., single vs multiple case bases), and (2) how knowledge is processed by the system (i.e., single vs multiple processing agents).

[1] The Agency will be detailed in the next chapter.

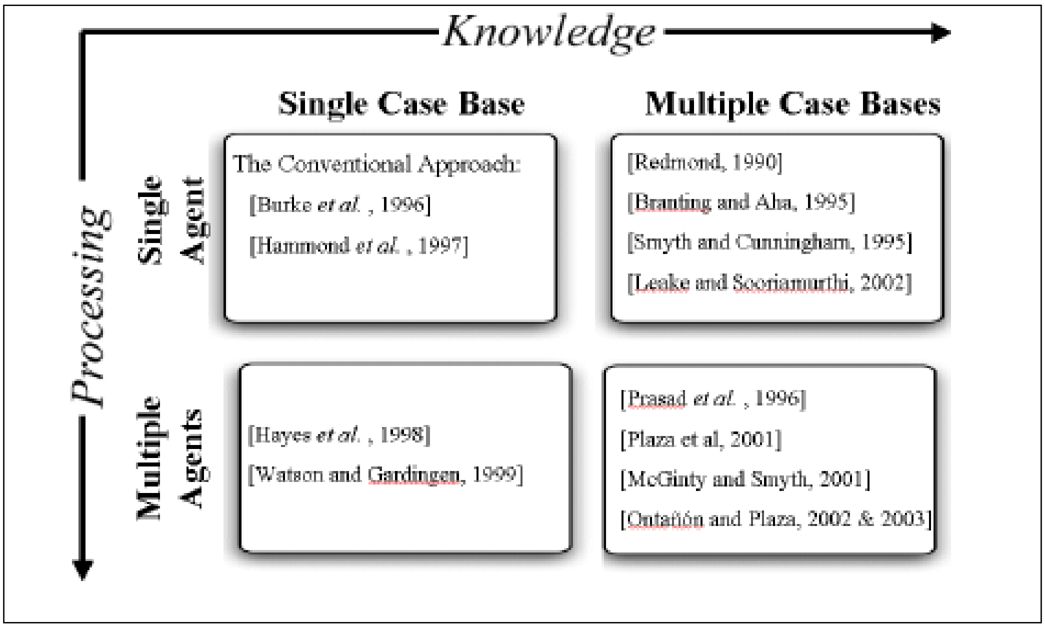

Fig 1.12. Distributed CBR Systems [Plaza, McGinty 2006].

The DCBR approach has the following advantages:

- The most complete reasoning system is the humans system. And they do it as psychological models.
- Is very suitable for ensuring the Parallelism which for satisfying from the resources of the high performance computing HPC for giving more powerful solutions - hardware and software.
- Helping to organize systems in modular fashion for increasing the maintainability and scalability of systems.
- Some applications will have improved efficiency and an important speed up.
- It offers simple system maintainability and a good flexibility.
- It ensures the modeling of specialized reasoning subsystems.

- **Knowledge-Intensive Case Based Reasoning**

A knowledge-intensive case-based reasoning method assumes that cases, in some way or another, are enriched with explicit general domain knowledge. The role of the general domain knowledge is to enable a CBR system to reason with semantic and pragmatic criteria, rather than purely syntactic ones. By making the general domain knowledge explicit, the case-based system is able to interpret a current situation in a more flexible and contextual manner than if this knowledge is compiled into predefined similarity metrics or feature relevance weights. A knowledge intensive CBR method calls for powerful knowledge acquisition and modelling techniques, as well as machine learning methods that take advantage of the general knowledge represented in the system. [10]

There are many developed system which use the knowledge intensive variant someone have used just a rule based system to represents the domain knowledge as GREEK [10] and [11] in other works they used a fuzzy rule based system as [55] and [56] or production rules as [].

The problem of these kinds of systems is the inheritance of the traditional critics of rule based systems as conflicts, uncertainty, vagueness, ambiguity and others. Also as a biggest problem the complexity of modeling if there are something to modelize as rule.

- **Trace Based Reasoning Systems**

As a variant of case based reasoning the trace based reasoning approach was introduced for response to a specific kind of application where the time and the dynamics is the crucial, also the systems where there are mass users with different profile and goals. It is focused on an observation process which extracts from the system actions and constructs traces and episodes which will be reused in another process of reasoning and knowledge extraction. The figure describe the trace based reasoning for more information see[25],[27].

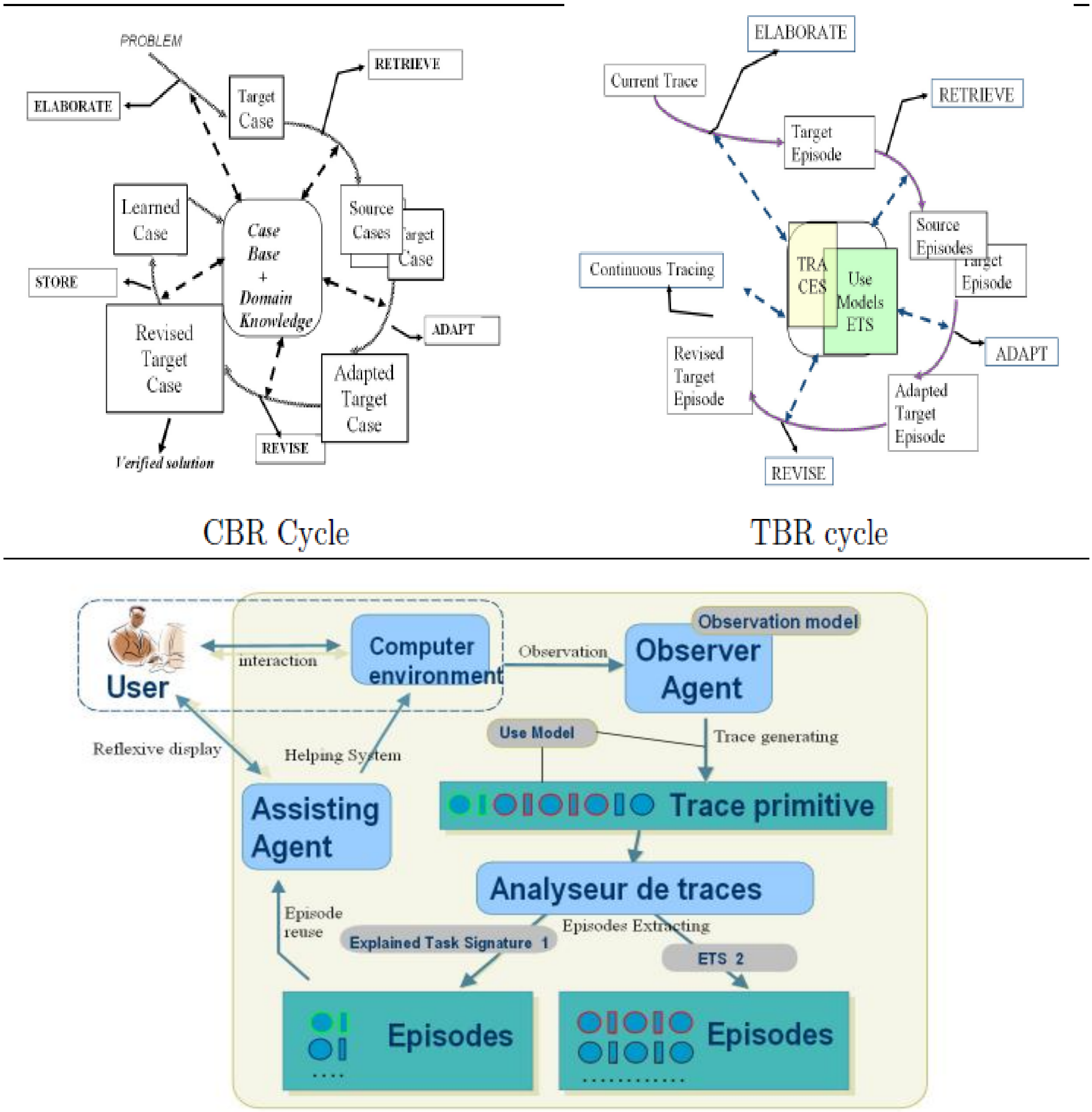

Fig 1.13 Trace based reasoning systems

10. Machine Learning and CBR

The Learning is an important area in AI and CBR system, before talking about the learning in the CBR systems we should define and clarify the learning computer system.

Definition (Learning System) A computer system is said to learn from experience E with respect to some class of tasks T and performance measure

P, if its performance at tasks in T, as measured by P, improves with experience E. *(Mitchell, 1997).*

In Machine Learning another aspect concerning the application of acquired knowledge is important. Basically, two contrary learning methods are distinguished (Mitchell, 1997):

Lazy Learning : Lazy learning methods defer the generalization required to solve problems beyond the presented training data until a new problem is presented. Such a procedure leads to a reduced computation time during training but to an increased computational effort when solving new problems.

Eager Learning: On the contrary, eager learning methods perform the mandatory generalization before new problems are presented to the system by constructing a hypothesis about the appearance of the unknown target function of the domain. After constructing a hypothesis of the target function based on some training data, new problems might be solved very efficiently with respect to computation time. However, eager methods cannot consider the current problem during the generalization process.

A CBR system is said to *learn,* if its performance at tasks of some class of tasks T, measured by a given performance measure P, improves through changes in the knowledge containers triggered by experience E.

As discussed in Section 4.2 there are four knowledge containers, the achievement of an improvement in a CBR system's performance is realized by adding or removing knowledge items from these containers, or by shifting knowledge from one container to another container.

1-Vocabulary learning

The vocabulary represents the basis for all other domain knowledge incorporated in a CBR system. Therefore, high quality of this knowledge is absolutely essential to ensure reasonable problem-solving capabilities. For example, choosing the wrong attributes for characterizing case knowledge will prevent accurate retrieval results, even if the similarity measure is quite sound. Due to the fundamental character of the vocabulary, the development of strategies to learn it is a really hard task. Nevertheless, basically, two operations to improve an initially given vocabulary can be distinguished:

• Many works in Machine Learning have shown that *removing irrelevant attributes* can increase the accuracy of classifiers significantly for example we can remove the attribute “color” from the car cases in the car repair CBR system.

• In particular, the CBR approach often requires the *introduction of additional attributes* to ensure reasonable retrieval results. Typically, these *virtual attributes* are used to represent important relations between other, already given attributes. Virtual attributes are very important when applying CBR, because they may simplify the definition of adequate similarity measures significantly. They provide a possibility to avoid non-linear similarity measures by shifting the non-linearity to the definition of the vocabulary. For example, to classify rectangles with respect to the property “quadrate”, it is important to consider particularly the ratio between the height and width, although the height and width do already describe a given rectangle completely. Without a virtual attribute that makes this relation explicit, the similarity measure would have to consider this crucial relation to enable correct classifications. This is an example for the possibility to shift knowledge between the vocabulary and the similarity measure. Although, *feature selection* is a classic topic of Machine Learning, approaches to support the definition of an accurate case representation when developing a CBR application are very rare.

Today, the acquisition of the vocabulary is usually still a creative process that can only be carried out appropriately with intensive help of domain experts. Nevertheless, in the future existing feature selection strategies developed to improve classifiers might be adapted to apply them in the more general CBR context.

Unfortunately, suitable approaches to facilitate the determination of crucial virtual attributes are rare. In the field of Machine Learning the branch of *constructive induction* aims on constructing accurate representations from given raw data. Due to the high combinatorial complexity only learning strategies guided by human domain experts might be feasible. Learning the vocabulary only seems to be suitable during the development phase of a CBR application. Because the representation of all other knowledge relies on the defined vocabulary, changing the vocabulary always necessitates maintenance of the other knowledge containers. Such a maintenance procedure is a complex and time-consuming task that cannot be automated completely (Heister and Wilke, 1997). Thus, one usually tries to avoid changes in the vocabulary during the lifetime of CBR applications as far as possible.

2-Case base learning CBL

Obviously, learning according to the traditional CBR cycle is a form of lazy learning. Here, the training data —given in form of cases—is only stored during the training phase. How to use this data to solve new problems is not decided until such a new problem is presented to the system. Several algorithms to realize this original learning approach of CBR have been developed very early (Aha, 1991). These case-based learning (CBL) algorithms, which mainly focus on traditional classification tasks, can be summarized as follows:

CBL1: This is the simplest algorithm. Here, all presented cases are stored in the case base.

CBL2: The aim of this algorithm is to avoid storage of irrelevant cases. Only cases classified incorrectly using already stored cases are added to the case base. However, the success of this strategy also relies on the cases' presentation order. Hence, this strategy might cause classification failures in future problem-solving situations.

CBL3: This modification of the CBL2 algorithm also removes those cases from the case base that decrease the overall classification accuracy of the system.

Therefore, CBL3 keeps track of the frequencies with which cases contribute to correct classifications. Cases coupled with significantly low frequencies are removed from the case base. However, removing cases might cause classification failures in the future, too. The CBL3 algorithm can also be seen as a kind of maintenance technique because it administrates the case knowledge in order to preserve high classification accuracy with time when storing new cases. In the last years a lot of other approaches to case base maintenance have been developed. Such work can also be seen as a contribution to improve the retain phase and so the learning facilities of CBR.

The aim of many of these techniques is to minimize the size of the case base while preserving the problem-solving competence (Smyth and Keane, 1995b; Smyth and McKenna, 1998; Leake and Wilson, 2000; Roth-Berghofer, 2002). Others also try to discover and eliminate inconsistencies within the case base (Reinartz et al., 2000)

Another towards in the case base maintaining was proposed as after the learning but it represents an optimization processed for avoiding the noises which generate a disorder for reasoning in some decision systems.

3-Similarity measures and learning

Although similarity measures play a crucial role in CBR applications, clear methodologies for defining them have not been developed yet. One approach to simplify the definition of similarity measures involves the use of machine learning techniques.

There are many machine learning approaches which have been developed in order to facilitate the definition of similarity measures. We will describe here someone [Stahl 2005]:

- **Feature Weights:** Because in many CBR systems only simple weighted distance metrics are employed, modifying the weights assigned to features in feature-value based case representations is often the only possibility to influence the similarity measure. Here, one also distinguishes between global and local (e.g. case specific) weighting methods.
- **Local Similarity Measures:** Most commercial CBR tools allow us to define local similarity measures for each feature in order to be able to incorporate more domain specific knowledge. Suitable learning techniques must be able to learn the particular parameters used to describe such local similarity measures.
- **Probabilistic Similarity Models (PSM):** Another possibility to represent similarity measures are probabilistic models. Here, the similarity function is encoded using probability distributions which have to be determined by using appropriate techniques (e.g. frequency counts, kernel estimation techniques, neural networks, etc.).

For characterizing learning techniques, Wettschereck and Aha have introduced the following categorization:

- **Incremental Hill-climbers:** Here, single training examples (typically based on ACUF or AUF) trigger the modification of the similarity measure after each pass through the CBR cycle. Existing approaches increase or decrease feature weights in classification scenarios, where success driven (te = (q, cr, 1)) and failure driven (te = (q, cr, 0)) policies can be distinguished.
- **Continuous Optimizers:** The idea of continuous optimizers is to collect a sufficiently large training data set first and to apply optimiza-

tion approaches afterwards in order to generate a similarity measure that shows optimal results on this training data.

Typically, this is realized by minimizing a particular error function which compares generated outputs with corresponding utility feedback contained in the training data. For learning feature weights, gradient descent approaches have shown good results. While most existing approaches apply ACUF or AUF, we have proposed an approach that utilizes RCUF in order to enable learning in the utility-oriented matching scenario. For more complex local similarity measures we have developed a corresponding evolutionary algorithm. PSM are usually also learnt by applying continuous optimizers which either optimize probabilistic error functions or estimate underlying probability distributions by applying statistical and Bayesian methods.

- **Ignorant Methods:** These methods do not exploit explicit feedback, but only perform a statistical analysis of the ACUF contained in CB, for example, to determine accurate feature weights based on class distributions. Concerning the incorporation of background knowledge into the learning process, few approaches have been developed so far. Approaches that use background knowledge in order to improve the performance of an evolutionary algorithm have been presented in.

In this section we have given an overview on techniques that have been applied for learning similarity measures in CBR. The choice of one of these techniques depends on the following aspects:

– The desired semantic of the target similarity measure

– The type of the training data and the corresponding approach to acquisition

– The representation of the similarity measure to be learned

– The applied learning algorithm

– Whether background knowledge is used to improve the learning process

4-Learning Adaptation Knowledge

The most aspects discussed concerning learning of similarity measures also hold for the second container containing reuse-related knowledge, namely adaptation knowledge. However, one difference can be noticed: In contrast to similarity knowledge, adaptation knowledge usually is described in form of a common representation formalism, namely rules. Although several approaches to learn rules have been developed in Machine Learning, only few strategies to learning adaptation knowledge in the CBR context can be found in literature. For example, Wilke et al. (1996) present a general framework for learning adaptation knowledge but they do not discuss concrete learning algorithms. Further, Hanney and Keane (1996, 1997) have developed a general approach to learn adaptation rules from case knowledge and Leake et al. (1996b) present an approach that learns adaptation knowledge in form of "adaptation cases".

11. CBR and Data Mining

Data Mining is defined as "the process of extracting trends or patterns from data" (Wright,1998). It allows a search, for valuable information, in large volumes of data (Weiss & Indurkhya, 1998). The explosive growth in databases has created a need to develop technologies that use information and knowledge intelligently. Therefore, Data mining techniques has become an increasingly important research area (Fayyad, Djorgovski, & Weir, 1996). [28]

The data mining is successfully applied by implementing the case based reasoning approach in deferent domains as bioinformatics in [29] and [30], distance learning [32] industrial applications [31], and other domains. The CBR is well cited as an important paradigm for data mining in the realized data mining applications in [28] and Knowledge Discovery in Databases KDD in [33].

12. CBR in health sciences applications

The main pioneering systems in CBR in the health sciences, with their application domain and type of task, are, ranked by date by (I.Bishistaridz 2008) :

- SHRINK, psychiatry, diagnosis (1987) [34];
- PROTOS, audiology disorders, diagnosis (1987) [3];
- CASEY, heart failure, diagnosis (1988) [35];
- MEDIC, dyspnoea, diagnosis (1988) [58];
- ALEXIA, hypertension, assessment tests planning (1992) [14];
- ICONS, intensive care, antibiotics therapy (1993) [28];
- BOLERO, pneumonia, diagnosis (1993) [36];
- FLORENCE, health care planning (1993) [15];
- MNAOMIA, psychiatry, diagnosis, treatment planning, clinical research assistance (1994) [6];
- ROENTGEN, oncology, radiation therapy (1994) [5];
- MACRAD, image analysis (1994) [37].

After these systems the development of health science enriches the state of the art by a diversity of relevant application in the majority of critical domain diagnosis home care and therapy pacification.

13. Some realized CBR System

Many applications and frameworks which Implement this paradigm are developed in deferent fields such as classification and diagnosis, helpdesk, knowledge management, planning, configuration and design and electronic commerce also e-learning. Some applications are successfully commercialized and other is developed just as a researches works. We describe here some successful deployed CBR systems.

CYRUS (Computerised Yale Retrieval and Update System) is the first CBR system which uses the Schnak's dynamic memory model was developed in 1984 by Janet Kolodner. It stores and retrieves events such as travels and meetings of Cyrus Vance during the period in which he was the US secretary of state. It inspired many of the subsequently developed CBR systems.

In 1986 Kristian Hammond developed a CBR system called **CHEF,** whose task was to create recipes.

MEDIATOR, developed by Robert Simpson, was reasoning in the domain of dispute mediation based on which a solution would be suggested. It was able to reason about the disputes of different proportions, starting room benign quarrels between two children to large-scale conflict involving two states. Similarly, Katia ycara's PERSUADER negotiated disputes in a more specific domain of labour-management disputes Sycara & Navinchandra, 1989).

Phyllis Koton designed **CASEY** that supported heart failures diagnostics (Koton, 1988). JULIA, designed by Tom Hinrichs (Hinrichs, 1992), completes the contemporary list of a series of CBR systems developed as part of PhD projects at the US universities.

CLAVIER, is a system for laying out composite parts to be baked in an industrial convection oven. CBR has been used extensively in help-desk applications such as the Compaq SMART system. As of this writing, a number of CBR decision support tools are commercially available, including k-Commerce from eGain (formerly Inference Corporation), Kaidara Advisor from Kaidara (formerly AcknoSoft) and SMART from Illation.

ISOR, Rainer Schmids, Olga Vorobieva (2006), is a case-based reasoning system for long-term therapy support in the endocrine domain and in psychiatry.

ISOR performs typical therapeutic tasks, such as computing initial therapies, initial dose recommendations and dose updates.

CBR-WORKS The CBR shell CBR-Works has been developed in the research projects INRECA5, WIMO6, and INRECA-II at the University of Kaiserslautern in co-operation with tecInno GmbH (now empolis knowledge management GmbH). This system is written in the programming language Smalltalk and has been employed in numerous research projects and several commercial applications.

Case-Based Mark-up Language (CBML) is an XML based language for representing CBR components. It allows developers to create a case-based view on relevant portions of a knowledge base. It allows us to make the formal definition of the structure of our cases and similarity measures completely independent of the application code and allows CBR components to be exchanged between heterogeneous CBR systems. We believe that a CBR system should be viewed as a medium to be used in conjunction with the mainstream corporate information system and anticipate that a standard way of representing CBR components will facilitate this.

We can cite also **INRECA** case-based reasoning (CBR) system (Esprit project 6322) which is deeply compared and evaluated with five other industrial CBR tools, namely **CBR EXPRESS** (Inference, USA), **ESTEEM** (Esteem Software, USA), **KATE tools** (AcknoSoft, France), **REMIND** (Cognitive Systems, USA) and **S3-CASE** (tecInno, Germany), and twenty CBR-related research prototype systems (developed at the University of Trondheim, University of Texas at Austin, Carnegie-Mellon University, Massachusetts Institute of Technology, Yale University, IIIA Barcelona, University of Würzburg, University of Technology at Aachen, University of Technology at Berlin, GMD Sankt Augustin et al., and the University of Kaiserslautern), according to a set of systematically chosen evaluation criteria called decision support criteria. These criteria include technical criteria dealing with the limitations and abilities of the systems, ergonomic criteria concerning the consultation of the executable system and application development, application domain criteria dealing with concept structure, knowledge sources, and knowledge base characteristics as well as application task criteria like integration of reasoning strategies, decomposition methods, and task properties. Our evaluation builds upon the evaluation of the above mentioned commercial CBR tools (which has been carried out in 1994 and published in 1995 at AI Intelligence, Oxford, UK) by using the same data, applying the same criteria and carrying out the same experiments with the INRECA system.

Conclusion

The aim of this chapter is to draw an extended overview of the CBR paradigm in which we have cited and presented many theoretical aspects needed for the use and the development of CBR systems. We have explained also the relationship between the CBR and some related domains as the Knowledge representation, adaptation, Knowledge Based System KBS, the Machine Learning ML and the Distributed Artificial intelligence DAI. We have also cited some variants and realized systems with their important impacts.

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Chapter 2 Distributed Reasoning with Multi-Agent System integration

Abstract: The distributed reasoning through agency improves many criteria for the development of strong and flexible reasoning systems. As new trends of parallel machine learning algorithms the distributed reasoning consists of distributing the reasoning through a set of cognitive agents which collaborate for realizing their local goals and for achieving the global goals of the reasoning system. In this chapter we will present a summary of distributed reasoning by citing some aspects and definitions for explaining the Multi-Agent System paradigm. After that we will present the agent typology, following this a brief description about learning in multi-agents systems and the important issues in distributed reasoning. We will Finalize this chapter by an overview of some useful frameworks (JATLite, JAFMAS, JADE and FIPA-OS the JAGENT) which facilitate the development of multi agent applications.

1. Conceptualization of Multi agent system

1.1 The agent

The term agent, outside AI, has been used in two general senses:

a) After Aristotle, and then developed up to present, philosophers have used the term agent to refer to an **entity that acts with purpose within a social context".**

b) A legal notion of agent as **a person who acts on behalf of a principal for a specific purpose and under limited delegation of authority and responsibility"** was already present in Roman law, and has been also applied in economics.[2]

We notice that the second design of agent implies in some sense the first one.

Stan Franklin and Art Graesser found [1] out that basically, all definitions of the term agent proposed in AI, were based on at least one these general senses of the term. They reviewed a set of such definitions to establish what does distinguish an agent from traditional software. Using this analysis, and two definitions widely accepted in AI: i) The definition proposed by Michael Wooldridge and Nick Jennings in his survey Intelligent Agents: Theory and Practice[2]; and ii) The definition proposed by Stuart Russell and Peter Norvig in his book Artificial Intelligence, a Modern Approach[3], we can define an agent as follows:

An agent is a temporal persistent computational system, able to act ***autonomously*** *to meet its objectives or* ***goals****, when it is situated in some* ***environment****.*

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[2] W. Muller-Freienfels. Agency. In *Encyclopedia Britannica*. Encyclope-dia Britannica, Inc., 1999. Internet version.

Even when this definition could be perceived as quite general, it provides an abstract top-level view of agents based on their situation (Fig 3.1). In this view, an agent is seen as taking sensory inputs from the environment where it is situated, and producing actions as output in response to perception. These actions modify the environment in an interaction that is usually continuous and non-terminating, as reflected by the temporal persistent character of agents. In other definition they add the reasoning engine which is the most important component of agent.

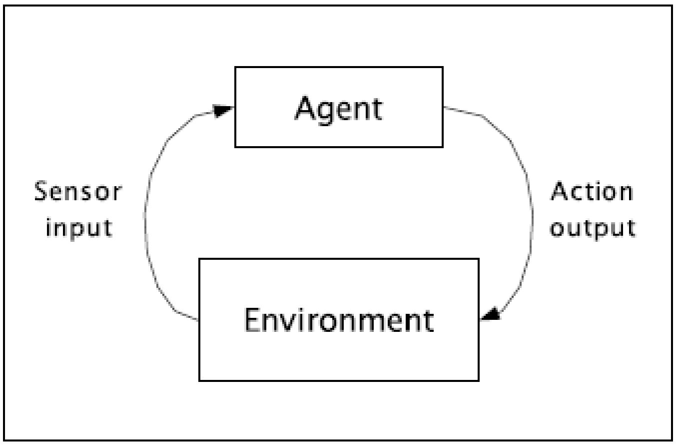

Fig 2.1 Agent and the environment

Stuart Russell and Devika Subramanian [4] find three advantages on this view:

i) It allows us to view the cognitive faculties of agents in the service of finding the right thing to do.

ii) It allows room to consider different kinds of agents, even those that are not supposed to have such cognitive faculties.

iii) It allows more freedom to consider various specifications, boundaries, and interconnections of subsystems composing agents.

Another advantage, particularly related to the temporal persistence, is that agents can be seen in the context of Computer Science, as reactive systems, i.e., systems that interact with its environment frequently and often do not terminate.

1.2 The environment

An environment is the space where an agent, or a group of agents, is situated. It is argued that the environment by excellence is the real world, it is the approach proposed by Rodney Brooks [5] where all agents are conceived as robots. Some others, as Oren Etzioni [6], consider that virtual environments, as operating systems or the web, are also valid as the real world when talking of situatness and agency, and so, it is not necessary to demand all agents to have robotic implementations. I belief that both kind of environments are valid to conceive agents situated in them and that, what it is really important, is the interaction of the agent with its environment through action and perception, as described by the top level view of agency, i.e., in an autonomous, temporal persistent way. For a better understanding of this interaction, observe the following classification of environment properties, suggested by Stuart Russell and Peter Norvig [7]:

Accessible vs. Inaccessible. If an agent has access to the complete state of the environment through its sensors, then we say that such an environment is accessible to that agent. An environment is effectively accessible if the agent has access to all aspects in the environment that are relevant to the choice of action. Observe that accessibility depends not only on the environment itself, but on the perceptual capabilities of the agent. The more accessible an environment is, the easier to build agents situated on it. The reason for this is that in such environments, the agent has access to the information necessary to take decisions.

Deterministic vs. non-deterministic. If the next state of the environment is completely determined by its current state and the actions selected by the agents, then we say the environment is deterministic. If the environment is inaccessible, then it may appear to be non deterministic. Thus, it is often better to think of an environment as deterministic or non-deterministic from the point of view of the agent. Non-determinism captures two important notions: i) The fact that agents have a limited sphere of influence, i.e., they have at best partial control over their environment; and ii) the fact that actions can fail to have the desire result. For this, the more deterministic, an environment, is the easier to build agents on it.

Episodic vs. non-episodic. In an episodic environment, the experience of the agent is divided into “episodes", each of them consisting of the agent perceiving and then acting. The quality of the action depends just on the episode itself, i.e., action in subsequent episodes do not depend on what actions occurred in previous episodes. Given the temporal persistent nature of agents, they must continually make local decisions that have global consequences. Episodes reduce these consequences, and so it is easier to designing agents situated on episodic environments.

Static vs. Dynamic. If the environment can change while an agent is deliberating, then we say that the environment is dynamic for that agent; otherwise it is static. If the environment does not change with the passage of time but the agent's performance score does, then we say that the environment is semi-dynamic. Dynamic environments have two important consequences: i) An agent must perform perceptual actions, e.g., information gathering functions, because even if it has not executed any action between times t0 and t1, it cannot assume that the environment state is the same at t0 and t1; and ii) Other processes in the environment can interfere with the actions of the agent. So, it is simpler to design agents in static environments than in dynamic ones.

Discrete vs. continuous. If there are a limited number of distinct clearly defined possible states for an environment, we say it is discrete, otherwise it is continuous. It is easier to build software agents that deal with discrete environments, because computers are discrete systems too, and even when they can simulate continuous systems to any degree of accuracy, some information is lost while mapping from a continuous to a discrete representations. So, the information used by discrete agents in continuous environments is inherently approximate.

This categorization suggests that different kinds of environments are possible. Each environment, or class of environments, requires somewhat different agent programs to deal with them effectively. The more complex environment class is formed by those that are inaccessible, non-episodic, dynamic, continuous environments.

1.3 Autonomy

When we concept a software agents, the most important criteria to respect is the autonomy where this terms means “under self-control", the capability to act free from external and internal oppressive forces. In the context of software agents, autonomy emphasizes the assumption that, although we generally intend software agents to act on our behalf, they nevertheless act without direct human or other intervention, and have control over their internal states and over their actions.

1.4 Goals

In the AI tradition *goals* described situations that are desirable for an agent, and are defined as a body of knowledge about the environment, that enter into the behavior of the intelligent systems as something the system strives to realize [7]. This definition of a goal is related to the concept of *problem state space* composed by the following elements:

- **Initial state**. The state of the environment, the agent knows itself to be in Operators. The set of possible actions viable to the agent. The term operator is usually used when actions are described in term of the state reached by an agent by carrying out that action.

- **State space.** The set of all states reachable from the initial state by any sequence of operators. There is a subset of such states identified as fin*al states*, i.e., states defining goals.
- **Goal test.** A function that determines if a state is a goal state. Usually goals are expressed as a set of states or a property that the state must satisfy, e.g., check mate in chess.

Covrigaru and Lindsay [8] introduce some axes of categorization for goals in relation to autonomy. Types of goals include:

Built-in vs. acquired. Every goal based system requires a set of goals built-in at the moment of its design. They are part of the definition of the system. Acquired goals are created by the system after it starts its activities and they include, but are not limited to, sub-goals.

Implicit vs. explicit. If a goal is defined in terms of states in a state space and can be manipulated by the system, we say it is an explicit goal. Implicit goals are building in the structure of the system and cannot be manipulated directly by it, i.e., a learning agent has the implicit goal of improving its performance over time.

Endogenous vs. exogenous. Endogenous goals are created by and within the system as a reaction to some stimulus from the environment or as sub-goals in a process of problem solving. Exogenous goals are created outside the system and become its goals either at the time the system is designed or through its sensors, but in either case, these are already formulated as goals, e.g., commands or requests.

Single vs. multiple. There are systems with a single goal, e.g., the xbiff demon has as unique goal to notify its user if an email has arrived, while some email agents, as the one proposed by Pattie Maes [9] have different goals:

notify the user when an email arrived; learn what to do with the messages, observing the user.

Sub-goals vs. top level goals. Sub-goals are created during the process of achieving other goals and depend on the existence of the goals within they were created. Top level goals can be pursued by the system in dependently and do not stand in a goal-sub-goals relation. Usually, built-in goals can be seen as top-level goals.

Achievable vs. homeostatic. Achievable goals have a well-defined set of initial and final states in the state space; reaching any of the final states marks the achievement and termination of such a goal. Homeostatic goals are achieved continuously. They do not terminate when the system is in a final state; when a change occurs and the system is not more in a final state, activity to reach one of such states is re-initiated, e.g., even xbiff has an homeostatic goal, since it notifies its user every time there is a new message in the mailbox.

The conclusion of Covrigaru and Lindsay [8] is that a system is more likely to be perceived as autonomous, if it has a set of multiple top-level goals and some of them are homeostatic.

1.5 Multi Agent system

A multi-agent system comprises a group of intelligent agents working towards a set of common global goals or separate individual goals that may interact. In such a system, each of the agents may not be individually capable of achieving the global goal and/or their goals may have interactions - leading to a need for coordination among the set of agents. Due to its partial view of the problem solving situation, an agent may have access only to a part of the environment, and communication bandwidth limitations and heterogeneity of representations may limit its view of other agents' states. An agent may have to communicate and negotiate with other agents to resolve any uncertainties (arising out of the partial or imperfect views of the global problem-solving context) to the extent that it can make positive contributions to the ongoing problem solving process [11].

2. Agent typology

Nwana [10] has defined some indispensable criteria for the agent topology as cooperation; learning and autonomy (see Fig 2.2). With these criteria we can define the class of the agent we can cite heir the following classes:

1. ***Autonomous agent:*** These agents can sense and act autonomously in an environment. Although they are autonomous, their actions work twoards a goal. The environment can be simple and static or complex and dynamic.
2. ***Information Agents*** are agents that can access, retrieve, and manipulate information obtained from any number of information sources. They also can answer queries about the information that they can access.
3. ***Intelligent Agent.*** These are agents that act on the behalf of the user or another program to carry out a set of operations. They do so with some degree of independence and autonomy.
4. ***Interface Agents*** are agents that support and provide assistance to a user through observing and monitoring the users actions in an interface. The agent learns from the actions and suggests or implements more efficient or easier ways of accomplishing tasks.
5. ***Collaborative Agents*** rely on the social ability of agents in any system to cooperate and autonomously perform tasks for the user. They have some common interface language in order to cooperate and communicate with other agents.

1. ***Mobile Agents*** are capable of movement between computers across a local area network (LAN), wide-area network (WAN), or any other

communication medium. Typically they gather information for a user and report results either by traveling back to the user or transmitting them Again, this is not an exhaustive list of agent classes, but rather some of the most widely used and agreed upon generalizations.

Some other classes of agents which are not explicitly covered here are hybrid agents, reactive agents, behavioral agents, and entertainment agents. Additionally, this list is not mutually exclusive. For instance, a mobile agent can be intelligent and collaborative as well.

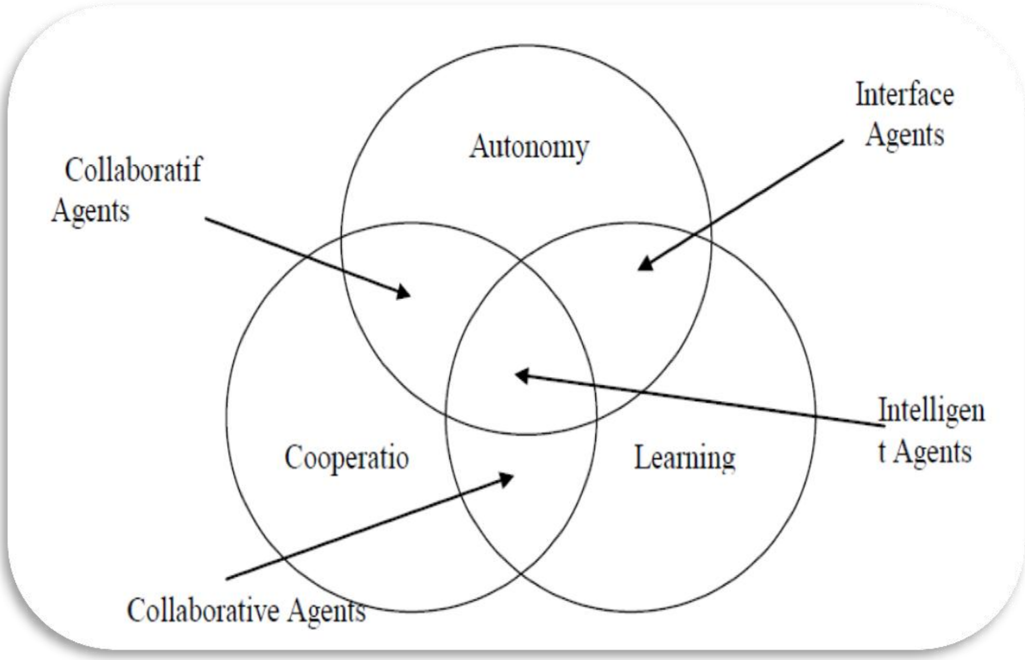

Fig 2.2.Nwana classification.

3. Machine Learning and Distributed reasoning in Multi-Agents

The distributed reasoning based on multi-agent architecture needs to apply the machine learning technics for improving the global performance of the reasoning system but the specificity of multi-agent, which is very complex, needs novel algorithms and strategies of learning more relevant and adapted to the complex architecture of the multi-agent paradigm. Learning in multi-agent environments constitutes a research and application area whose importance is broadly acknowledged for these last years in AI domain. This acknowledgment is largely based on the insight that multi-agent systems typically are very complex and hard to specify in their dynamics and behavior, and that they therefore should be equipped with the ability to self-improve their future performance. There is a rapidly growing body of work on particular algorithms and techniques for multi-agent learning.

The machine learning in multi agents is considered into two sides: 1- Single agent learning and 2- Cooperative learning where the learning is done via multi agent collaborative approaches. The single agent learning consists of reusing the traditional machine learning algorithms via a cognitive agent which contains sensors and inferring engine.

Multi-agent learning is established as a relatively young but rapidly developing area of research and application in DAI (e.g. Imam, 1996; Sen, 1996; Weiß & Sen, 1996; Weiß, 1997). There are three classes of mechanisms which make multi-agent learning different from single-agent learning: multiplication, division and interaction [19]. This classification provides a 'positive' characterization of multi-agent learning. For each mechanism, a general 'definition' is provided with some examples of realized systems.

1- Learning Multiplication

If each agent in a multi-agent system is given a learning algorithm, the whole system will learn. In the case of multi-plied learning there are several learners, but each of them learns independently of the others, that is, their interactions do not impact their individual learning processes. There may be interactions among the agents, but these interactions just provide input which may be used in the other agents' learning processes. The learning processes of agents but not the agents themselves are, so to speak, isolated from each other. The individual learners may use the same or a different learning algorithm. In the case of multi-plied learning each individual learner typically pursues its own learning goal without explicitly taking notice of the other agents' learning goals and without being guided by the wish or intention to support the others in achieving their goals. (The learning goals may mutually supplement each other, but this is more an ‘emerging side effect’ than the essence of multi-plied learning.) In the case of multi-plied learning an agent learns ‘as if it were alone’, and in this sense has to act as a ‘generalist’ who is capable of carrying out all activities that as a whole constitute a learning process. This method exist in some realized multi agent systems as Ohko, Hiraki and Anzai (1996) in robotics application, Haynes, Lau and Sen (1996) in case based reasoning system, Vidal and Durfee (1995) for prediction of other agents actions, Terabe et al. (1997) for agents tasks allocation by learning from observation of each other's' abilities and Bazzan (1997) which apply the evolutional principles of mutation and selection as mechanisms for improving coordination strategies in multi-agent environments. These are essentially examples of the multi-plied learning approach because the agents do not influence each other in their learning processes.

2- Learning division

In the case of ‘divided learning’ a single-agent learning algorithm or a single learning task is divided among several agents. The division may be according to functional aspects of the algorithm and/or according to characteristics of the data to be processed in order to achieve the desired learning effects. The division of the learning algorithm or task is typically done by the system designer, and is not a part of the learning process itself. Interaction is required for putting together the results achieved by the different agents, but as in the case of multi-plied learning this interaction does only concern the input and output of the agents' learning activities. The benefit, of this mechanism, is that it allows the agents to working with more flexibility by increasing the autonomy of each one. A further potential benefit is that a speed-up in learning may be achieved. This mechanism is realized in several applications as Sekaran and Hale (1994) concentrated on the problem of achieving coordination without sharing information, Plaza, Arcos and Martin (1997) for protein purification, Parker (1993) concentrated on the question of how cooperative behavior can be learnt in multi-robot environments and Weiß (1995) in groups of agents which achieves a common goals.

3- Learning interaction

This learning mechanism is based on the fact that agents interact during learning. Some interaction also occurs in the two previous mechanisms, but it mainly concerns the input or output of the individual agents' learning processes. The term ‘interaction’ covers a wide category of mechanisms with different potential cognitive effects such as explanation, negotiation, mutual regulation, and so forth. The complexity of these interactions makes up the difference between interactive learning on the one hand and multiplied/divided learning on the other. This mechanism occur in several research works as Sugawara and Lesser (1993) in the diagnosis of network traffic application, Bui, Kieronska and Venkatesh (1996) in negotiation-intensive application where the agents learn from observation to predict others' preferences and others' answers and Nagendra Prasad, Lesser and Lander (1995) in the context of automated system design where the agents learn organizational roles.

4. Some existing distributed reasoning issues

The multi-agent systems are wildly enriched by researchers, for this we find in the literatures many issues discussed and resolved by several methods and propositions in deferent contexts. A brief description of some main issues of research, specification and design in cognitive multi-agent systems, are discussed as specified in Fig2.3.

2.1 Theories for specification

From the point of view of theoretical specification, most formal agent models draw from modal logics or logics of knowledge and belief. The possible worlds model for logics of knowledge and belief was originally proposed by Hintikka (Hintikka, 1962) and formulated in modal logic using Kripke semantics. In this model, the agent beliefs and knowledge are characterized as a set of possible worlds, with an accessibility relation holding between them. The main disadvantage of the model is the logical omniscience problem that consists in the logic predicting that agents believe all the logical consequences of their belief.

Because of the difficulties of logical omniscience, some alternate formalisms for represented belief have been proposed, many of them including also other mentalistic notions besides knowledge and beliefs. For example, Konolige (Konolige, 1986) developed the deduction model of belief in which beliefs are viewed as symbolic formula represented in a meta-language and associated with each agent. Moore (Moore, 1985) formalized a model of ability in a logic containing a modality for knowledge and a dynamic like part for modeling action. Cohen and Levesque (1990) proposed a formalism that was originally developed as a theory of intentions ("I intend to") with two basic attitudes: beliefs and goals. The logic proved to be useful in analyzing conflict and cooperation in agent communication based on the theory of speech acts. One of the most influential model nowadays is the one developed by Rao and Georgeff (1991) based on three primitive modalities, namely belief, desire and intentions (the so called BDI model).

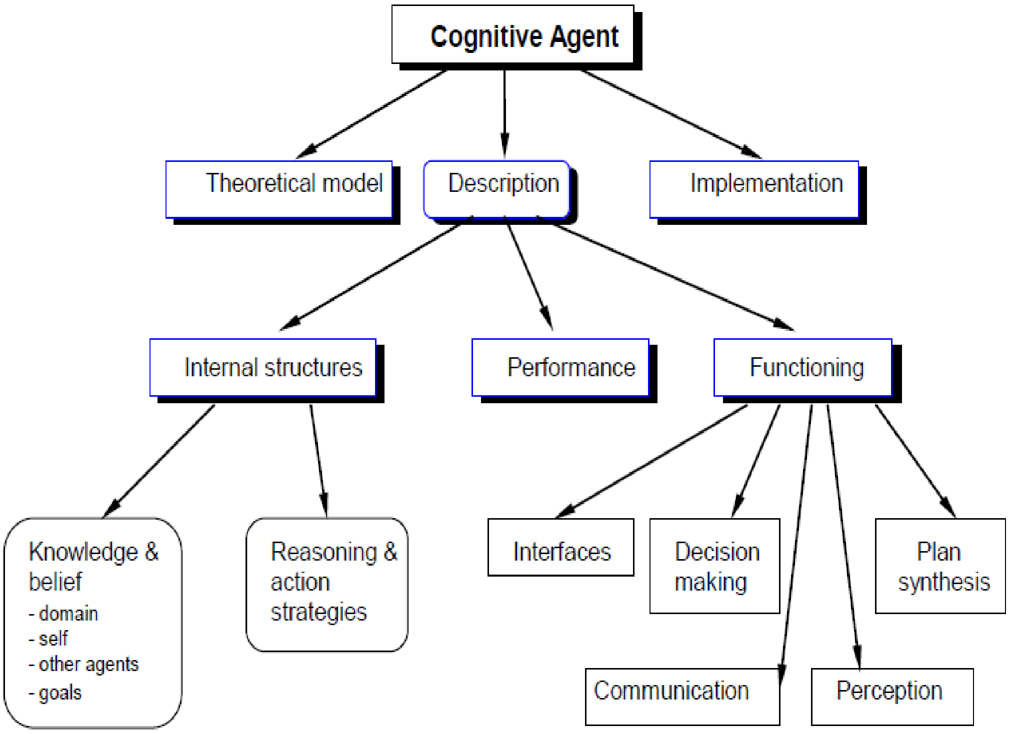

Fig2.3. Levels of specification and design of intelligent agents in a MAS

2.2 Communication

Interaction among agents in a MAS is mainly realized by means of communication. Communication may vary from simple forms to sophisticated ones, as the one based on speech act theory. A simple form of communication is that restricted to simple signals, with fixed interpretations. Such an approach was used by Georgeff in multi-agent planning to avoid conflicts when a plan was synthesized by several agents. A more elaborate form of communication is by means of a blackboard structure. A blackboard is a shared resource, usually divided into several areas, according to different types of knowledge or different levels of abstraction in problem solving, in which agents may read or write the corresponding relevant information for their actions. Another form of communication is by message passing between agents.

In the MAS community, there is now a common agreement that communication among agents means more than communication in distributed systems and that is more appropriate to speak about interaction instead of communication. When people communicate, they perform more than just exchanging messages with a specified syntax and a given protocol, as in distributed systems. Therefore, a more elaborate type of communication that tends to be specific to cognitive MAS is communication based on the speech act theory (Searle, 1969, Vanderveken, 1994). In such an approach, interaction among agents take place at least at two levels: one corresponding to the informational content of the message and the other corresponding to the intention of the communicated message. If interaction among agents is performed by means of message passing, each agent must be able to deduce the intention of the sender regarding the sent message. In a speech act, there is a distinction between the locutionary act (uttering of words and sentences with a meaning), the illocutionary act (intent of utterance, e.g., request, inform, order, etc.), and the prelocutionary act (the desired result of utterance, e.g., convince, insult, make do, etc.). One of the best known example of interaction language based on speech act theory is the KQML (Knowledge Query and Manipulation Language) language proposed by ARPA Knowledge Sharing Effort in 1992. KQML uses the KIF (Knowledge Interchange Format) language to describe the content of a message. KIF is an ASCII representation of first order predicate logic using a LISP-like syntax.

2.3 Coordination

An agent exists and performs its activity in a society in which other agents exist. Therefore, coordination among agents is essential for achieving the goals and acting in a coherent manner. Coordination implies considering the actions of the other agents in the system when planning and executing one agent's actions. Coordination is also a means to achieve the coherent behavior of the entire system. Coordination may imply cooperation and in this case the agent society works towards common goals to be achieved, but may also imply competition, with agents having divergent or even antagonistic goals. In this later case, coordination is important because the agent must take into account the actions of the others, for example competing for a given resource or offering the same service.

Many coordination models were developed for modeling cooperative distributed problem solving, in which agents interact and cooperate to achieve their own goals and the common goals of the community as a whole. In a cooperative community, agents have usually individual capabilities which, combined, will lead to solving the entire problem. Cooperation is necessary due to complementary abilities, to the interdependency that exists among agent actions and to the necessity to satisfy some global restrictions or criteria of success. In a cooperative model of problem solving the agents are collectively motivated or collectively interested, therefore they are working to achieve a common goal. Such a model is fit for closed systems in which the agent society is a priori known at design time and in which the system designer imposes an interaction protocol and a strategy for each agent.

Another possible model is that in which the agents are self motivated or self interested agents because each agent has its own goals and may enter in competition with the other agents in the system to achieve these goals. Competition may refer to resource allocation or realization/distribution of certain tasks. In such a model, the agents need to coordinate their actions with other agents to ensure their coherent behavior. Besides, even if the agents were able to act and achieve their goals by themselves, it may be beneficial to partially and temporarily cooperate for better performance, forming thus coalitions. Such a model is best fit for open systems in which agents are designed by different persons, at different times, so their are not all known at design time.

When coordinating activities, either in a cooperative or a competitive environment, conflicts may arise and one basic way to solve these conflicts is by means of negotiation. Negotiation may be seen as the process of identifying interactions based on communication and reasoning regarding the state and intentions of other agents. Several negotiation approaches have been proposed, the first and best known one being the contract net protocol of Smith and Davis. In such a model, a central agent decomposes the problem into sub-problems, announces the sub-problems to the another agents in the system and collects their propositions to solve the sub-problems. Oddly enough, although this negotiation approach is the best known one in the MAS community, it involves in fact almost no negotiation, because no further stages of bargain are performed.

In distributed problem solving based on collectively motivated MAS, the contract net model was used, for example, to achieve cooperation by eliminating inconsistencies and the exchange of tentative results (Klein, 1991), multi-agent planning (Georgeff, 1984, Pollack, 1992) in which agents share information to build a common plan and distribute the plan among agents.

Negotiation is central in self-interested MAS. Zlotkin and Rosenschein (1989) use a game theoretic approach to analyze negotiation in multiagent systems. In 1991, Sycara proposes a model of negotiation in which agents make proposals and counter-proposals, reason about the beliefs of other agents and modify their beliefs by cooperation. Durfee and Montgomery develop a hierarchical negotiation protocol which allows agents to flexibly discover and solve possible conflicts. Kraus (Kraus, 1997, Kraus et. al., 1995) uses negotiation strategies for resource allocation and task distribution. Introduction of economic theory approaches in negotioan strategies for MAS is a current direction of research and investigation (Kraus, 1997, Kraus, 1996, Brafmann, Tennenholtz, 1997).

2.5 Organizations

During the last years, an important direction of research that was identified is the social theories of agent organizations, organizational knowledge being a key type of knowledge in MAS. Malone defines the organization as a coordination pattern of decision-making and communication among a set of agents who perform tasks to achieve goals in order to reach a global coherent state, while Ferber see an organization as a pattern that describes how its members interact to achieve a common goal. Such a pattern may be static, conceived a priori by the system designer, but may be also achieved in a dynamic way, especially in case of open systems.

Several models of organizations in MAS were developed, varying from simple structures to more elaborate ones, and depending on the centralized or decentralized characteristic of the organization. Among the simple models we may cite the groups, the teams and the interest groups. A group allows the cooperative coordination of its members to achieve a common goal. The entire task is divided in a set of subtasks that are allocated to the members of the group. The team structure implies in most cases a set of agents acting in a common environment and communication among agents in order to distribute subtasks and resolve inconsistencies. The interest groups are organizations in which the members share the same interests and may cooperate to achieve their own goals.

A more elaborate model of organizations is the hierarchical one, based on the traditional master/slave relation. In such a structure, there is a manager that is responsible for the division of tasks, assignment of subtasks to slaves, and the control of task completion. The slaves have to share the necessary information to achieve tasks and are supposed to be obedient. The structure is replicated at several hierarchical levels. A refinement of a hierarchical organization is the decentralized organization or multi-division hierarchy in which the organization comprises several divisions and each division is a hierarchical organization functioning in the way described above. Top-level decision making is performed only for long-term strategic planning. Hierarchical organizations are mainly fit for cooperative-like systems and closed systems.

At a decentralized level, the predominant MAS structure is the market. The simplest market organization implies the existence of suppliers, able to perform tasks to produce goods or services, and of buyers, namely agents that need the goods or services produced by the suppliers. The basic model associated with such a structure is the competitive MAS, with self interested agents that are competing either to supply or to buy goods or services. Such a model is well suited for open systems. One of the main disadvantage of such an approach is the heavy load induced by communication among the agents. In order to decrease the amount of communication, a compromise can be realized by constructing what is called a federation community. In such an organizations, the agents in the system are dived into groups, each group having associated a single “facilitator” to which the agents surrender a degree of autonomy. A facilitator serves to identify the agents that join or leave the system and enables the communication with agents located in other groups.

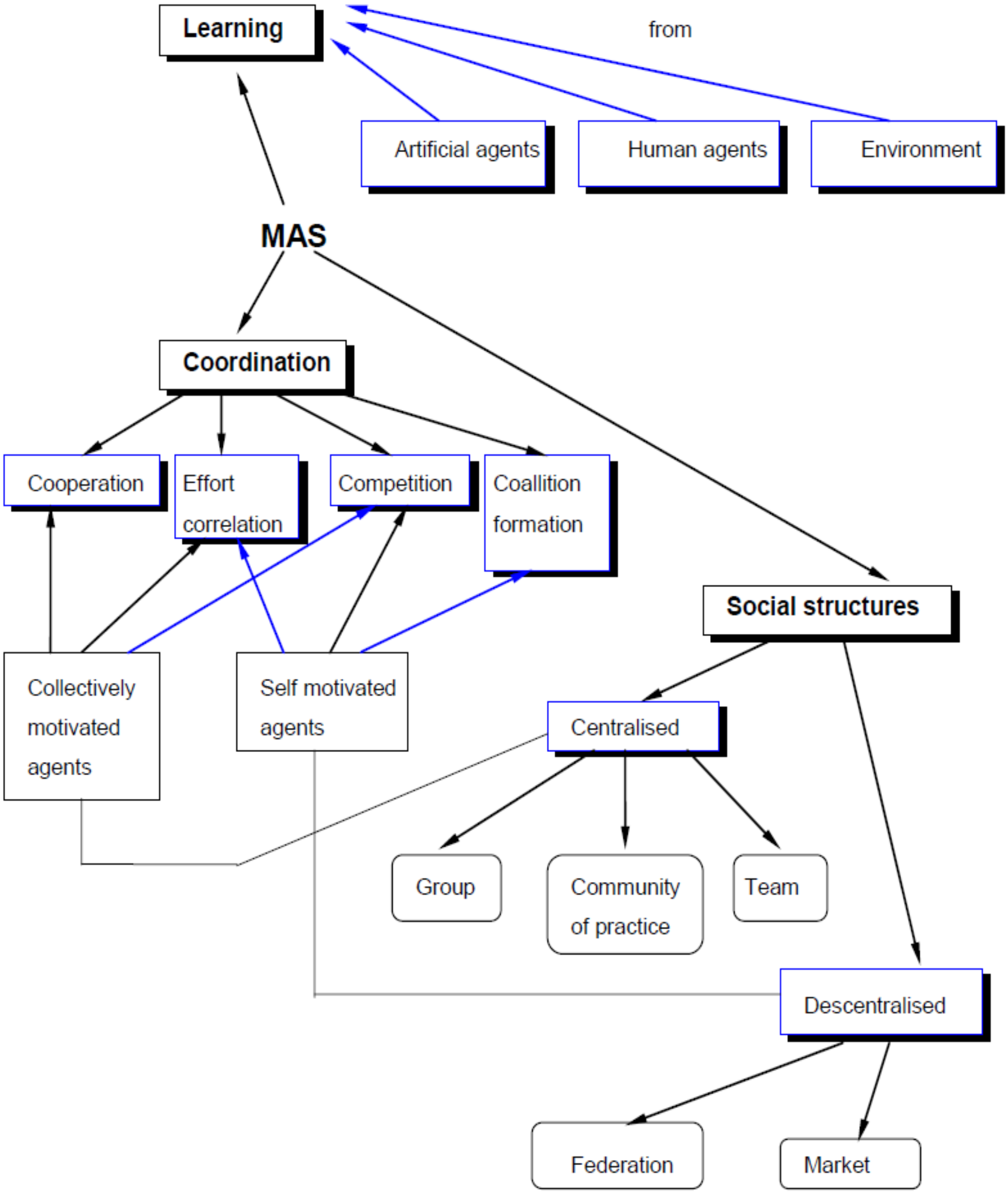

Fig 2.4. Cognitive interactions in a MAS

This Figure represents a scheme of the basic aspects that should be considered when studying and designing MAS, aspects that I consider to correspond to cognitive interactions in cognitive MAS.

5. Multi-Agent Development Frameworks

An agent development framework provides a set of templates and codes that facilitates or implements basic elements of the multi agent system. It may also provide templates for various types of agents or constructs that agents can use. Basic communication can be offered with a simplistic way and standardized for ensuring the comprehension and the interoperability.

The key differences between most development frameworks are in the ensured services and the implementation of architecture also some time the provided communication and agent functionality. We will describe here some frameworks and their criteria.

1. JATLite

JATLite provides a set of Java templates and a Java agent infrastructure that allows agents to be built from a common template. The template for building agents utilizes a common high-level language and protocol [12]. This template provides the user with numerous predefined Java classes that facilitate agent construction. The classes are also provided in layers so that the developer can easily decide what classes are needed for a given system. In this way, if the developer decides not to use KQML for example, the classes in the KQML layer can be omitted. However, if that layer is included, parsing and other KQMLspecific functions are then automatically included in any agent developed from the JATLite base classes.

The key difference between JATLite and the other systems is the agent communication infrastructure packaged with it [12]. Traditional agent systems use some type of Agent Name Server (ANS) for making the required connections between agents. An agent uses an ANS to look up the IP address of another agent and then make a TCP socket connection directly to that agent for the purpose of exchanging messages. With such an ANS, if the IP address of the other agent changes, the first agent finds out when the next attempt to send a message fails. If the second agent "crashes" in any way, it is the responsibility of every other agent with whom it was communicating to properly save the failed messages and resend them later. JATLite uses the Agent Message Router (AMR) to act as the “server” and receive messages from the registered agents and routes the message to the correct receiver [12]. Received messages are also queued to the file system to ensure a resend can be accomplished if a failure should occur. This provides more assurance a message will be successfully transmitted but also places the burden of communication on a central machine. If a crash or other error occurs in the AMR, no communication can occur and all queued messages are lost.

2. JAFMAS

The Java-based Agent Framework for Multi-Agent Systems (JAFMAS) is a Java-based development framework that also provides a set of Java templates and a Java agent infrastructure to allow agents to be built from a common template [13]. The core classes provided by JAFMAS provide for both directed and multicast communications. Borrowing heavily from COOL, a language for representing, applying, and capturing cooperation knowledge in multi agent systems, JAFMAS defines the social behavior of agents. Like COOL, JAFMAS defines all interactions between agents as “conversations” and information exchange is performed through the conversation in the way of performatives or through messages between agents involved in a conversation. The key difference between JAFMAS and other systems is the use of multicast messaging to establish an agent’s identity [13]. Multicast is a Java provided datagram socket class that allows joining “groups” of other multicast hosts on a network. It differs from broadcasting in that messages are sent to all members of the ”group”, not the entire network. This ensures bandwidth is conserved and only agents which are affected by a message actually receive it. More importantly, it frees up a multi-agent system from relying on a central registry for agent identity and message routing. This ensures a system can function even if an agent should fail.

1. FIPA-OS

The Foundation for Intelligent Physical Agents (FIPA) is an international organization that is dedicated to promoting the industry of intelligent agents by openly developing specifications supporting interoperability among agents and agent based applications. This occurs through open collaboration among its member organizations, which are companies and universities that are active in the field of agents. FIPA makes the results of its activities available to all interested parties and intends to contribute its results to the appropriate formal standards bodies where appropriate.

The FIPA specifications are developed through direct involvement of the FIPA membership. The status of a specification can be either Preliminary, Experimental, Standard, Deprecated or Obsolete. More detail about the process of specification may be found in the FIPA Document Policy [16] and the FIPA Specifications Policy [17]. A complete overview of the FIPA specifications and their current status may be found on the FIPA Web site. FIPA is a non-profit association registered in Geneva, Switzerland. As of June 2002, the 56 members of FIPA represented many countries worldwide.
FIPA-OS is a component-orientated toolkit for constructing FIPA compliant Agents using mandatory components (i.e. components required by ALL FIPA-OS Agents to execute), components with switchable implementations, and optional components (i.e. components that a FIPA-OS Agent can optionally use). The messages between agents and devices description are described by ontology.

3. JADE

JADE (Java Agent Development framework) is a middleware for the development of applications, both in the mobile and fixed environment, based on the Peer-to-Peer intelligent autonomous agent approach. JADE enables developers to implement and deploy multi-agent systems, including agents running on wireless networks and limited-resource devices [14].

- **JAGENT**

The JAGENT is a framework to develop and test multi agents systems. It manages agents, world (represented by a squaring) and algorithms creation. It is under GPL license and it is open sources. The JAgent architecture was designed using the MVC pattern; the classes will be linked to a view already done. IT contains a GUI composed by a demonstration and a graph launcher frames. The first interface lets the developer to enter the different parameters of the system and see the agents interacting. The second one helps to check the performance of several algorithms, represented by graphs. All system parameters can be used in the painting of these graphs [15].

Conclusion

In this chapter we have presented a general overview of distributed reasoning by drawing the majority of theoretical concepts and definitions the typology of agent is also cited following this, we have mentioned the existing kinds of multi-agents learning. The essential issues in the area of distributed reasoning are described in a nutshell and finally for an easy implementation of multi agents system we have indexed some famous development framework.

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Chapter 3 Fuzzy Systems Theory and applications for reasoning under uncertainty

Abstract The fuzzy theory is introduced by Lotfy Zadah 1965 for giving a new extension of the traditional theory sets. This theory is widely and successfully used and combined with other paradigms as Rule based systems, Artificial Neuronal Networks, Case based Reasoning and others for resolving many problems applied in many automatic systems where the uncertainty exists considerably. Before illustrating the fuzzy sets theory it is important to realize what uncertainty actually is. Following this, we will describe the important theoretical aspects of fuzzy sets and their applications properties with the different forms of fuzzy sets applications. Finally we will cite the contribution of fuzzy sets in the transparency of the reasoning systems.

1. *Uncertainty overview*

The uncertainty is a term used in subtly different ways in a number of fields, including philosophy, statistics, economics, finance, insurance, psychology, engineering and science. It applies to predictions of future events, to physical measurements already made, or to the unknown. Uncertainty must be taken in a sense radically distinct from the familiar notion of risk, from which it has never been properly separated. Klir&Yuan

❖ *What is relationship between uncertainty, probability, vagueness and risk?*

The essential fact is that 'risk' means in some cases a quantity susceptible of measurement, while at other times it is something distinctly not of this character; and there are far-reaching and crucial differences in the bearings of the phenomena depending on which of the two is really present and operating.... It will appear that a measurable uncertainty, or 'risk' proper, as we shall use the term, is so far different from an immeasurable one that it is not in effect an uncertainty at all.

Risk is defined as uncertainty based on a well-grounded (quantitative) probability. Formally, Risk = (the probability that some event will occur) X (the consequences if it does occur). Genuine uncertainty, on the other hand, cannot be assigned such a (well grounded) probability. Furthermore, genuine uncertainty can often not be reduced significantly by attempting to gain more information about the phenomena in question and their causes. Moreover the relationship between uncertainty, accuracy, precision, standard deviation, standard error, and confidence interval is that the uncertainty of a measurement is stated by giving a range of values which are likely to en-close the true value. This may be denoted by error bars on a graph, or as value ± uncertainty, or as decimal fraction (uncertainty).

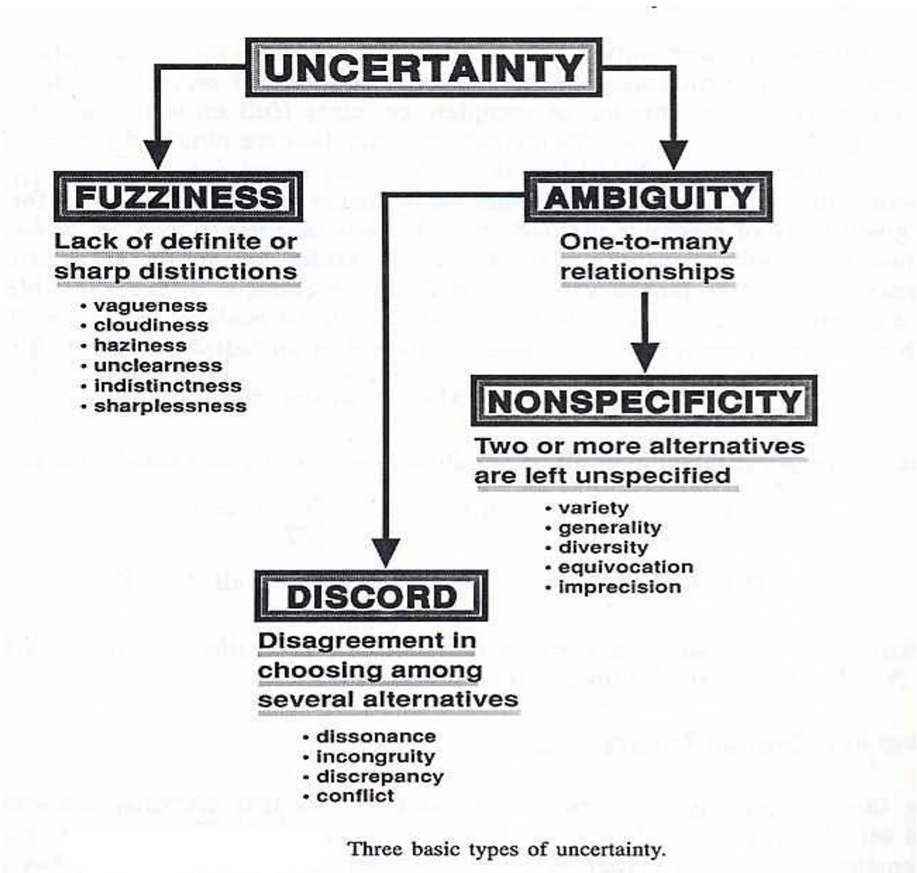


Fig 3.1 kinds of uncertainty (Figure from Klir&Yuan)

Often, the uncertainty of a measurement is found by repeating the measurement enough times to get a good estimate of the standard deviation of the values. Then, any single value has an uncertainty equal to the standard deviation. However, if the values are averaged and the mean is reported, then the averaged measurement has uncertainty equal to the standard error which is the standard deviation divided by the square root of the number of measurements. When the uncertainty represents the standard error of the measurement, then about 68.2% of the time, the true value of the measured quantity falls within the stated uncertainty range.

Therefore no matter how accurate our measurements are, some uncertainty always remains. The possibility is the degree that thing happens, but the probability is the probability that things be happen or not.

So the methods that we deal with uncertainty are to avoid the uncertainty, statistical mechanics and fuzzy set (Zadeh in 1965).

2. *Fuzzy sets*

The Fuzzy sets have been introduced by Lotfi A. Zadeh (1965). What Zadeh proposed is very much a paradigm shift that first gained acceptance in the Far East and its successful application has ensured its adoption around the world. Fuzzy sets are an extension of classical set theory and are used in fuzzy logic. In classical set theory the membership of elements in relation to a set is assessed in binary terms according to a crisp condition — an element either belongs or does not belong to the set. By contrast, fuzzy set theory permits the gradual assessment of the membership of elements in relation to a set; this is described with the aid of a membership function valued in the real unit interval [0, 1]. Fuzzy sets are an extension of classical set theory since, for a certain universe, a membership function may act as an indicator function, mapping all elements to either 1 or 0, as in the classical notion.

2.1 Definitions

A fuzzy set is any set that allows its members to have different grades of membership (membership function) in the interval [0,1]. A fuzzy set on a classical set X is defined as follows:

$$\tilde{A} = \{(x, \mu_A(x)) \mid x \in X\}$$

The membership function $\mu_A(x)$ quantifies the grade of membership of the elements x to the fundamental set X. An element mapping to the value 0 means that the member is not included in the given set, 1 describes a fully included member. Values strictly between 0 and 1 characterize the fuzzy members.

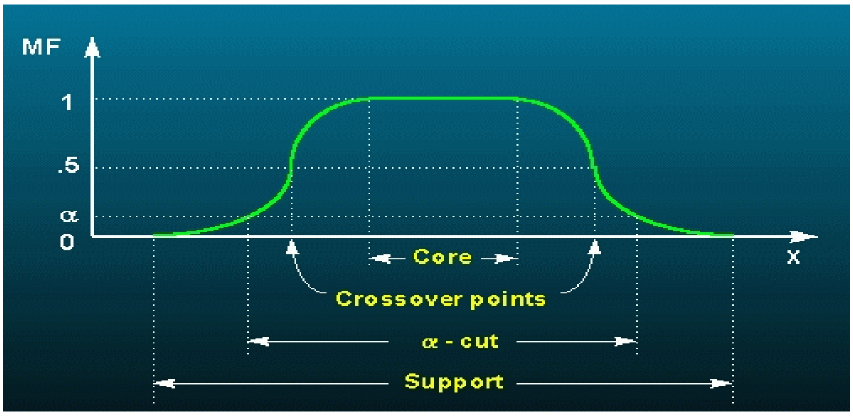


Fig 3.2 Membership function terminology

Universe of Discourse: the universe of discourse is the range of all possible values for an input to a fuzzy system.
Support: the support of a fuzzy set F is the crisp set of all points in the universe of discourse U such that the membership function of F is non-zero.

$$\text{Supp}A = \{x \mid \mu_A(x) > 0, \ \forall x \in \text{X}\}$$

Core: the core of a fuzzy set F is the crisp set of all points in the universe of discourse U such that the membership function of F is 1.

$$\text{core}A = \{x \mid \mu_A(x) = 1, \ \forall x \in \text{X}\}$$

Boundaries: the boundaries of a fuzzy set F is the crisp set of all points in the universe of discourse U such that the membership function of F is between 0 and 1.

$$\text{Boundaries}A = \{x \mid 0 < \mu_A(x) < 1, \ \forall x \in \text{X}\}$$

Crossover point: the crossover point of a fuzzy set is the element in U at which its membership function is 0.5.
Height: the biggest value of membership functions of fuzzy set.

$$\mu(x) = 0.5$$

Normalized fuzzy set: the fuzzy set of

$$\text{Height}(A) = 1$$

Cardinality of the set: $\text{X}: \ \textit{finite}$

$$|A| = \sum_{x \in \text{X}} \mu_{\text{A}}(x) = \sum_{x \in \text{Supp}(A)} \mu_{\text{A}}(x)$$

Relative cardinality:

$$\|A\| = \frac{|A|}{|\text{X}|}$$

Convex fuzzy set: $\text{X} \in \text{R}$, a fuzzy set A *is* Convex, if for $\forall \lambda \in [0, 1]$

$$\mu_A(\lambda x_1 + (1-\lambda)x_2) \ge \min(\mu_A(x_1),\ \mu_A(x_2))$$

2.2 Type of membership functions

1. Numerical definition (discrete membership functions)

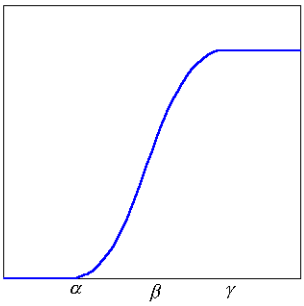
$$A = \sum_{x_i \in X} \mu_A(x_i)/x_i$$

2. Function definition (continuous membership functions)

Including of S function, Z Function, Pi function, Triangular shape, Trapezoid shape, Bell shape.

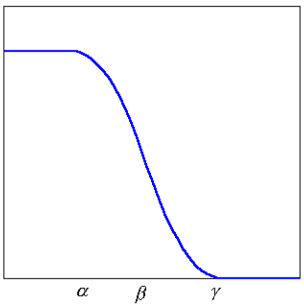
$$A = \int_X \mu_A(x)/x$$

(1) S function: monotonical increasing membership function



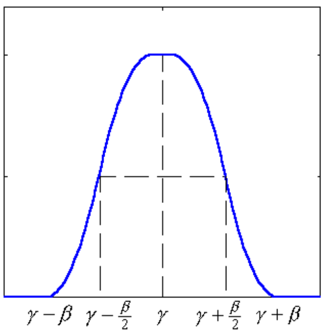
$$S(x;\alpha,\beta,\gamma) = \begin{cases} 0 & \text{for } x \le \alpha \\ 2(\frac{x-\alpha}{\gamma-\alpha})^2 & \text{for } \alpha \le x \le \beta \\ 1-2(\frac{x-\alpha}{\gamma-\alpha})^2 & \text{for } \beta \le x \le \gamma \\ 1 & \text{for } \gamma \le x \end{cases}$$

(2) Z function: monotonical decreasing membership function



$$Z(x;\alpha,\beta,\gamma) = \begin{cases} 1 & \text{for } x \le \alpha \\ 1-2(\frac{x-\alpha}{\gamma-\alpha})^2 & \text{for } \alpha \le x \le \beta \\ 2(\frac{x-\alpha}{\gamma-\alpha})^2 & \text{for } \beta \le x \le \gamma \\ 0 & \text{for } \gamma \le x \end{cases}$$

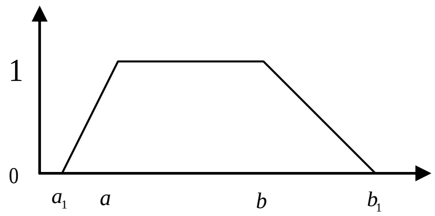
(3) Π function: combine S function and Z function, monotonical increasing and decreasing membership function



$$\Pi(x;\beta,\gamma) = \begin{cases} S(x;\ \gamma-\beta,\ \gamma-\frac{\beta}{2},\ \gamma) & \text{for } x \le \gamma \\ 1-S(x;\ \gamma,\ \gamma+\frac{\beta}{2},\ \gamma+\beta) & \text{for } x \ge \gamma \end{cases}$$

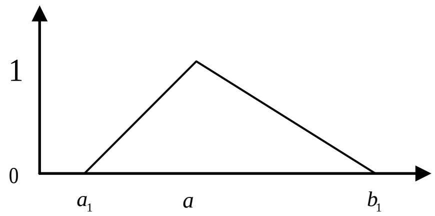
Piecewise continuous membership function

(4)Trapezoidal membership function



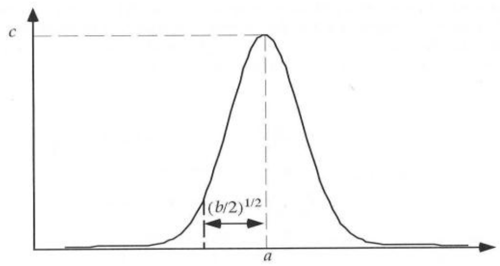
$$\mu_A(x)=\begin{cases}0 & for\ x\le a_1\\ \frac{x-a_1}{a-a_1} & for\ a_1\le x\le a\\ 1 & for\ a\le x\le b\\ \frac{b_1-x}{b_1-b} & for\ b\le x\le b_1\\ 0 & for\ b_1\le x\end{cases}$$

(5) Triangular membership function



$$\mu_A(x)=\begin{cases}0 & for\ x\le a_1\\ \frac{x-a_1}{a-a_1} & for\ a_1\le x\le a\\ \frac{b_1-x}{b_1-a} & for\ a\le x\le b_1\\ 0 & for\ b_1\le x\end{cases}$$

(6) Bell-shaped membership function



$$A(x) = ce^{-\frac{(x-a)^2}{b}}$$

While variables in mathematics usually take numerical values, in fuzzy logic applications, the non-numeric linguistic variables are often used to facilitate the expression of rules and facts. A linguistic variable such as age may have a value such as young or its antonym old. However, the great utility of linguistic variables is that they can be modified via linguistic hedges applied to primary terms. The linguistic hedges can be associated with certain functions.

2.3 Fuzzy sets operations

After know about the characteristic of fuzzy set, we will introduce the operations of fuzzy set. A fuzzy number is a convex, normalized fuzzy set

$\tilde{A} \subseteq \mathbb{R}$ whose membership function is at least segmental continuous and has the functional value $\mu_A(x) = 1$ at precisely one element. This can be likened to the funfair game "guess your weight," where someone guesses the contestants weight, with closer guesses being more correct, and where the guesser "wins" if they guess near enough to the contestant's weight, with the actual weight being completely correct (mapping to 1 by the membership function). A fuzzy interval is an uncertain set $\tilde{A} \subseteq \mathbb{R}$ with a mean interval whose elements possess the membership function value $\mu_A(x) = 1$. As in fuzzy numbers, the membership function must be convex, normalized, and at least segmental continuous.

a) Set- theoretic operations

- Subset: $A \subseteq B \Leftrightarrow \mu_A \leq \mu_B$
- Complement: $\overline{A} = X - A \Leftrightarrow \mu_{\overline{A}}(x) = 1 - \mu_A(x)$
- Union: $C = A \cup B \Leftrightarrow \mu_c(x) = \max(\mu_A(x), \mu_B(x)) = \mu_A(x) \vee \mu_B(x)$
- Intersection: $C = A \cap B \Leftrightarrow \mu_c(x) = \min(\mu_A(x), \mu_B(x)) = \mu_A(x) \wedge \mu_B(x)$

b) Logic operations

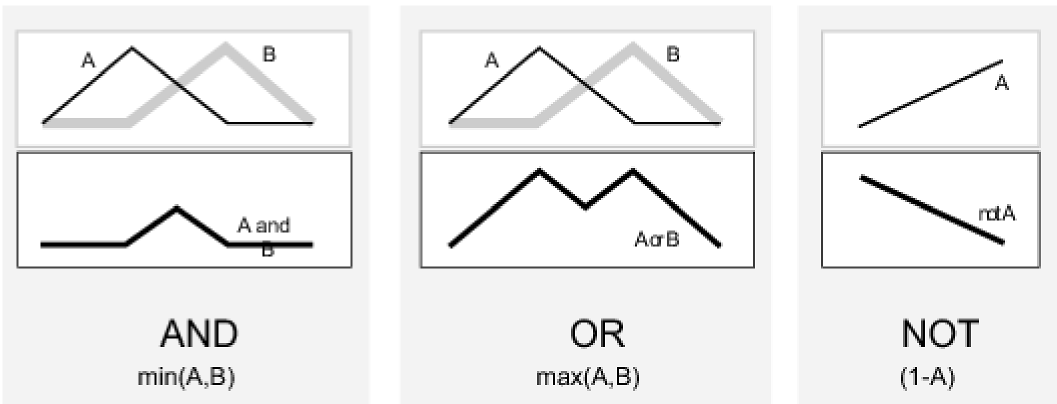


Fig 3.3 Fuzzy logic operators

c) Operational laws of triangular fuzzy numbers

Although one can create fuzzy sets and perform various operations on them, in general they are mainly used when creating fuzzy values and to define the linguistic terms of fuzzy variables. At some point it may be an interesting exercise to add fuzzy numbers to the toolkit. These would be specializations of fuzzy sets with a set of operations such as addition, subtraction, multiplication and division defined on them.

According to the characteristics of triangular fuzzy numbers and the extension principle put forward by Zadeh (1965), the operational laws of triangular fuzzy numbers, $\tilde{A} = (l_1, m_1, r_1)$ and $\tilde{B} = (l_2, m_2, r_2)$ are as follows:

(1) Addition of two fuzzy numbers $(l_1, m_1, r_1) \oplus (l_2, m_2, r_2) = (l_1 + l_2, m_1 + m_2, r_1 + r_2)$

(2) Subtraction of two fuzzy numbers

$(l_1, m_1, r_1) \Theta (l_2, m_2, r_2) = (l_1 - r_2, m_1 - m_2, r_1 - l_2)$

(3) Multiplication of two fuzzy numbers $(l_1, m_1, r_1) \otimes (l_2, m_2, r_2) \cong (l_1 l_2, m_1 m_2, r_1 r_2)$

(4) Division of two fuzzy numbers $(l_1, m_1, r_1) \varnothing (l_2, m_2, r_2) \cong (l_1 / r_2, m_1 / m_2, r_1 / l_2)$

2.4 Uncertainty measurement

There are three type of uncertainty: 1-non-specificity (imprecision) 2-vagueness and 3-strife discord. The uncertainty measurement was ensured in the classical sets by the Hartley function (1928): $U(A) = c.log_b|A|$ where $|A|$ denote the cardinality of the set A and c, b are positive constants (b>1 and c>0), the choice of b and c determine the unite of uncertainty measurement the commune used unit is: b=2 and c=1 $U(A) = \log_2|A|$.

In the 1980s the uncertainty of fuzzy sets is defined by the following formula:

$$U: P(A) - \{\phi\} \to \mathbb{R}^+$$
$$U(A) = \frac{1}{h(A)} \int_0^{h(A)} log_2 |{}^{\propto}A| d\propto$$

Where $|{}^{\propto}A|$ denotes the cardinality of the α-cut $h(A)$ the height of A. This function is called also the non-specificity function.

The fuzziness of the set A is measured by the following measurements:

$$f(A) = \sum_{x \in X} (1 - |2A(x) - 1|)$$

3. Data defuzzification

When we through the operations of fuzzy set to get the fuzzy interval, next we will convert the fuzzy value into the crisp value. Below are some methods that convert a fuzzy set back into a single crisp (non-fuzzy) value. This is something that is normally done after a fuzzy decision has been made and the fuzzy result must be used in the real world. For example, if the final fuzzy decision were to adjust the temperature setting on the thermostat a ‘little higher’, then it would be necessary to convert this ‘little higher’ fuzzy value to the ‘best’ crisp value to actually move the thermostat setting by some real amount.

Maximum Defuzzify: finds the mean of the maximum values of a fuzzy set as the defuzzification value. Note: this doesn't always work well because there can be x ranges where the y value is constant at the max value and other places where the maximum value is only reached for a single x value. When this happens the single value gets too much of a say in the defuzzified value.

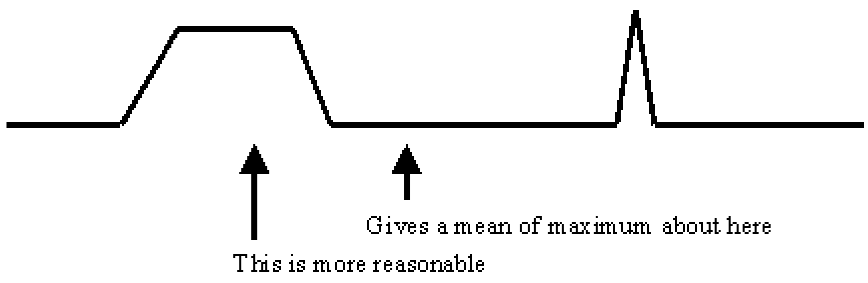


Fig 3.4 Defuzzification

Moment Defuzzify: moment defuzzifies a fuzzy set returning a floating point (double value) that represents the fuzzy set. It calculates the first moment of area of a fuzzy set about the y axis. The set is subdivided into different shapes by partitioning vertically at each point in the set, resulting in rectangles, triangles, and trapezoids. The center of gravity (moment) and area of each subdivision is calculated using the appropriate formulas for each shape. The first moment of area of the whole set is then:

$$x' = \frac{\sum_{i=1}^{n} x_i' \cdot A_i}{\sum_{i=1}^{n} A_i}$$

where xi' is the local centre of gravity, A_i is the local area of the shape underneath line segment (pi-1, pi), and n is the total number of points. As an example,

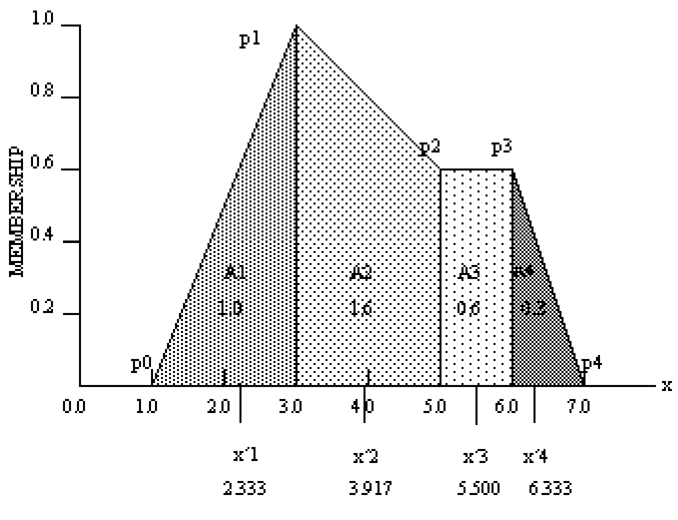


Fig 3.5 Center of gravity of fuzzy sets.

For each shaded subsection in the diagram above, the area and center of gravity is calculated according to the shape identified (i.e., triangle, rectangle or trapezoid). The center of gravity of the whole set is then determined:

x' = (2.333*1.0 + 3.917*1.6 + 5.5*0.6 + 6.333*0.3)/(1.0+1.6+0.6+0.3) = 3.943…

Center of Area (COA): defuzzification finds the x value such that half of the area under the fuzzy set is on each side of the x value. In the case above (in the moment defuzzify section) the total area under the fuzzy set is 3.5 (1.0+1.6+0.6+0.3). So we would want to find the x value where the area to the left and the right both had values of 1.75. This occurs where x = 3.8167. Note that in general the results of moment defuzzify and center of area defuzzify are not the same. Also note that in some cases the center of area can be satisfied by more than one value. For example, for the fuzzy set defined by the points:

(5,0) (6,1) (7,0) (15,0) (16,1) (17,0)

the COA could be any value from 7.0 to 15.0 since the 2 identical triangles centered at x=6 and x=16 lie on either side of 7.0 and 15.0. We will return a value of 11.0 in this case (in general we try to find the middle of the possible x values).

Weighted Average Defuzzify: finds the weighted average of the x values of the points that define a fuzzy set using the membership values of the points as the weights. This value is returned as the defuzzification value. For example, if we have the following fuzzy set definition:

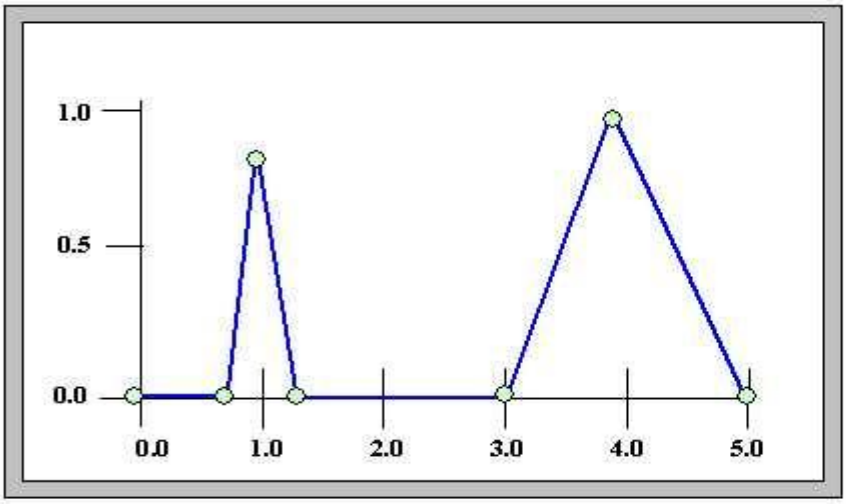


Fig 3.6 fuzzy set example

Then the weighted average value of the fuzzy set points will be:

(1.0*0.9 + 4.0*1.0) / (0.9 + 1.0) = 2.579

This is only moderately useful since the value at 1.0 has too much influence on the defuzzified result. The moment defuzzification is probably most useful in this case. However, a place where this defuzzification method is very useful is when the fuzzy set is in fact a series of singleton values. It might be that a set of rules is of the Takagi-Sugeno-Kang type (1st order) with formats like:

If x is A and y is B then c = k

where x and y are fuzzy variables and k is a constant that is represented by a singleton fuzzy set. For example we might have rules that look like:

where the setting of the hot valve has several possibilities, say full closed, low, medium low, medium high, high and full open, and these are singleton values rather than normal fuzzy sets. In this case medium low might be 2 on a scale from 0 to 5.

An aggregated conclusion for setting the hot valve position (after all of the rules have contributed to the decision) might look like:

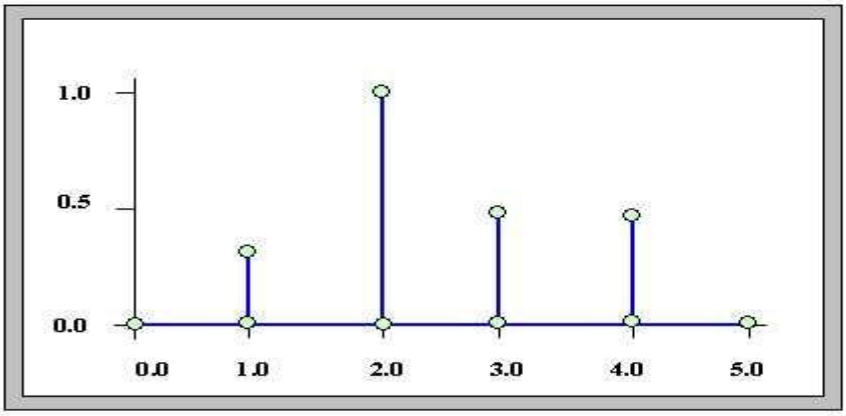


Fig 3. 7 The aggregation conclusion of the fuzzy set cited in fig3.6

And the weighted average defuzzification value for this output would be:

(1.0*0.25 + 2.0*1.0 + 3.0*0.5 + 4.0*0.5) / (0.25 + 1.0 + 0.5 + 0.5) = 2.556

Note that neither a maximum defuzzification nor a moment defuzzification would produce a useful result in this situation. The maximum version would use only 1 of the points (the maximum one) giving a result of 2.0 (the x value of that point), while the moment version would not find any area to work with and would generate an exception. This description of the weighted average defuzzify method will be clearer after you have completed the sections on fuzzy values and fuzzy rules.

After the process of defuzzified, next step is to make a fuzzy decision. Fuzzy decision which is a model for decision making in a fuzzy environment, the object function and constraints are characterized as their membership functions, the intersection of fuzzy constraints and fuzzy objection function. Fuzzy decision-making method consists of three main steps:

1. **Representation of the decision problem:** the method consists of three activities. (1) Identifying the decision goal and a set of the decision alternatives. (2) Identifying a set of the decision criteria. (3) Building a hierarchical structure of the decision problem under consideration
2. **Fuzzy set evaluation of decision alternatives:** the steps consist of three activities. (1) Choosing sets of the preference ratings for the importance weights of the decision preference ratings include linguistic variable and triangular fuzzy number. (2) Evaluating the importance weights of the criteria and the degrees of appropriateness of the decision alternatives. (3) Aggregating the weights of the decision criteria.
3. **Selection of the optimal alternative:** this step includes two activities. (1) Prioritization of the decision alternatives using the aggregated assessments. (2) Choice of the decision alternative with highest priority as the optimal.

4. Fuzzy sets and the other paradigms (hybrid reasoning)

i. Fuzzy logic

Before illustrating the mechanisms which make fuzzy logic machines work, it is important to realize what fuzzy logic actually is. Fuzzy logic is a superset of conventional (Boolean) logic that has been extended to handle the concept of partial truth- truth values between "completely true" and "completely false". As its name suggests, it is the logic underlying modes of reasoning which are approximate rather than exact. The importance of fuzzy logic derives from the fact that most modes of human reasoning and especially common sense reasoning are approximate in nature. The essential characteristics of fuzzy logic are as follows.

- In fuzzy logic, exact reasoning is viewed as a limiting case of approximate reasoning.
- In fuzzy logic everything is a matter of degree.
- Any logical system can be fuzzified.
- In fuzzy logic, knowledge is interpreted as a collection of elastic or, equivalently, fuzzy constraint on a collection of variables.
- Inference is viewed as a process of propagation of elastic constraints.

Example

For example, a simple temperature regulator that uses a fan might look like this:

IF temperature IS very cold THEN stop fan
IF temperature IS cold THEN turn down fan
IF temperature IS normal THEN maintain level
IF temperature IS hot THEN speed up fan

There is no "ELSE" – all of the rules are evaluated, because the temperature might be "cold" and "normal" at the same time to different degrees.

The AND, OR, and NOT operators of boolean logic exist in fuzzy logic, usually defined as the minimum, maximum, and complement; when they are defined this way, they are called the Zadeh operators. So for the fuzzy variables x and y:

NOT x = (1 - truth(x))
x AND y = minimum(truth(x), truth(y))
x OR y = maximum(truth(x), truth(y))

There are also other operators, more linguistic in nature, called hedges that can be applied. These are generally adverbs such as "very", or "somewhat", which modify the meaning of a set using a mathematical formula.

ii. Fuzzy neuronal networks

An artificial neural network (ANN), usually called neural network (NN), is a mathematical model or computational model that is inspired by the structure and/or functional aspects of biological neural networks. A neural network consists of an interconnected group of artificial neurons, and it processes information using a connectionist approach to computation. In most cases an ANN is an adaptive system that changes its structure based on external or internal information that flows through the network during the learning phase. Modern neural networks are non-linear statistical data modeling tools. They are usually used to model complex relationships between inputs and outputs or to find patterns in data.

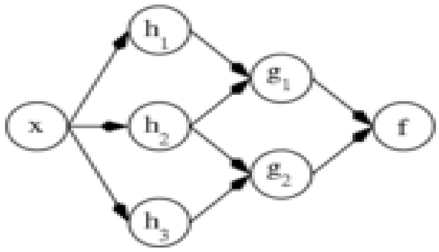


Fig 3.8. Artificial neural network.

ANFIS is an adaptive network which permits the usage of neural network topology together with fuzzy logic. It not only includes the characteristics of both methods, but also eliminates some disadvantages of their lonely used case. Operation of ANFIS looks like feed-forward back propagation network. Consequent parameters are calculated forward while premise parameters are calculated backward. There are two learning methods in neural section of the system: Hybrid learning method and back-propagation learning method. In fuzzy section, only zero or first order Sugeno inference system or Tsukamoto inference system can be used [1, 14]. Output variables are obtained by applying fuzzy rules to fuzzy sets of input variables. For example,

Rule 1: If x is A1 and y is B1 then f1 = p1x + q1y + r1

Rule 2: If x is A1 and y is B2 then f2 = p2x + q2y + r2

Figure 1 shows equivalent ANFIS architecture

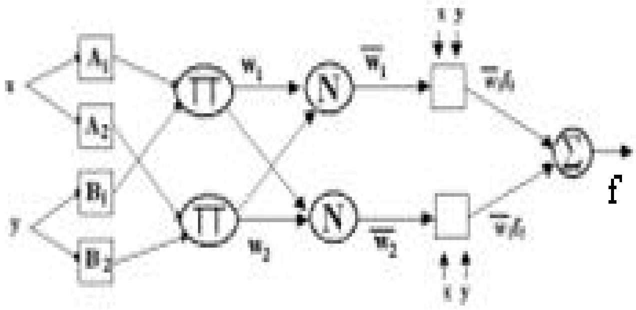


Fig3.9 Neuro-fuzzy network.

iii. Fuzzy models in Case Based Reasoning

There are some works which combine between the fuzzy approach and the Case based reasoning as [30] in which they incorporate the traditional case base paradigm by the Fuzzy Logic concepts in a flexible, extensible component-based architecture. Also [32] which enforce the case based reasoning by a fuzzy logic system. We cite also [31] in which they introduce a fuzzy model for the representation of a CBR system. Another work [36] introduces in the traditional process of CBR a Data fuzzification stage for more flexible and accurate models. In our approach we combine the fuzzy sets and the global-local similarity measures for generating three responses Similar, not similar and unknown for more transparency, flexibility and accuracy.

The fuzzy sets is also combined with other reasoning approaches as genetic algorithms GA which is a sub field of evolutional algorithms EA, and also merged with the decision trees and constraints programming.

Conclusion

Reasoning under uncertainty exists in the majority of systems which increase the faults in the reasoning processes. In this chapter we have introduced the fuzzy systems theory and models which propose a high level of transparency with a considering grade of precisions. But there are many other ways to resolving and representing the uncertainty as belief function possibility measures ranking function relative likelihood and others. In this chapter we have presented the representation of uncertainty with the fuzzy sets.

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Part 2 contributions

In the remaining of this thesis we will explain some of our contributions in the realization of the reasoning system for medical applications

The first chapter introduces the IK-CBRC which implements and combines the case based reasoning, the fuzzy sets and the multi agent system. This combination is done for improving more performance, flexibility and accuracy which are an important challenge for the medical applications. It contains also a deep description of the developed system with two applications in the cardiac arrhythmias diagnosis and the breast cancer diagnosis. The validation is done by citing the system criteria and some empirical experiments also by a comparison with the related applications.

The second chapter introduces some aspects of the Explanation aware computing (Exact) including definitions, engineering and applications. Flowing this introduction we try to explain the medical application needs and challenges for the Exact domain. We propose also a cognitive agent for medical explanations related to the IK-CBRC decisions and the explanation level of abstraction.

In the third chapter we will describe an original scenario of reusing the terminological explanations for ensuring an adapted document recommendation system by categorization of users via their information extracted from social networks.

Chapter I: KI-DCBRC: Knowledge-intensive case based classification system for medical computer aided diagnosis[3]

Abstract. – The classification is one of the most important and complex techniques used in the bioinformatics and most of health science applications. In this chapter a novel strong and a scalable classification system dedicated for medical applications is presented. This classification system implements the case based reasoning paradigm enriched by partial domain knowledge. It is based also on a Multi Agent approach. In this research work we present also an original and personalized fuzzy similarity measures function. Through the system criteria and some empirical experiments applied in the cardiac arrhythmias and breast cancer diagnosis we conclude that the classification system achieves such average accuracies and performance better than most of the cited approaches.

[3] This work is presented in the Doctoral consortium of International Conference on Case Based Reasoning ICCBR 2010, Alexandria, Italy. The chairmen : Klaus-dieter ALTHOFF Mentor: Roth-Bergopher

1. Introduction

Bioinformatics focuses on making the results of research applicable to human being and, thus, on translating research results into practice. As the ultimate goal of bioinformatics research is to provide better care to patients. [13] Bioinformatics applications including decision support systems, computer aided diagnosis, image and signal processing and microarray analyses are a critical kind of applications for this they must ensure a high level of accuracy and explanations for different kind of users (experts or doctors and simple users) also they will provides a good flexibility for the particular cases.

The automatic classification consists of associating an object, characterized by a pattern which represents a pragmatic view of this object, with a predefined class. There are many methods and approaches from the artificial intelligence which prove a good performance to accomplish the automatic classification as well as Artificial Neural Network ANN [16][72][73], Rule Based System (RBS) [20], Decision Tree [20], Bayesian Networks [9], hybrid methods [18][77] and other paradigms. However, each one of these approaches has a weakness as complexity, uncertainty, vagueness, stiffness and others. These weaknesses are sometime accepted and sometime not accepted relatively to the application domain according to the context of the application.

The Case Based Reasoning CBR is an intelligent approach inspired from many disciplines. It draws the human reasoning model. It consists to use the prior expertise to resolve a new problem [14]. The knowledge intensive case based reasoning is a variant of CBR in which the cases is enriched by partial domain knowledge [10]. Also the distributed case based reasoning is a variant of CBR in which the reasoning is distributed through a set of agents and the cases through a set of case bases [1]. These variants have been developed to ameliorate the accuracy and the performance of the reasoning systems also to enriching the semantic of reasoning with rules extracted from the domain experts.

Fuzzy sets [57] are an extension of classical set theory and are successfully used and merged with rule based systems [20] and with Artificial Neuronal Networks [19]. In classical set theory the membership of elements in relation to a set is assessed in binary terms according to a crisp condition an element either belongs or does not belong to the set. By contrast, fuzzy set theory permits the gradual assessment of the membership of elements in relation to a set; this is described with the aid of a membership function valued in the real unit interval [0, 1].[57]

As an application for Bioinformatics we have developed a strong classification system for satisfying the medical applications demands and competition. Our system proposes a high level of accuracy, optimized performance, a good adaptability for different domains and it generates different abstraction level of explanations. These characteristics is ensured by applying the intensive-knowledge case based reasoning approach and a novel personalized similarity measures algorithm which uses the fuzzy sets with the traditional global-local similarity measures for generating three measures which indicate the rate of membership of the query in three sets: 1) similar, 2) unknown and 3) not similar, these measures increases not just the accuracy of the system but also the semantic. Also we have distributed the reasoning through a set of cognitive agents each one specialized for attending their local goals and they collaborate for attending the global goals. This trend is better than the traditional ones not just for the generated explanations which provide a high level of transparency, but also because it proves significant amelioration in the system performances and the flexibility when we change the application domain. We have applied our classification system in tow medical domains the cardiac arrhythmias and the breast cancer diagnosis. For the evaluation we have done some empirical experiments through two international data sets, 1) cardiac arrhythmia data set extracted from the MIT-BIH database [25] and 2) breast cancer data set constructed and tested by Dr William H. Wolberg. The comparison with the existing works demonstrates that the proposed system achieves such average accuracies and performance better than most of the current state-of-the-art algorithms.

In this chapter we explain many aspects of the realized system. First of all, we will present a general stat of the art by introducing the different used paradigms, and then we will give a deep presentation of the classification system in which we have proposed a conceptual and an operational model. We will also present a novel similarity measures function used for increasing the precision. Finally we will present two applications of this classification system in tow medical domains with a deep comparison with other techniques.

2. The case based reasoning

The case based reasoning approach is widely and successfully applied in many domains as games, recommendation systems, information retrieval, bioinformatics, industrial applications and others. It represents a good and easy method of knowledge extraction, discovery and modeling.

The CBR is an intelligent approach inspired from many disciplines it draws a human reasoning model [2]. It consists of using the prior expertise to resolve a new problem. This expertise is stored as a set or collection of cases called cases base. Each case represents one problem associated with its solution. The main idea of case based reasoning is that two similar problems have the same solutions or the solution can be generated from the similar problems.

The case is a contextualized piece of knowledge representing an experience that teaches a lesson fundamental to achieving the goals of the reasoning system [12]. It is composed from two parts problem part and solution part but Bergmann [5] distinguishes between the following two components of cases:

Characterization Part: The case characterization part contains all information required to decide whether a case can be reused in a certain situation. That means this part of the case can be seen as an index used to estimate the utility of cases.

Lesson Part: The lesson part describes all additional information that might be useful for the actual reuse of the case. Note that the lesson part may also be empty. In this situation, the information contained in the case characterization part is already sufficient to reuse the case.

There is any contradiction between these descriptions because there are many developed CBR systems and many mechanisms used to represent the cases as ontology, graphs, attributes, first order logic and others. Also the solution in some cases can be generated from a set of similar problems.

In CBR research, a generic process model introduced by Aamodt and Plaza (1994) [2] is commonly accepted. This process model describes the basic steps of problem-solving when applying CBR. This model describe the CBR life cycle as a four process summarized below.

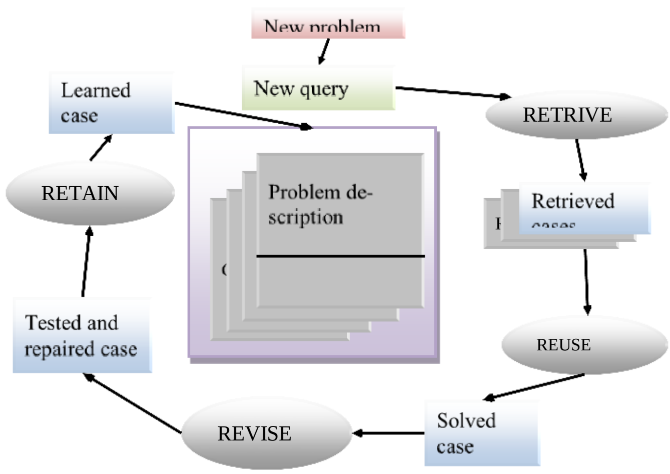


Fig.I.1. Case-based reasoning process model

- The first process consists of retrieving from the cases base the similar case or cases which can be useful to solve the current problem by using similarity measures techniques.
- In the Second process, reuse, all solutions (cases) retrieved by the retrieve process are reused to find the potential solution.

- The Third one called revise process; which revises and checks the solution to fit the specifics of the current problem.
- Finally, the retain process, which updates the memory by adding the resolved problem as a new case to the cases base.

According to Richter in the CBR system we can distinguish four different knowledge containers (vocabulary, case knowledge, adaptation knowledge, and similarity measure). [3]

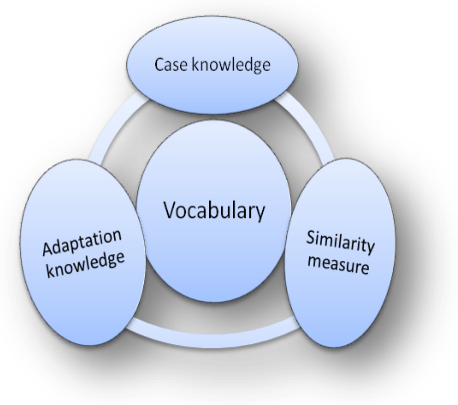


Fig.I. 2. Knowledge containers in the CBR system

- Vocabulary container: the set of attribute, entities and structures used to represent the cases (problems and solutions). It can be characterized as the language words used to talk about the domain it called also the ontology knowledge container.
- Case knowledge contains the past structured experience which will be exploited by the system. In other words it is situation-specific knowledge obtained from the past situations in problem solving.
- Similarity measure container: General knowledge required to select or to retrieve the similar cases to be reused in a particular problem situation.
- Adaptation knowledge General knowledge needed to allow an efficient reuse of retrieved cases. It takes a form of Heuristics and algo-

rithms used to modify the solution and to evaluate their usability for the new situations.

2.1 The local-global similarity measures

When we have a complex case representations consisting of attributes with various different value types, the traditional similarity and distance measures are not appropriate. Instead one needs a more flexible similarity measure that can be adapted on a particular attribute-value based case representation.

The local similarity consists to compute the Measure similarity on the attribute or feature level, and the global similarity consists of computing the similarity on the case or object level.

The following definitions represent a mathematical model of global-local similarity measures with some used functions.

Definition1. Let D = (A1,A2, . . ., An) be a case characterization model, w be a weight vector, and simi be a local similarity measure for the attribute Ai. A global similarity measure for D is a function Sim : DD × DD → [0, 1], of the following form:

$$Sim(q, c) = \pi(sim1(q.a1, c.a1), \ldots, simn(q.an, c.an), w) \quad (5)$$

Where π: [0, 1]2n→ [0, 1] is called aggregation function that must fulfil the following properties:

$$\forall \vec{w} : \pi(0, .., 0, \vec{w}) = 0$$

π is increasing monotonously in the arguments representing local similarity values.

The aggregation function π can be arbitrarily complex. However, in practice usually quite simple functions are used, for example:

$$\pi(\mathrm{sim}_1,..,\mathrm{sim}_n,\vec{w}) = \sum_{i=1}^{n} w.\mathrm{sim}_i \text{ (Weighted Average Aggregation)} \quad (6)$$

$$\pi(\mathrm{sim}_1,..,\mathrm{sim}_n,\vec{w}) = (\sum_{i=1}^{n} w.\mathrm{sim}_i^p)^{1/p} \quad \text{(Minkowski Aggregation)} \quad (7)$$

$$\pi(\mathrm{sim}_1,..,\mathrm{sim}_n,\vec{w}) = \max_{i=1}^{n} w.\mathrm{sim}_i \quad \text{(Maximum Aggregation)} \quad (8)$$

$$\pi(\mathrm{sim}_1,..,\mathrm{sim}_n,\vec{w}) = \min_{i=1}^{n} w.\mathrm{sim}_i \quad \text{(Minimum Aggregation)} \quad (9)$$

Definition2. Let D = (A1, A2,.., An) be a case characterization model.

The vector $\vec{w}$ = (w1, w2,.., wn) with wi ∈ [0, 1] and $\sum_{i=1}^{n} w_i = 1$,is called weight vector for D, where each element wi is called attribute weight for Ai.

Definition3. A local similarity measure for an attribute A is a function

SimA : Arange × Arange → [0, 1]. Where Arange is the value range of the attribute A.

There are many developed similarity functions as linear, threshold, exponential, sigmoid, Cosinus and other similarity functions which permit the computing of local similarity function between tow attributes. In the practice the local similarity functions representation strongly depends on the basic value and value type of the attribute.

For example the sigmoid Similarity function is defined as:

Lets Q the query and C the case, qi ci : the attribute number i respectively of the query and the case, D denotes the space of case characterization models.

$$sim(Q,C) = \sum_{i=1}^{N} w_i \frac{1}{1+e^{\frac{\delta(q_i,c_i)-\theta}{\alpha}}} \quad (6)$$

Where N the number of attributes, wi the weight of the attribute Ai, The parameters α and θ characterizes the detour point of the function and δ(qi,ci) represents the difference function defined as:

δ:DxD→IR

$$\delta(\mathrm{qi},\mathrm{ci}) = \begin{cases} -\ln(\mathrm{c}) - \ln(\mathrm{q}) & \text{for } \mathrm{q},\mathrm{c} > 0 \\ -\ln(-\mathrm{c}) - \ln(\mathrm{q}) & \text{for } \mathrm{q},\mathrm{c} < 0 \\ \text{Undefined} & \text{else} \end{cases} \tag{7}$$

2.2 The distributed case based reasoning.

The distributed case based reasoning consists of distributing the reasoning through a set of autonomic agents and we talk about distributed reasoning. Also the cases through a set of case bases and we talk about distributed case base. This notion increases the flexibility of the reasoning system and ameliorates the performance and the speedup of the reasoning because the reasoning is distributed through a set of local reasoning sub systems. There are many works in the distribution of reasoning as [4][51][52][53][54] but each one has its proper realization and strategy.

Enric Plaza and Lorraine McGinty [1] have classified the realized CBR systems in four classes by using two key criteria: (1) how knowledge is organized/managed within the system (i.e., single vs multiple case bases), and (2) how knowledge is processed by the system (i.e., single vs multiple processing agents).

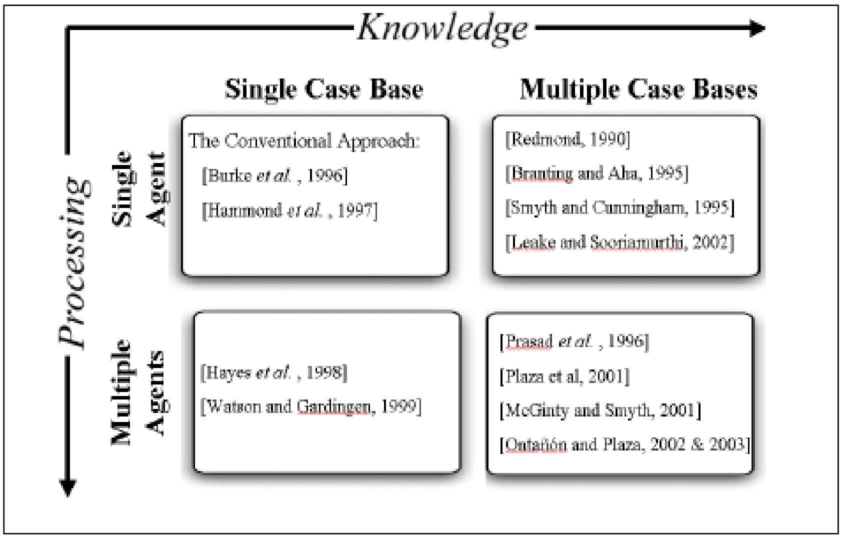


Fig. I. 3. Distributed CBR Systems [Plaza, McGinty 2006].

The DCBR approach has the following advantages:

- The most complete reasoning system is the humans system. And they do it as psychological models.
- Parallel machines exist - hardware and software.
- Helping to organize systems in modular fashion
- Some applications will have improved efficiency and speed up.
- It offers simple system maintainability and a good flexibility.

Research efforts in the area of distributed CBR concentrate on the distribution of resources with the intent of improving the performance of CBR systems. Although the phrase distributed CBR can be used in a number of different contexts. [1]

2.3 The knowledge-intensive case based reasoning

A knowledge-intensive case-based reasoning method assumes that cases, in some way or another, are enriched with explicit general domain knowledge. The role of the general domain knowledge is to enable a CBR system to reason with semantic and pragmatic criteria, rather than purely syntactic ones. By making the general domain knowledge explicit, the case-based system is able to interpret a current situation in a more flexible and contextual manner than if this knowledge is compiled into predefined similarity metrics or feature relevance weights. A knowledge intensive CBR method calls for powerful knowledge acquisition and modeling techniques, as well as machine learning methods that take advantage of the general knowledge represented in the system. [10] This trends consists to not used just the similarity knowledge but it merge it with the explicit knowledge which is modeled from the domain experts, it increase the accuracy and the generality of the reasoning systems, but it inherits the complexity of knowledge extracting from the domain experts if it exist in some novel domains.

There are many developed system which use the knowledge intensive variant someone have used just a rule based system to represents the domain knowledge as GREEK [10] and [11] in other works they used a fuzzy rule based system as [55][56].

3. Fuzzy sets

The fuzzy sets [57] generalize the classical sets by considering the membership as a graded concept. The membership degree of an element x to a fuzzy set A denoted by μA(x), take a value in the interval [0,1].

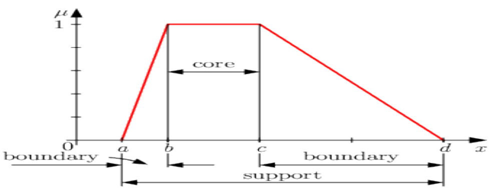


Fig.I. 4**.** The characteristics of membership function

The support of a fuzzy set A is the crisp set that contains all the elements of X that have nonzero membership grades in A.

$$\mathrm{supp}(A) = \{x \in X, \mu_A(x) > 0\} \qquad (8)$$

The core of a normal fuzzy set A is the crisp set that contains all the elements of X that have the membership grades of one in A.

$$\mathrm{core}(A) = \{x \epsilon X, \mu_A(x) = 1\} \qquad (9)$$

The boundary is the crisp set that contains all the elements of X that have the membership grades of 0< μA(x) <1 in A.

$$\mathrm{bnd}(A) = \{x \epsilon X, 0 < \mu_A(x) < 1\} \qquad (10)$$

Having two fuzzy sets A and B based on X, then both are similar if:

Core (A)=Core (B) and Supp(A)=Supp(B) (11)

If the support of a normal fuzzy set consists of a single element x0 of X, which has the property Supp(A)=Core(A)={x0}, Then this set is called a singleton and the membership function is called triangular function.

Fuzzy models have been widely and successfully used in many areas such as data mining [28], data analysis [26] and image processing [27]. Also it have been successfully integrated with other approach as artificial neuronal network (neuro-fuzzy approach)[19][26][30][33] and rule based systems (Fuzzy Logic) [20][32][27][28][29] [31]. Also more effort have done in the explanation of results for more interpretability

Traditionally, fuzzy rules and subsets are generated from human expert knowledge or by using some machine learning algorithms [66] or heuristics, which brings about good high-level semantic generalization capability. On the other hand, some researchers have made efforts to build fuzzy models from observational data, leading to many successful applications [29],[30],[31],[32],[33]. Also, more and more efforts have been made to approach the problem of interpretability and transparency of data-driven by fuzzy models [34],[35],[36],[37],[38], [39],[40],[41].

4. The classification system KI-DCBRC

The diversity of approaches and intelligent techniques can generate a Varity of alternatives for smart applications also the competition in the software computing domains demand more investigation in all software criteria and options. The combination of different approaches involves the inheritance of the different positives of the combined techniques in the same time it decrease the weaknesses of these approaches and techniques.

As cited above the distributed case based reasoning system consists of distributing the reasoning through a set of agents and the cases through a set of case bases also the knowledge intensive case based reasoning consists of enriching the cases by a set of rules, which represents a partial domain knowledge. To describe our system we have defined two models: 1) The conceptual model which describes the sub systems and the components of the system, and 2) operational model which explain the dynamic and the behavior of the system.

4.1 Conceptual model

This model gives a conceptual description of the system and their sub systems, the agents, the case bases, the similarity knowledge bases, the adaptation knowledge base and the domain knowledge base. It also describes the relationship between the agents and the knowledge bases. The log files contain the historic of all transactions (rules used similarity measures and learning parameters).

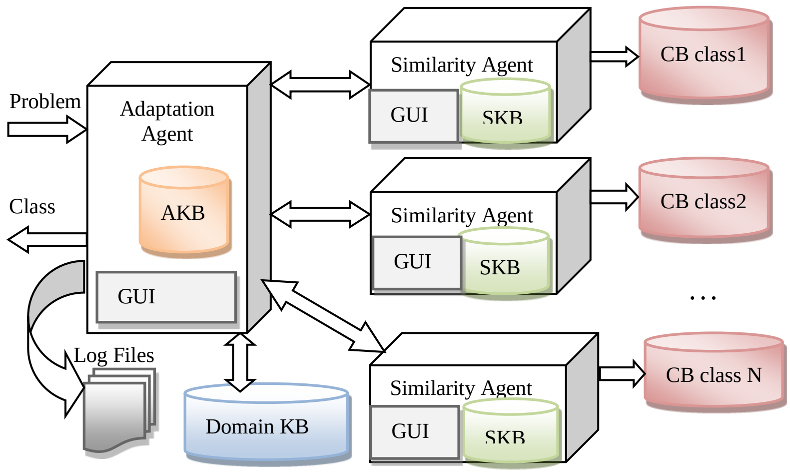


Fig.I. 5. The conceptual model of the classification system KI-DCBRC.

SKB, AKB: Similarity, Adaptation Knowledge Base. GUI: General User Interface

The classification system contains two kinds of agents Adaptation agent and Similarity agent. Each case base contains cases from the same class. Each agent use a predefined knowledge which contains ontology, rules and heuristics to achieves their local goals.

The main goal of the system is to generate the class of the query but each autonomic agent realizes its tasks for achieving their local goals by using their specialized knowledge. Each agent has a specific Graphical User Interface for introducing the data and classification parameters (test base, case bases, weight vectors and the adaptation knowledge) also for applying some optimization algorithms. The interfaces also is very useful for the explanation step and the retain step. These interfaces assure a high level of explanation and flexibility which we can't find in another framework or classifier.

4.2 Operational model

This model aims to explain the behavior and the communication between the different cognitive agents, as presented in FigI.12. The UML[4] sequence diagram: The user defines the query by using the general user interface of the adaptation

[4] UML: Unified Modeling Language.

agent. After that, the adaptation agent infers from the knowledge base which contains a partial knowledge extracted from the domain experiences and expert's knowledge. If there are any solution inferred which mean that there are any rule from the domain for this query then the adaptation agent edit an ACL-XML message [59] which contains the different query parameters associated with the ontology which describes the semantic of each attribute. Following that, the adaptation agent sends this message to all the inscribed similarity agents. The similarity agent uses the defined similarity knowledge base for generating the degrees of memberships of the query in the fuzzy sets.

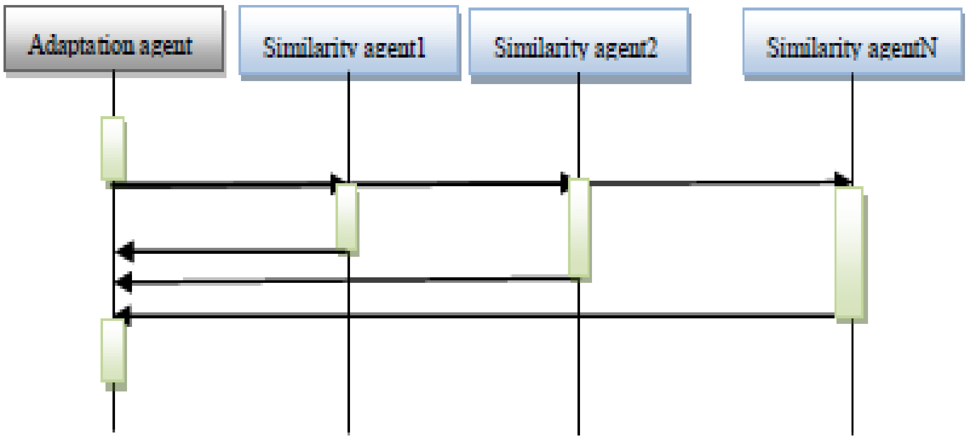


Fig.I.6. UML sequence diagram.

The similarity knowledge base contains the similarity measures parameters extracted from the data sets by using some data mining approaches it contains also an ontology which describes the case base vocabulary.

First of all the similarity agent receives the ACL-XML message, next it will do a semantic association between the message parameters and the case base attributes by using the defined ontology, then the agent generates and sends the degrees of membership by using the selected similarity function, described in the section 3.4, and some measures useful for the explanation step. Another ACL-XML message is constructed by the similarity agent which contains the needed information for the adaptation and explanation step.

Following that, the adaptation agent receives the ACL-XML messages generated by the similarity agents, after this the adaptation agent generates the class by using the existing rules in the adaptation knowledge base. The adaptation agent stores the trace of its decisions (Rules, Degrees of membership and similarity parameters) in the log files.

The retain process is ensured by using the GUI of the adaptation agent in the operational step or by using the GUI of the similarity agent in the learning step.

4.3 Implementation

There are many frameworks and platforms for the Multi-Agent Systems design and implementation as JADE [61], JAGENT [62] FIPA-OS [63] and others but in this work we have used our proper framework which is specific for our system and we can personalize the system more than other one also in some of these frameworks it is very difficult to manage the system performance. Our multi agent system is implemented by using the JAVA threads and we respect the FIPA ACL specification [59] for the communication between the agents.

For increasing the flexibility of the system the user can define the case base model and it's ontology, the domain knowledge base also he can select the similarity function and it's parameters via the GUI of each agent.

The user can personalize the classification through selecting the similarity parameters and the machine learning algorithm and also the knowledge bases. The case bases and agents are separated, and then the user can change the case base of each similarity agent by using the GUI the same thing for the domain knowledge base.

The domain knowledge base which contains the tacit knowledge is designed from the expert knowledge or heuristics and encoded in an XML rules which will be stored in an XML file associated with the DTD file. The system infer from this knowledge base by using an open source engine of inferring JRULENGINE [15] which use the Java Specification Requests (JSRs) rule engine API [64].

The communication between agents respects the FIPA Agent Communication Language specification [59]. Each message contains the attributes values associated with the ontology which describe the semantic of these values. Each message is written in XML.

After attending the goal of each agent, they generates the suited results associated with some details as local similarity measures, the membership degree of unknown fuzzy sets, the membership degree of not similar fuzzy sets, global similarity measures and others which are useful for the explanation and analyze of the classification. The system generates also a log files which contains the historic of the agents behaviors and results.

4.4 A novel Fuzzy similarity measure approach for classification

In the developed reasoning system the user can personalize the similarity measures by selecting the similarity function (as sigmoid, exponential, linear…etc) and it's parameter through the GUI of each similarity agent. After some experiment and comparative works, published in some international conferences, [14], [67],[68] and [69] between some similarity functions and strategies we have introduced a novel fuzzy similarity measures model which we recommend for the users of our software. The proposed model is developed for increasing the accuracy of the system. It combines the local-global similarity functions and the fuzzy sets theory. It also generates not just the traditional response (the class) but it generates the Unknown response if the similarity agents generates a high degree of membership in the unknown set it generates also non similar response when the similarity agents generates a high degree of membership in the non_similar set.

4.4.1 Fuzzy similarity measures.

As described above we have defined three fuzzy sets similar S, not similar N and unknown U with the membership functions μ_S, μ_N and μ_U

$$\mu_s(x) = \begin{cases} 0 \text{ if } x \leq a \\ \frac{x-a}{1-a} \text{ if } x > a \end{cases} \quad (10)$$

$$\mu_n(x) = \begin{cases} 0 \text{ if } x \geq b \\ \frac{b-x}{b} \text{ if } x < b \end{cases} \quad (13)$$

$$\mu_u(x) = \begin{cases} 0 \text{ if } x \leq b \text{ ou } x > a \\ \frac{x-b}{0.5-b} \text{ if } x > b \text{ and } x \leq 0.5 \\ \frac{a-x}{a-0.5} \text{ if } x < a \text{ and } x > 0.5 \end{cases} \quad (14)$$

We have used the triangular function for representing the fuzzy sets, where the variable x represents the global similarity measures between the query and the case. The support of the fuzzy sets is defined intuitively by using the agents GUI or by using a machine learning algorithm. The similarity agent compute the global similarity between the query and the cases by using the selected function (sigmoid, exponential, linear or the threshold).

Properties

Lets U, S and N are three fuzzy sets which represent the same class.

- $\bigcap U, S, N = \emptyset$
- $\cup U, N, S = [0,1]$

Related work.

There are some works which combine between the fuzzy approach and the Case based reasoning as [56] in which they incorporate the traditional case base paradigm by the Fuzzy Logic concepts in a flexible, extensible component-based architecture. Also [55] which enforce the case based reasoning by a fuzzy logic system. We cite also [65] in which they introduce a fuzzy model for the representation of a CBR system. In our approach we combine the fuzzy sets and the global-local similarity measures for generating three responses Similar, not similar and unknown.

4.5 Weights definition

To define the weights vectors which mean the importance degree of each feature, we have used a machine learning algorithm: The gradient decent. With the following performance function:

Let q, c1 and c2 from the same class.

$P: DD \times DD \times DD \rightarrow [0, 1]$

$$P(q,c1,c2) \rightarrow P(q,c1,c2)=|1-|sim(q,c1)-sim(q,c2)| \qquad (11)$$

And we have proposed the learning rate=0.1.

This algorithm is translated to the following java method code:

```
public void weightlearning(case q,case c1,case c2) {
double e1,e2,x1,l=10,dw=0.1, sg = 0; int i=0;double
e1=java.lang.Math.abs(globalsim(q,c1)-globalsim(q,c2));//the initializa-
tion of error
while (l>0.00001) //stop criteria
{ for (i = 0; i <=9; i++)
{x1=java.lang.Math.abs(localsim(q.content[i],c1.content[i])-
localsim(q.content[i],c2.content[i])); // Local error
weight[i] = weight[i]- x1*l/dw;//weight updating
```

```
sg=sg+weight[i];}
for (i = 0; i <=9; i++) { weight[i]=weight[i]/ sg;}//Normalization
e2=java.lang.Math.abs(globalsim(q,c1)-globalsim(q,c2)); // the new error
     if (e2>e1){l=l/5;} //updating the stop criteria
          }}}
```

5. Applications of KI-DCBRC

We have applied the developed system in two important and critical medical domains the cardiac arrhythmias and the breast cancer diagnosis which can be classified in the signal and image processing applications. In this section we will describe some aspects of the applications domains and how we have applied our classification system in these domains. And then we will present the empirical experiments used for the evaluation and comparison of our system with the existing used approaches in each application domain.

5.1 Cardiac arrhythmias diagnosis

The important source of cardiac diagnosis is the electrocardiogram ECG which draws the electrophysiology of the heart.

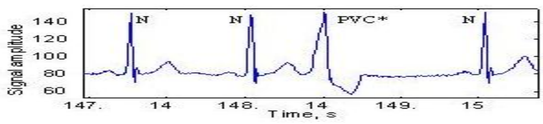


Fig.I.07. PVC and normal beats on the surface ECG signal

The ECG signals used in this work are recordings collected between 1975 and 1979 by the laboratory of BIH arrhythmia (Beth Israel Hospital) in Boston in the United States, which is known as the MIT-BIH data base [25]. The ECG signals are sampled at a frequency of 360 Hz. Two or more cardiologists have made the diagnosis for these various records and they have annotated each cardiac cycle.

A premature ventricular contraction (PVC) is an extra heartbeat resulting from abnormal electrical activation originating in the ventricles before a normal heartbeat would occur. PVCs are common, particularly among older people. This arrhythmia may be caused by physical or emotional stress, intake of caffeine (in beverages and foods) or alcohol. Other causes include coronary artery disease (especially during or shortly after a heart attack) and disorders that cause ventricles to enlarge, such as heart failure and heart valve disorders.

They are more common in patients with sleep disordered breathing than in those without [42]. Although the risk associated with presence of PVCs is generally considered to be low [43], recent studies in subjects with no history of coronary artery disease have found that the risk of death and coronary events is [43],[44] fold greater in subjects with PVCs compared to those without [44],[45]. With regard to the specific risk for arrhythmic death, a study involving over 15,000 healthy men found that the presence of any PVC was associated with a 3-fold risk of sudden cardiac death [46]. Presence of complex PVCs increases arrhythmic death risk further [43],[46].

We have used a data set designed and constructed from the MIT-BIH database. This data set contains a pattern of heart beat (see Table1) with 10 attributes and the classes attribute which indicate the class of the heart beat (PVC, Normal or other). The parameters used were calculated using an algorithm developed and implemented in the LISI laboratory at the University of Rennes 1. This algorithm is based on the technique introduced by Pan J. and Tompkins W.J [47].

Table 1. The cardiac dataset pattern.

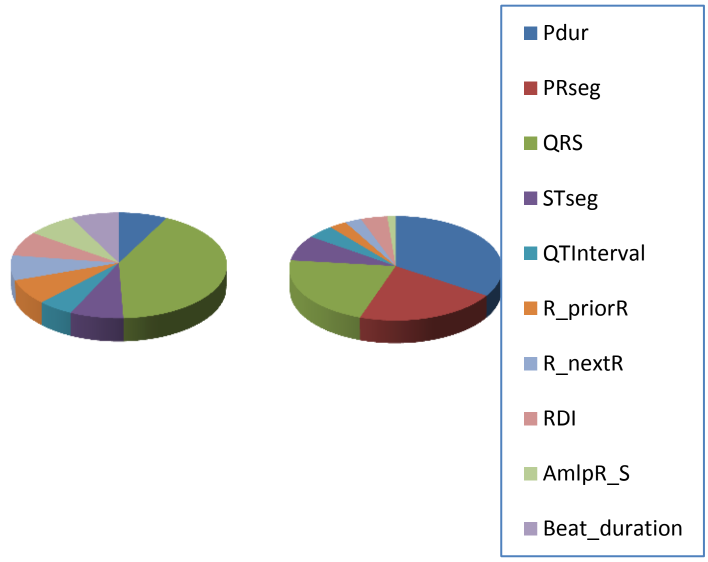
Attribute	**Type**	**Description**
Pdur	REAL	The duration of the wave P.
PRseg	REAL	The PR segment.
QRS	REAL	The QRS larger.
STseg	REAL	The ST segment.
QTInterval	REAL	The QT Interval.
R_priorR	REAL	Distance between the current R and the prior one.
R_nextR	REAL	Distance between the current R and the next one.
RDI	REAL	Distance between R and R’
AmpR_S	REAL	Distance between R and S.

Beat_duration	REAL	The Beat duration.

5.1.1 Empirical experiments.

a- The weight vectors

The weight vectors represent the importance degree of features. It can be defined from the knowledge domain (defined by the experts) in this experiment we have applied a machine learning algorithm (see 4.5), and then we have obtained the optimal weights vector with the minor errors. Each similarity agent is associated with a specialized case base for a specific class then we have applied the same machine learning algorithm two times for a specialized capitalization of knowledge. We have used a pie sector diagram for the weights visualization.



Normal **PVC**

Fig.I.08**.** The degree of importance of the attributs defined by using the gradient descent algorithm.

The obtained results for the PVC class represents a minor similarity with the knowledge extracted from the knowledge experts where they consider just the P_duration attribute which will be null and there are any consideration of importance degree in the normal class where they put just a general rules for the normal beat recognition. Also these results explain that the QRS duration attribute is the most significant in the normal cardiac beat class and explain that the rest features are less important. And for the PVC class there are three significant features: Pduration, P_Rsegment and the QRS duration.

b- Case bases learning.

We have used the Case Base Learning algorithm CBL1 and CBL2 defined by D. Aha [8] for the cases bases learning and optimization. The first algorithm consists of retaining all classified cases in the case base, and the second consists of retaining just the less similar cases for optimizing the case base. After some experiments by using all part of the training base we have obtained a case base with just 14.13% of the training base which mean increasing the performance by 85.87%, with the same rate of accuracy.

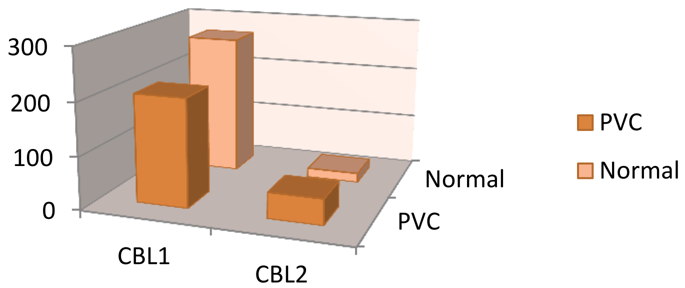


Fig.I.9. The case bases learning and optimization.

With the obtained case bases and weight vectors we have applied the classifier for a test data set which contains 400 heart beat 100 normal 100 PVC from the training base and 200 from other classes (Left Bundle Branch Block and Right Bundle Branch Block), we have varied the local similarity function by using the exponential in some experiments and the sigmoid in other ones with the same data. Also for the comparison we have done some experiments with just the domain knowledge base. The figure FigI.10 represents the correctly recognized beats for each combination.

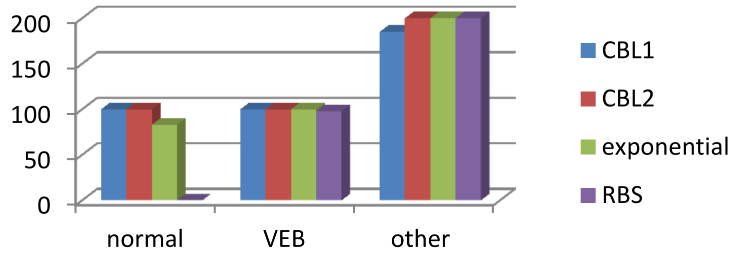


Fig.I.010**.** Recognized queries by using the sigmoid function with CBL1 and CBL2 and the exponential function with CBL2 and the rule based system.

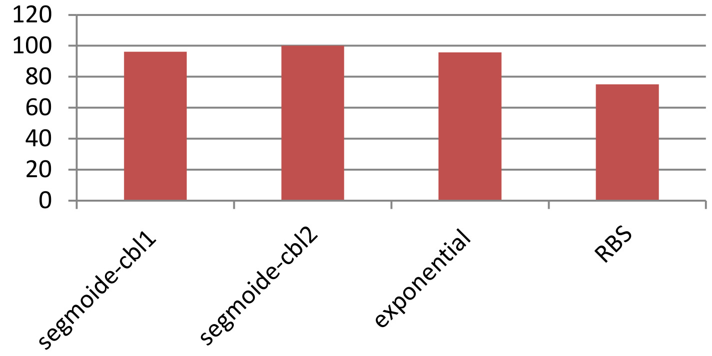


Fig.I.011**.** The rate of correct classifications.

In these experiments we have used the fuzzy similarity measures function but we have changed the local similarity function (sigmoid and exponential function) we have also used tow case base learning algorithms (CBL1 and CBL2). The best rate of correct classification is obtained when we have used the sigmoid function with CBL2 algorithm, we have obtained 100% the second 96.25% when we have used the sigmoid function with the CBL1 Algorithm **this prove that the Cbl2 algorithm optimize not just the performance but also the accuracy of the system.**

Also generally the rate of correct classification by using the sigmoid is better than the obtained with the exponential, this mean that the sigmoid function is **better** than the exponential function in the side of **accuracy** but not in the **complexity** side. And finally when we have used just the rule based system which represents the domain knowledge modeled from the expert knowledge's we have obtained just 75%.

5.1.2 Comparison with other works.

There are some works in the cardiac arrhythmias diagnosis in which they apply different approach and intelligent techniques for the classification and automatic recognizing. Some of these works apply the Artificial Neuronal Network (ANN) as [16][71][72][73][74], others have used the Fuzzy approach [17] and [76], another researchers have used the hybrid model [18][19][75][77] the rest which we have find apply the Fuzzy decision Tree[20].

To compare between two classifiers there are not just the crucial parameter which is the rate of correct classification, which is successfully achieved in this work, but there are another criteria as flexibility where the decision system should response to the particular cases which need specialized kind of learning which exist just in the CBR. The second criteria is transparency and results explanation for more interpretability and for trusting the decisions of the system, The adaptability also is another important criteria when new disease can be integrated in the system. the scalability and other important parameters are cited and detailed in the sections 3 and 4.

In the realized experiments the rate of correct classification is from 96.25% to 100% the best rate is obtained when we have used the sigmoid similarity measures function and the Case Base Learning algorithm 2 CBL2. Also each decision can be explained by giving the rules used with the similarity measures and the importance degree of each feature all this information will be stored in a log files accessible by the users and visualized by a general user interface described in the next chapter. The classification system is a multithreading system in which every thread is executed independently with the others also the used case base learning algorithm 2 has optimized the performance by 87.87% of the traditional time. Finally for proving the adaptation and the flexibility of our system we have applied our system in another important medical domain the breast cancer classification and we have obtained also an important rate of correct classification.

5.2 Breast cancer diagnosis

Cancer is a class of diseases in which a group of cells display 1) uncontrolled growth (division beyond the normal limits), 2) invasion (intrusion on and destruction of adjacent tissues), and sometimes 3) metastasis (spread to other locations in the body via lymph or blood). These three malignant properties of cancers differentiate them from benign tumors, which are self-limited, and do not invade or metastasize. Cancer affects people at all ages with the risk for most types increasing with age [48]. Cancer caused about 13% of all human deaths [50] in which the breast cancer represent (519 000 deaths). Risk factors include: tobacco use, being overweight or obese, low fruit and vegetable intake, physical inactivity, alcohol use, sexually transmitted HPV-infection, urban air pollution, indoor smoke from household use of solid fuels [49]. Early detection of breast cancer is enhanced and unnecessary surgery avoided by diagnosing breast masses from Fine Needle Aspirates (FNA's)[21]. Many techniques are used in the diagnosis of breast cancer as well as Microarray [9], Cytology [21] [22][23] and Mammography [70].

5.2.1 The breast cancer data set.

In order to obtain more objective and precise measurements, Dr. William H. Wolberg in University of Wisconsin Hospital, have constructed a dataset. With an image analysis program, known as Xcyt[5], [21, 22, 23], some cellular features is computed from 699 images of malignant and benign cancerous tissues. The data set pattern contains 11 features: The id number, the class (Benign, Malignant) and 9 attribute which describes the morphology of the cancerous cells. This data set contains 699 instances in which there are 65.5% benign and 34.5% malignant. It contains also 16 instances that contains a single missing (i.e., unavailable) attribute value, denoted by "?".

[5] The software is available for execution over the Internet, providing previously unavailable predictive accuracy to remote medical facilities. http://dollar.biz.uiowa.edu/xcyt/

Table 2. The breast cancer dataset pattern.

Attribute	Domain
id number	
Clump Thickness	1-10
Uniformity of Cell Size	1-10
Uniformity of Cell Shape	1-10
Marginal Adhesion	1-10
Single Epithelial Cell Size	1-10
Bare Nuclei	1-10
Bland Chromatin	1-10
Normal Nucleoli	1-10
Mitoses	1-10
Class	2 or 4

In the class attribute 2: Benign 4: Malignant

5.2.2 Empirical experiments.

As the first application in cardiac arrhythmias diagnosis we have done many experiments with the described data set with different parameters and algorithms. We have used 683 instances which mean 97.77% of the dataset. Some of these instances were used for the learning and optimization with different strategy. And we have constructed a test base which contains 400 instances (200 from each class).

We have used the gradient descent described in section3.6 and we have obtained the following pie sector diagrams FigI.18 which indicate the degree of importance of each feature after the learning step. Each Pie diagram is generated by a similarity agent by using 100 positive exemplars.

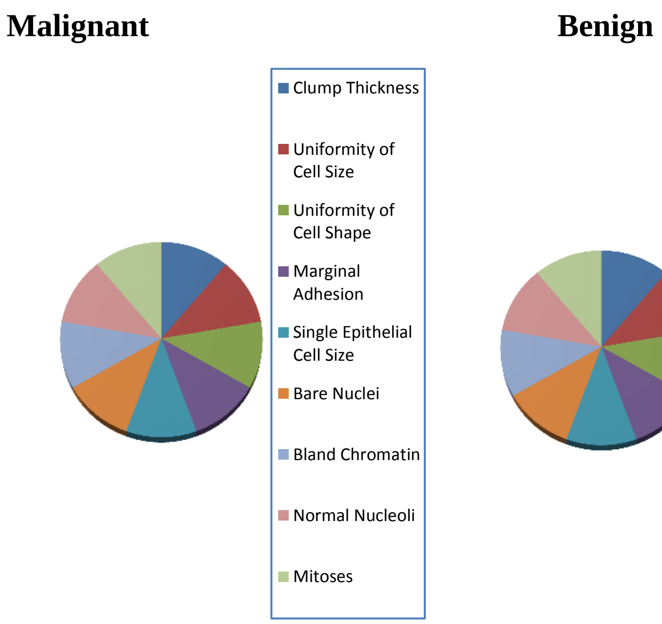


Fig.I.012**.** Importance degree of each feature for malignant and bengin classes Case base learning.

After the extraction of the good weights vectors with the minor errors we have applied some empirical experiments for the case base learning and optimization. First of all we have randomly stored some cases from the training dataset in the case bases after that we have increased the number of these cases in the case bases by adding the same number of instances with any constraints about these cases just the symmetry in the case bases i.e the same case in the case bases. And we have obtained the following bar chart which represents the rate of correct classification for each experiment.

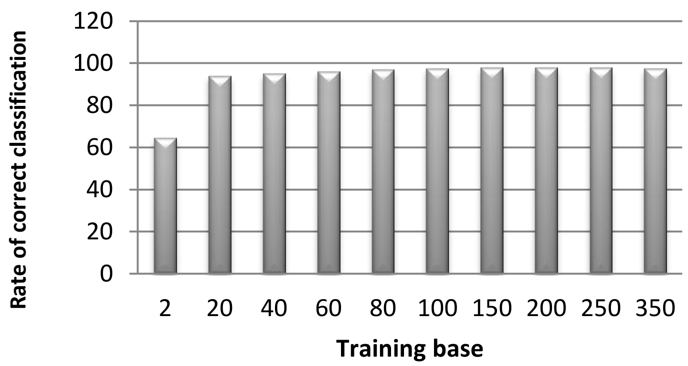


Fig.I.013**.** Rate of correct classification for different case bases size.

In this experiment we have measured the rate of correct classification for different number of cases in the case base randomly chosen. We can infer from this experiment that there is a relationship between the number of cases in the case base and the accuracy of the system but we can perceive that after 150 cases in the case bases the accuracy become stable in 98% and after 250 cases in the case bases the accuracy decrease to 97.5%. This selection is randomly done and proves that the size of the training base is not significant in some cases and can decrease the accuracy of the system. Another method for defining the cases bases by using some heuristics as the CBL2 case base learning algorithms which consists to retain just the significant cases from the training and the test base.

After applying the case base learning algorithms 1 and 2 we have obtained the following case base sizes:

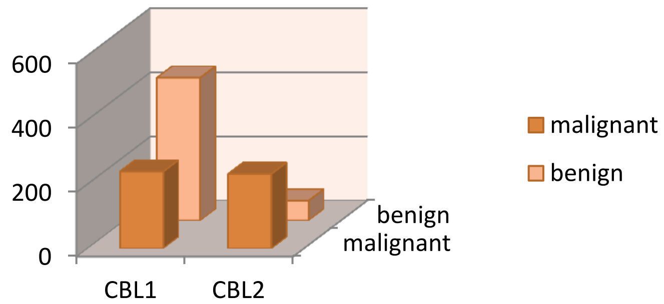


Fig.I.14. Number of cases in the cases base after using the case bases Learning algorithms CBL1 and CBL2.

The Case base learning algorithm CBL2 which consists to store just the non-similar cases in the case base has optimized the case base to 43% of the training base without changing the precision of the classification see fig.I.21. We can infer from this experiment that the CBL2 optimization algorithm increases the performance of our system by 57% because we eliminate the computing of similarity measures between the queries and the 43% of instances. Another remark can be inferred from the less optimization rate for the malignant class that the optimization with this algorithm depended on the type of data not the optimization algorithm.

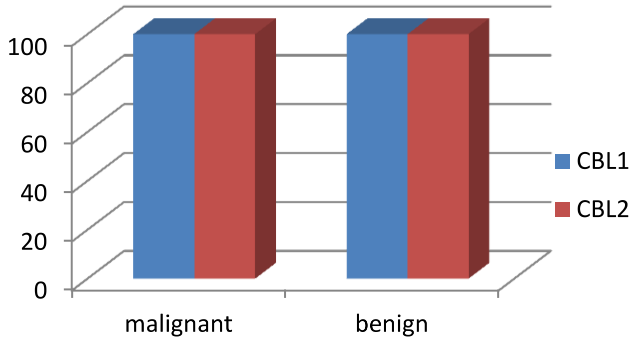


Fig.I.015**.** Rate of correct classification by applying case base learning algorithms CBL1 and CBL2.

In this experiment we have used all cases in the data sets and we have used 200 cases for the test. We have obtained the rate of correct classification 100% in both experiments this prove that the used optimization algorithm CBL2 is very useful and powerful.

5.2.3 Comparison with related works

The used data set has been tested by several researchers due of the impact of the concerned domain. In this section we cite and compare the obtained results with the works of O. L. Mangasarian and W. H. Wolberg in [21] [22][23] where they used the linear programming approach for just 50% of dataset for the learning and the testing steps and they have obtained 93.5% as a rate of correct classification. The second use of this database is in [24] also by O. L. Mangasarian and W. H. Wolberg by using the nearest neighbor algorithm and just 50% of dataset they have obtained 93.5% as a rate of correct classification.

We have obtained different rate of correct classification for different configuration of the system from 98% to 100%. The obtained results prove that our classifier is very robust and better than the others algorithms used. Also in these experiments we have proved that there is any relationship between the number of instances used for learning and the system accuracy.

6. Syntheses and conclusion

In this chapter a smallest description about the reused paradigms for the classification is presented. Following this, we have described the developed reasoning system and a novel fuzzy similarity measures approach for enriching the retrieving process. We have explained two applications of this reasoning system.

The empirical experiments trough a significant data and many alternatives of computing demonstrate that our investigation gives an important progress in the accuracy side, the transparency side and the performance side. These progresses are appeared as a consequence of the combination of some strong and smart approaches in which our system inherit the majority of their proses and some minor disadvantages as the complexity of knowledge modeling in the rule based systems.

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Chapter II: Explanation aware computing for medical application: Toward Explanation agent for medical decision support with KI-DCBR system

Abstract: The interaction between the medical applications and the expert users will be held with a high level of trust because they touch a critical kind of applications which concerns the health of the human beings and in some time their life. The explanations and provenances is not just a simple option which can be integrated in medical application for increasing the usability but it is a necessity for the doctors in their decision process. It helps also applications to be credible and generates more comprehensible decisions. The medical applications users is some time a professional one which need a deep explanations for their future decisions in other side there are a simple users as patients who need just some useful tips for the protection and health care with a little explanations; there are also a technical user or the developer which need a technical explanations for maintaining the systems. Then an explanation based on the profile of the user is very important in the new medical applications.

1. Introduction

In human to human interaction, the ability to explain its own behavior and course of action is a prerequisite for a meaningful interchange; therefore a truly intelligent system has to provide comparable capacities. [1] Explanation aware computing has become a necessity not just an option for much kind of applications and users as medical applications, recommendation systems and others in the same time it is a good option for other kind of application. Although the explanation takes many callings as justification, provenances…etc, it focuses on ensuring an easy and trusted uses of interactive and complex applications.

The medical applications are now an important domain of application which uses many resources and theories as intelligent artificial, mathematics, physics and biology for serving and protecting the human life. The medical applications interact not just with a specific kind of users but it touches a wide use for different kind of users. As a kind of medical applications the decision support systems where the decision is supported by an implicit or explicit knowledge extracted from data or modeled from the expertise of doctors and scientists.

We have developed a case based reasoning system for medical diagnosis and classification [1] through a predefined pattern from the signals or images or symptoms of the patient the system can generates the disease of this patient. We have also evaluate this system by using two medical data sets cardiac arrhythmias and breast cancer [1][2]. The explanation aware computing for reasoning systems is very useful for getting the trust of the users of the reasoning systems and for accepting the proposed solutions or detecting the source of errors for the expert users.

The explanation will give more semantics to the user for the interpretation and also the regularizations (learning for decrease the faults of the system) then the agent will generate some explanations understood with the doctors. This chapter will contains a description about explanation aware computing by presenting the explanation kinds, explanation user's goals, explanation and expert systems explanation and case based reasoning and the developed explanation agent.

2. Explanation aware computing

The term explanation can be interpreted in two different ways in AI [Aamodt, 1991, p. 59]. One interpretation deals with explanation as part of the reasoning process itself, for example used in the search for a diagnostic result in order to support a particular hypothesis. The other interpretation deals with usage aspects: attempting to make the reasoning process, its result, or the usage of the result understandable to the user. [9]

2.1 Kinds of explanation

The focus of these early extensions was usually to extend the explanation capabilities by adding the type of knowledge required by the user. These explanations could be divided into four types [Swartout and Smoliar, 1987; Chandrasekaran et al., 1989; Gregor and Benbasat, 1999]:

• Reasoning Trace: Producing an explanation from the trace of the reasoning process used by the system to find the solution. Examples are MYCIN's how and why explanations [Clancey, 1983].

• Justification: Providing justification for a reasoning step by referring to deeper background knowledge. This type of explanation was first offered by the XPLAIN system [Swartout, 1983].

• Strategic: Explaining the reasoning strategy of the system. The NEOMYCIN system first provided this kind of explanation [Clancey, 1983].

• Terminological: Defining and explaining terms and concepts in the domain. This type of explanation was identified in [Swartout and Smoliar, 1987].

2.2 Explanation user's goals

A systematic overview on explanation in philosophy and cognitive sciences and a historic overview of the use of explanations in artificial intelligence are given in [5]. Five goals a user can have with explanations are introduced, namely

1. Transparency (explain how the system reached the answer),
2. Justification (explain why the answer is a good answer),
3. Relevance (explain why a question asked is relevant),
4. Conceptualization (clarify the meaning of concepts),

5. Learning (teach the user about the domain).

i. Explanation-Aware Software Design and Computing

Software systems need the ability to explain reasoning processes and their results as those abilities substantially affect their usability and acceptance. Explanation aware computing (ExaCt) is the vision of software systems being smart in interactions with their users and Explanation-aware Software Design (EASD) aims at making software systems smarter in this regard. EASD looks at ways to guide software designers and engineers to a purposeful explanation-aware software system by making their designers and engineers explanation-aware. The long-term goal is to provide the respective methods and tools for engineering and improving such explanation capabilities [15].

The term explanation has been widely investigated in different disciplines such as cognitive science, artificial intelligence, linguistics, philosophy of science, and teaching. All these disciplines consider certain aspects of the term and make clear that there is not only one such concept but a variety of concepts. Explanations are in some sense always answers to questions, may the questions be raised explicitly or not. Explanations are an important vehicle to convey information to understand one another in everyday conversations. They support humans in their decision-making [14].

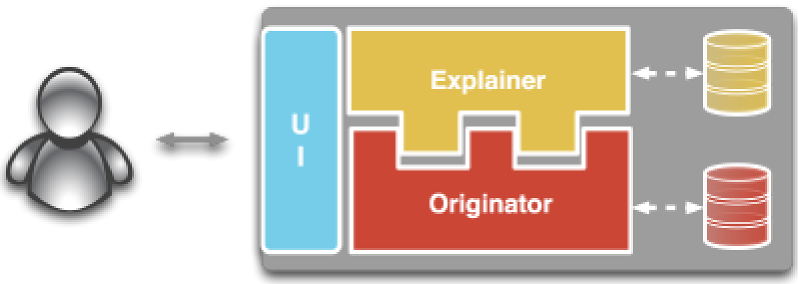


Fig.II.1. Communication participants in general explanation scenario [13]

In a general explanation scenario (Figure 1) we distinguish three main participants [13]: the user who is corresponding with the software system via its user interface (UI), the originator, i.e., the problem solver or 'reasoning' component, which provides the functionality for the original task of the software, and the explainer. Both, originator and explainer, have their own knowledge container to support their tasks as indicated by the two database symbols.

EASD models important aspects for understanding the originator and its application domain. Originator and explainer need to be tightly coupled to help the explainer provide knowledge about the inner workings of the originator.

ii. The mining and analysis continuum of explaining (MACE)

In the mining process, explanation features are involved before, during, and after the respective data mining main step, i.e., the modelling step. Therefore, we take a broad view regarding the data mining system as the originator, and provide explanation capabilities for each of the datamining steps. In short, the involved mechanisms can be described as follows: The input of the system is given by a (descriptive) specification of the process, the (source) data, and optional background knowledge. The system output is given by a data mining model, e.g., a set of patterns. The output is then accompanied by a "description" of the elementary mining steps, i.e., traces and/or logs of the respective events and steps of the process. The output can then be explained in terms of the input data, additional background knowledge and the intermediate results (trace). Additionally, setting up the specification itself is often a difficult task, for which appropriate explanation features are crucial.

iii. Knowledge based systems and EXACT

In early rule-based expert systems like MYCIN the user could ask how the system reached the conclusion presented and an explanation in the form of a reasoning trace from the system would be presented. This would offer the user a degree of transparency into how the system reached its conclusions. The user could also choose a why explanation that would provide a more local explanation that justified why a question was asked. [1]

iv. Case based reasoning and EXACT

Case-based reasoning is concerned with problems that are open-ended, and often changing, and uncertainty as well as incompleteness of theories and input descriptions are typically assumed. Viewing explanations as deductive proofs will be too severe a limitation for our purpose, and hence less relevant for the type of explanations CBR systems need to generate. A pragmatic view of explanation will therefore be accounted for in the following, while the Hempel-Oppenheim account sometimes will be used for comparison.

Roger Schank and colleagues further developed Schank's "dynamic memory" [Schank, 1983] theory of reminding, problem solving, and learning, into a theory of explanation generation and evaluation. As one of the founders of CBR as we know it today, he proposed a case-based approach to explanation, based on storing, indexing, and retrieval of "explanation patterns" [Schank, 1986]. Explanation patterns are specific or generalized cases of explanation events. A particular focus has been the exploration of case-based reasoning as a platform for creativity [Schank and Leake,1989]. In this model, creativity comes from retrieving explanations related to a situation, but using them in new ways - referred to as "tweaking" of explanations. Depending on the retrieval and adaptation processes used, CBR has the potential to provide solutions to a range of creativity tasks, from close to copying old solutions up to producing novel ideas. The following has been a focusing problem for studying various types of explanations: In 1984, Swale was the best 3-year-old racehorse, and he was winning all the most important races. A few days after a major victory, he returned from a light morning gallop and collapsed outside his stable. The shocked racing community tried to figure out why. Many hypotheses appeared, but the actual cause was never determined.

We have reviewed several attempts to define criteria for explanations and categorizations of different kinds of explanations. Philosophical accounts focus on criteria for scientific explanations, while the cognitive accounts describe how humans use explanations in a wide range of contexts. However, many explanations may be produced that are not perceived as useful in a given context. This happens even if they fulfill criteria of what is considered a good explanation.

The research on explanation within expert systems provides a focus for a situational context that is similar to what we find with most case-based reasoning systems.

Although the technology for generating and presenting advice is different from traditional rule-based expert systems, most CBR systems today are computer systems that give decision advice to human users. Because of this similarity in situational context, it is reasonable to believe that the typology of explanations useful in expert systems will be a good fit for CBR. In this section we introduce five explanation goals that are strongly influenced by expert systems.

Below the abstraction level of the explanation goals, we need to look at particular issues in applying these goals to CBR. For instance, traditional rule-based systems paraphrased the rules to form explanations. While CBR systems typically do not have rules, the basic unit of knowledge in CBR – the case – can also be used to produce explanations. It has long been an article of faith in the CBR community that displaying an earlier solved case that represents a situation similar to the present problem situation can serve as a good explanation for adopting the solution of the previous case. After presenting the explanation goals, we will examine this approach further. In addition, we will discuss if cases are really the only source of knowledge that should contribute to explanations in a CBR system.

3. Translational Bioinformatics challenges

Translational bioinformatics is bioinformatics applied to human health. Translational bioinformatics is focuses on making the results of research applicable to human being and, thus, on translating research results into practice. As the ultimate goal of Translation bioinformatics research is to provide better care to patients. [7]

Translational bioinformatics applications including decision support systems, computer aided diagnosis, image and signal possessing microarray analyses and other applications are a critical kind of applications, for this they must ensure a high level of accuracy and explanations for different kind of users (experts and simple users) also they will provide a special care and a good flexibility for the particular cases.

Translational bioinformatics has the opportunity to design clinical decision support systems based on the combination of medical Signals, images and video, -omics data and web-based knowledge resources see figII.2.

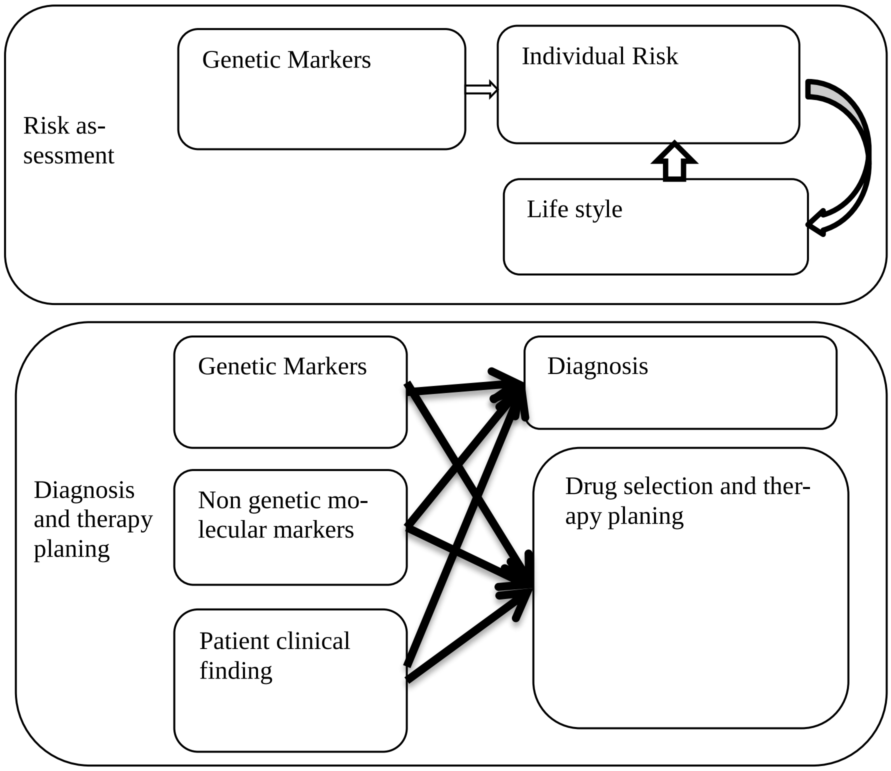


Fig.II.2. General flowchart for decision support systems in medicine (Recardo Bilazzi 2010)

4. Explanation aware computing for medical applications

The explanation aware computing becomes a necessity for all complex medical applications, where uncertainty and risks are the first preoccupation and highly considered because the human life is concerned. Several researchers contribute the explanation in their intelligent systems as:

- MYCIN [Clancey, 1983]: MYCIN was an early expert system that used artificial intelligence to identify bacteria causing severe infections, such as bacteremia and meningitis, and to recommend antibiotics, with the dosage adjusted for patient's body weight — the name derived from the antibiotics themselves, as many antibiotics have the suffix "-mycin". The Mycin system was also used for the diagnosis of blood clotting diseases. In early rule-based expert systems like MYCIN the user could ask how the system reached the conclusion presented, and an explanation in the form of a reasoning trace from the system would be presented. This would offer the user a degree of transparency into how the system reached its conclusions. The user could also choose a why explanation that would provide a more local explanation that justified why a question was asked.

Öztürk and Aamodt [1998]: Öztürk and Aamodt build a taxonomy of context categories based on this merger of the two different worlds of information (internal vs. external). Beside this categorisation, the authors impose the action, or task, oriented view on knowledge in general, and contextual knowledge in particular. The goal of an agent focuses the attention, and thereby the knowledge needed to execute tasks associated with the goal. The example domain in their paper is from medical diagnostics, where a physician attempts to diagnose a patient by the hypothesise-and-test strategy. The particular method of diagnostics in this case-based reasoning system is related to the strategy used by Strat. They differ insofar as Strat used contextual information to select the algorithms to be used, whereas Öztürk and Aamodt have, prior to run-time, defined the main structure of a diagnostic situation, and only use context to guide the sub-tasks in this process.

[Kofod-Petersen and Aamodt, 2006]: The architecture of this system has been implemented as an ambient intelligent system in a hospital ward. The personnel at the hospital ward are involved in many different activities, such as doing ward rounds, meetings and different forms of examinations. The system's main purpose is to recognise ongoing situations and proactively acquired digital information relevant for the user. When we now presume that the system has recognised that we are on a ward round, discussing medical conditions and treatments with several patients, it will try to prepare all the relevant information to be presented to the user. This includes all test results. The system can now ask other available artefacts for test results on the user, and the medical images database can offer a MR image whereas the patient record offers a textual description of the MRI. Because of limitations of handheld devices, the system will for example not be able to display high resolution MR images. When choosing which of the artefacts to query, the system will reject the medical image database and only query the electronic patient record database. The explanation used by the system is based on the knowledge that a high resolution image displaying device is not available on a ward round.

5. IK-CBRC for medical explanation

A case based reasoning system is developed for medical diagnosis and classification [1] through some parameter taken from the patient the system can generate the disease of this patient. We have also evaluated this system by a benchmark with two international medical data sets cardiac arrhythmias and breast cancer, the results and the comparison with the related works exist in [8,10,11,12] and [6,7].

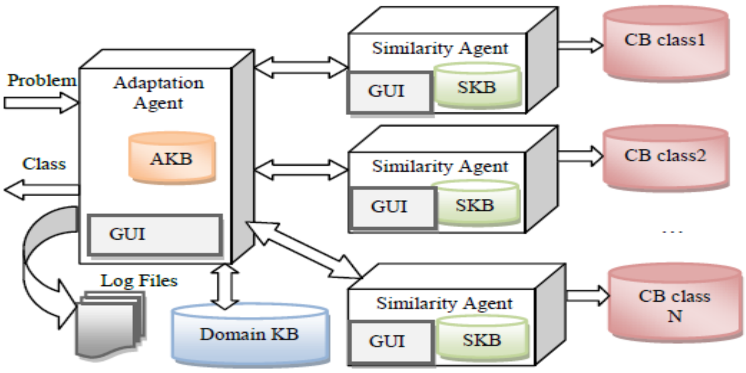


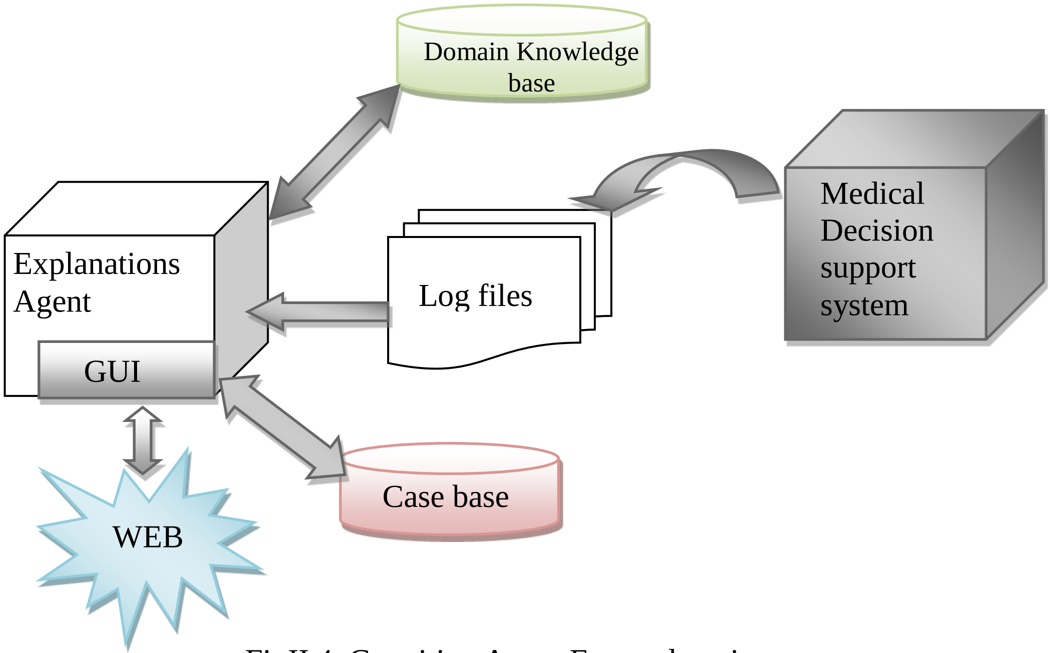
Fig II.3 KI-DCBRC: distributed decision support system

The reasoning system contains two kind of cognitive agents: 1-The similarity agent which computes the similarity between the query and the cases from the same classes by a selected similarity function chosen by the users 2- The adaptation agent which edits the query by interacting with the users, following this, he communicates with the similarity agents by sending query associated with an ontology which describe the features of the query. The adaptation is realized by inferring from a knowledge base which define the protocol of decision by weighting the responses of each cognitive agent. The reasoning is also enriched by a domain knowledge base which contains the rules extracted from the expert's knowledge.

The log files generated by the developed system contains all needed information for explanations as the agents messages and the computed similarity measures of each similarity agent also the uncertainty of responses the used adaptation rules and similarity parameters. This files can be visualized with text editor software but the contained information is large and there are a mass queries treated by the reasoning system. For these reasons a definition of separated component for explanation is suitable.

6. Cognitive agent for Explanation Aware computing

In this section a cognitive agent is described for medical explanation by reusing the stored information in the log files generated by KI-DCBRC and a case base which is used for generating an adapted explanation according to the level of abstraction and users' kind and goals. A Graphical User Interface is defined for the visualization of explanations. There are three levels of abstractions one for the novice users and one for the expert in medicine and one for the developers. The explanation agent should reuse some cases for ensuring the needed smart explanation adapted to the application users. The important impact of Fuzzy similarity model appears in the easy way of presentation where the users understand the linguistic variables more than similarity values. Some web resources are used for the novice explanation as wiki documents.



FigII.4. Cognitive Agent For explanation

The log files are constructed by the intelligent system which contains the different useful information about decisions of the cognitive agents. In Fig II.5 the log file contents is presented.

Query id: Pattern Query Agent 1: Similarity function and parameters Importance degree of features

Response NBS: NBU: NBN: Agent 2: Similarity function and parameters Importance degree of features Response NBS: NBU: NBN: Adaptation agent decision Rules used from RBS Rule used from AKB The class Doctor annotation (if exist elsewhere we ask the case based reasoning for explanation)

Fig II.5. Information logged by the DSS

The cognitive agent for explanation defines the following three levels of abstraction:

- Level1 ordinary explanations for novice users. In this level the agent present just the needed information about the class of the query, the disease, associated with the terminological explanations and the indexed links of useful wiki documents and the picture of the cardiac beat.
- Level2 deep explanations for medical doctor users. In this level the agent add, to the explanation presented in the prior level, the justification, the reasoning trace, and the strategy.
- Level3 maintaining explanations or debuggers for the developers. This level contains all kind of explanation for the deferent kind of users plus the professional information which help developers to understand the abnormality of the reasoning system.

The explanation agent interacts with the deferent kind of users by a smart graphical interface interaction between users and the cognitive agent, see Fig II.6.

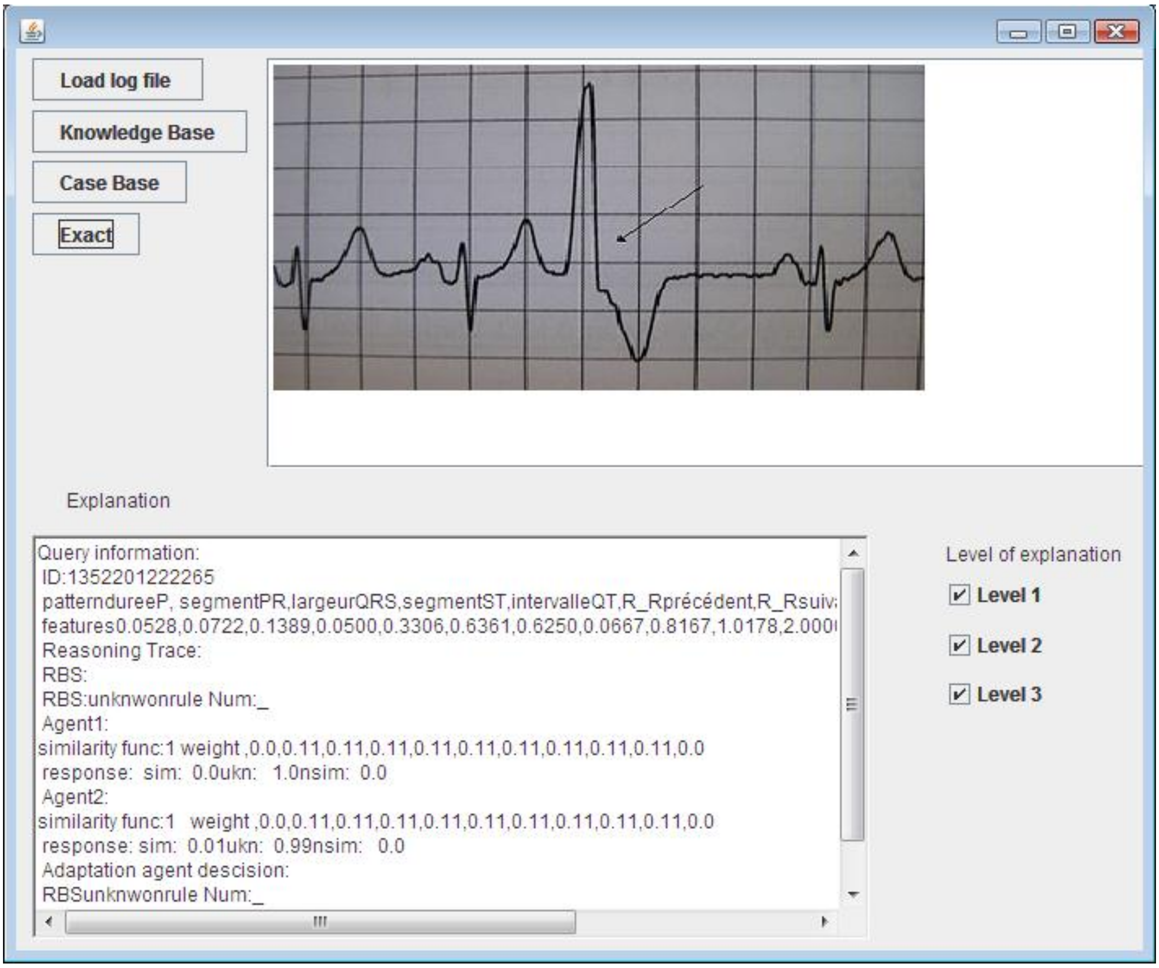


Fig.II.6. General User Interface of the explanations Agent

The figure presents an example of explanation where the user selects the level 3, and the log file which contains a decision about PVC cardiac arrhythmias the reasoning trace present an unknown response from the rule based system and a high rate of membership for the similar fuzzy set generated by the Agent1, the other agent: Agent2 present a high rate of membership for the query in the not similar fuzzy set. The terminological explanation also is presented with the wiki doc and the localization of the abnormality in the cardiac beat.

Another example of explanation is presented in the Fig II.7, where the log file contains the logged information about Benign Breast cancer query. The level of abstraction 1 is selected there are any domain knowledge base but the case base contains cases for an adaptive visualization of explanations.

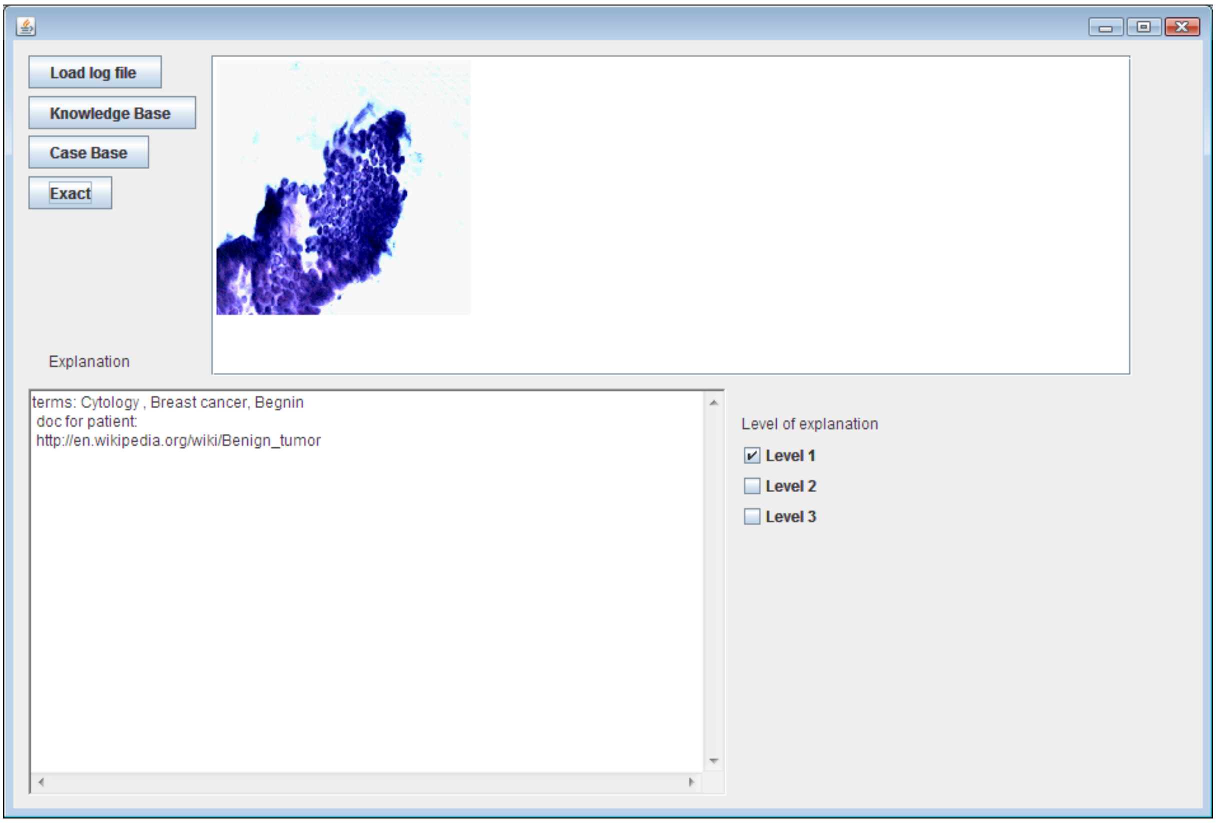


Fig.II.7. The explanations Agent gives explanation about breast cancer diagnosis

The separation between the explanation and the decision support system for more performance and make the explanation as an option which can be ignored by the novice users or in the mass classification of queries.

7. Conclusion

In this chapter an original agent for explanation is presented after a general overview of the explanation aware computing. The Exact for the complex smart system is developed for enriching the trust of the users and the transparency of these kinds of systems. Medical applications are a sub kind of the complex systems which have a specific needs and challenges as accuracy transparency and flexibility. In this chapter a cognitive agent for medical explanation is presented with multi-level of abstraction and an adaptive explanation for the kind of users.

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Chapter III: Web 2.0 centered participative reasoning system for computer aided diagnosis and prevention[6]

Abstract- The information in medical domain is crucial for each kind of medical application users and actors for more efficiency. The health 2.0 based on WEB 2.0 consists of enriching the traditional medical application and resources with new sophisticated solutions for a mass and interactive uses with collaboration and cooperation era. The explanation aware computing focuses in the enrichment of the trust between users and the intelligent applications. A health2.0 application is developed in the context of intelligent explanation for social network users by using the responses of a medical decision support system and a documents recommendation system for categorized users. In this chapter we present the technologies around this application, a CBR decision support system, with an adaptive explanations based on a social recommendation system.

[6] This work is presented in the Doctoral consortium of the 20th International Conference on Case Based Reasoning ICCBR 2012, Lyon, France The chairmen : D.Aha and T.Roth-Bergopher, Mintor: R.Webber.

1. Introduction

The internet users' population is estimated in 2011 to 2.26 billion person[7]. The web 2.0 including Blogs RSS Social networks attract the majority of internet users for their simplistic amiability and interactivity. The health 2.0 and homecare systems based on the web 2.0 technologies realize a tie between the health care actors (doctors, patients and the other users) for explanation and prevention. The Facebook web site is an interactive social network with a mass uses (880.5 million users in Dec 2012 on the world) launched in February 2004 contains an important API for developers. It also proposes an ubiquities ability for mobile devices.

Eight in ten Internet users have looked online for health information. Many say the Internet has had a significant impact on the way they care for themselves or for others [6]. Although many people depend on their doctors to diagnose and treat acute conditions such as a sudden high fever or a broken ankle, patients tend to take a more active role in managing chronic conditions [5]. The online support groups and document can influence how people understand their illness (e.g., [7]). Researchers have studied online health support for many chronic conditions including cancer [8, 9 and 11] hearing loss [10] chronic fatigue [7], mental health [13], some dermatological disease [14] and autism [12].

When people with chronic disease go online, they encounter resources that diverse individuals, groups, and organizations have created [3]. The web can function as a support network, a source of information, a place to compare treatment options, and a mechanism for sharing information with caregivers, family, and friends [16, 21]. Despite the prevalence and promise of online health information technologies, problems exist. In particular, online information can be inaccurate, incomplete, controversial, misleading, and alarming for individuals with health questions [11, 16]. Online content can have a substantial impact on patient beliefs and actions [4, 15, 22]. Thus, it is important to understand how inconsistent or contradictory online information and discussion affects patients.

[7] http://www.internetworldstats.com/stats.htm

The context of our application is to resolving the problem of information inconsistency by ensuring an adaptive and participative interaction between the users, doctors and the intelligent system for decision support, explanation and prevention as a home care solution. An online medical decision support system is developed for mass uses by applying a case based reasoning classification system enriched by a document recommendation system based on the explanatory responses and the users category and recommendations.

2. Around the application

2.1 Web 2.0

The term Web 2.0 was first introduced by O'Reilly in 2005, who defined it as "a network as platform, spanning all connected devices" [5] and later added "a more mature, distinctive medium characterized by user participation, openness and network effects"[3].

The most famous web 2.0 technologies as wiki, blogs, RSS and social networks attract more communities and persons for their simplicity and interactivity. In a survey done by Neilsen[8] company the social networks and blogs take 22.5% of the American's internet time (see FigureIII.1).

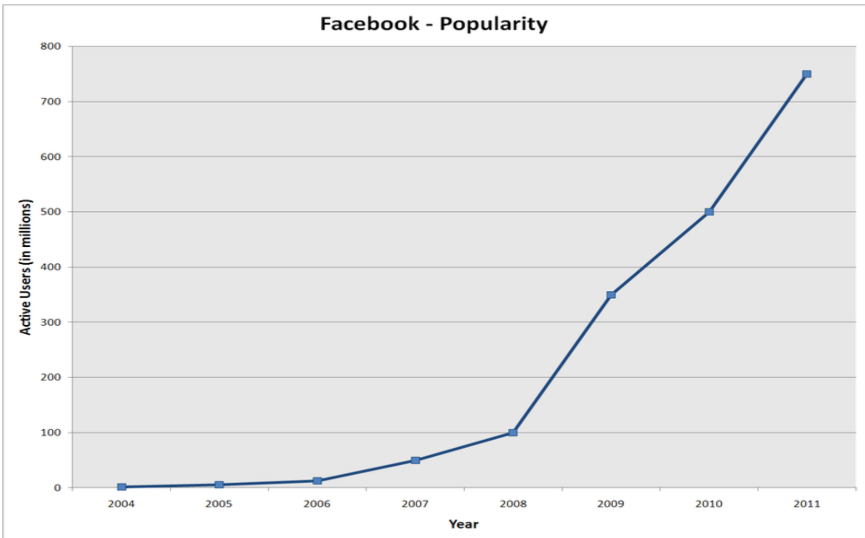
FigureIII.1: Top 10 online categories by share of total internet time home and work (May 2011)[Nielsen]

[8] *www.nielsen.com*

a. Social Network

Social networking is one of the most popular Web 2.0 applications. Users can create a profile and connect with other users as friends or colleagues on numerous different types of free and for-fee sites. Connected people are known as ‘‘friends’’ or ‘‘contacts.’’ Some sites are primarily professional (e.g., LinkedIn[3]), while other sites are primarily social (e.g., Twitter,4 Facebook,5 and MySpace6). Increasingly, all of these sites include a blend of content. These sites allow for rapid, widespread dissemination of information, which provides an opportunity for marketing ideas and services, but also has many privacy pitfalls.[2]

Although there are many social networks platforms but we will describe heir the Facebook platform, for its high level of extensibility. The Facebook web site is an interactive social network with a mass uses (One billion users in 2012 on the world see Figure2) launched in February 2004. It contains an important API for developers and an ubiquities ability for mobile devices see figure3.



FigureIII.2. The growth of social network users.

Facebook platform

Figure III.3 the Facebook platform

Twitter is another version of social networking using text messages, known as ‘‘tweets,’’ that must be less than 140 letters or numbers.4 People who agree to receive tweets are known as ‘‘followers.’’ Tweets can be sent and read from the Twitter Web site, cell phones, and via third party applications. Practices can use Twitter to alert willing patients of upcoming events. This can be used to encourage engagement with the practice so the patient is more likely to come in for care or refer others. Twitter, or group texting, can also be used to reinforce health teaching. For instance, women with gestational diabetes can receive a helpful tweet to encourage exercise. It is important to remember that Twitter is a public conversation. People can reply to tweets or forward tweets on to others, known as ‘‘retweeting.’’

b. Blogs

Blogs are similar to online personal diaries or professional commentaries. Authors of blogs are known as ‘‘bloggers.’’ They ‘‘post’’ stories and comments on the Web for others to read. Blogs can belong to individuals or organizations, such as ACNM’s blog Midwife Connection. These blogs can be a source of community referrals if the blogger comments favorably on care or services. Practices may want links to supportive blogs or blog posts on their Web sites. Clinicians also can blog about their experiences, but they must be careful not to disclose information that can be associated with patients. For instance, if a midwifery student is blogging about her experiences in clinic X, she should not state that she saw a patient with a herpetic lesion on Tuesday because this information is traceable back to a small number of women.

c. RSS and Google Alertes

RSS (which stands for ‘‘really simple syndication’’) feeds are a method of creating a personal publication from favorite news sources. An RSS feed lists new content from favorite news sites, both personal and professional. For instance, an RSS feed from PubMed could send new abstracts on the second stage of labor, or the sources of information as newspapers could feed in articles on birth and childbearing. The RSS feed requires a ‘‘reader’’ to receive the articles. Readers are free through many sources, including Google. The reader collects articles on favorite topics for review. This saves the effort of checking multiple news sources and can alert readers when important publications are released. RSS feeds can also show the new postings on favorite blogs. Several online instructional videos demonstrate how to sign-up.

Google Alerts are similar to RSS feeds in that they screen the Web, blogs, and news sources for user selected topics. When an interesting news article is found, an alert is sent to the user’s e-mail or cell phone.

2.2 Home care application and Health 2.0

The imminent convergence of Web 2.0 technologies with personal health monitoring, affordable broadband fixed and mobile communications, and distributed data storage has the capability to deliver vast improvements to the in-home care environment. The advent of tools such as life logging, voice-based search and low-cost sensory monitoring enrich this convergence, and can generate significant social improvements for the elderly.[3]

Many clinicians use media alerts to keep abreast of current events surrounding midwifery or birth. Another example of social networking the ACNM has partnered with other national agencies to sponsor health information texts to users’ phones in a program known as Text4Baby. These texts, tailored to the woman’s week of pregnancy or her infant’s birthday, are similar to tweets in that they provide communication via the cell phone, but they are not public and cannot receive replies.[2]

2.3 Explanation Aware Computing EXACT

In human to human interaction, the ability to explain its own behavior and course of action is a prerequisite for a meaningful interchange; therefore a truly intelligent system has to provide comparable capacities. [3] But on the case of human machine interaction where there are a complex recorded knowledge and a mass application users with a different goals and kinds and in sometime a critical kind of application as health science applications an adaptive explanations become a necessity not just an option.

These explanations could be divided into four types [Swartout and Smoliar, 1987; Chandrasekaran et al., 1989; Gregor and Benbasat, 1999]:

• Reasoning Trace: Producing an explanation from the trace of the reasoning process used by the system to find the solution. Examples are MYCIN's how and why explanations [Clancey, 1983].

• Justification: Providing justification for a reasoning step by referring to deeper background knowledge. This type of explanation was first offered by the XPLAIN system [Swartout, 1983].

• Strategic: Explaining the reasoning strategy of the system. The NEOMYCIN system first provided this kind of explanation [Clancey, 1983].

• Terminological: Defining and explaining terms and concepts in the domain. This type of explanation was identified in [Swartout and Smoliar, 1987].

Five goals a user can have with explanations are introduced, namely

1. Transparency (explain how the system reached the answer),
2. Justification (explain why the answer is a good answer),
3. Relevance (explain why a question asked is relevant),
4. Conceptualization (clarify the meaning of concepts),

and 5. Learning (teach the user about the domain). [1, 2]

2.3 Recommender systems

Recommender systems are very popular both for E-Commerce (e.g. Amazon, Netflix) and the research community [25, 26, 27, 28], as these can calculate potential interesting items for users based on their interests. One of the most successful technologies for this task is Collaborative Filtering (CF) [25, 27].

3. Health 2.0 application for social Explanation and medical prevention

3.1 Online CBR diagnosis system

An online distributed case based reasoning system is developed for medical diagnosis and evaluated with international databases for cardiac arrhythmia diagnosis in [18] and breast cancer diagnosis in [17]. The system is composed from specialized cognitive agents who infer from a diversity of knowledge bases for generating an accurate response. It contains a distributed case bases which contain some cases from the same classes.

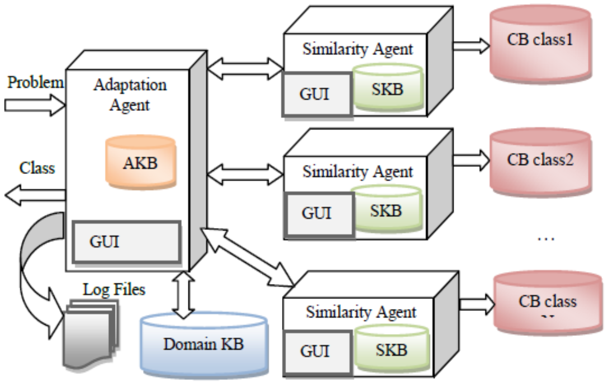


Figure III.4 KI-DCBRC an online decision support system for medical diagnosis.

The Similarity Knowledge Base SKB contains the specialized knowledge for measuring the rate of membership of the query in the class and the vocabulary knowledge which describes the case base. By using knowledge from different sources (experts rules, machine learning rules) the Adaptation Knowledge Base contains the rules for generating the most accurate response. Each agent contains an interactive interface for introducing the setting of the computing. The trace of the reasoning is recorded in an external log file.

The multi agent system and the accurate machine learning algorithms ensure the scalability and the usability of the system. The evaluation of this DSS gives satisfied results for two medical domains: cardiac arrhythmias (rate of correct classification between 98% and 100%) and100% for the breast cancer data in [18] and [17].

3.2 Exact in the reasoning system

The research on explanation within expert systems provides a focus for a situational context that is similar to what we find with most case-based reasoning systems. Although the technology for generating and presenting advice is different from traditional rule-based expert systems, most CBR systems today are computer systems that give decision advice to human users. Because of this similarity in situational context, it is reasonable to believe that the typology of explanations useful in expert systems will be a good fit for CBR [21]. As cited above there are four types of explanation 1) the trace of reasoning 2) Justification 3) strategic 4) terminological.

An independent cognitive agent is developed which reuses the log files and the explanation knowledge for explanation generation defined by three abstraction level each level for some kind of users as novice users, doctors and developers. This agent ensures all kind of explanations but the visualization of these explanations depends on the selected level of abstraction.

3.3 Recommendation system for medical documents

Social media brings many benefits to the software development process and the software engineering lifecycle: much faster and easier problem solving, more rapid and comprehensive testing of products throughout the lifecycle improving quality and time to market for software products. Social media has also changed the development process to include interaction design where feedback from users is used as part of the ongoing development process/lifecycle.[4]

The developed system contains an index of some Wikipedia documents for the novice users and scientific articles for the professionals. The index contains the link of the document associated with the key words, the kind of readers and the rate of recommendation. The affectation and recommendation is done by another CBR system which reuses the users' feedbacks.

For resolving the problem of online information which can be inaccurate, incomplete, controversial, misleading, and alarming for individuals with health questions

[4, 5], the users' feedbacks and recommendations controls the quality of information by considering the kind of the recommender for example the recommendation of document by a doctor for a novice user is more rated than the recommended by the novice user for novice user. Some rules are defined for storing and defining the most relevant rate of recommendation. The terminological explanations also are reused for the document recommendation.

3.4 Scenario of uses and integration

Figure III.5 explain exactly the components of the developed application. The decision support system described in the section III.1 also the explainer agent described in III.2 and the recommender system. All these components infer from the recorded knowledge for achieving their goals. The system contains also Facebook application which uses the FBQL and the FB-API for defining the category of the users via their stored profile information.

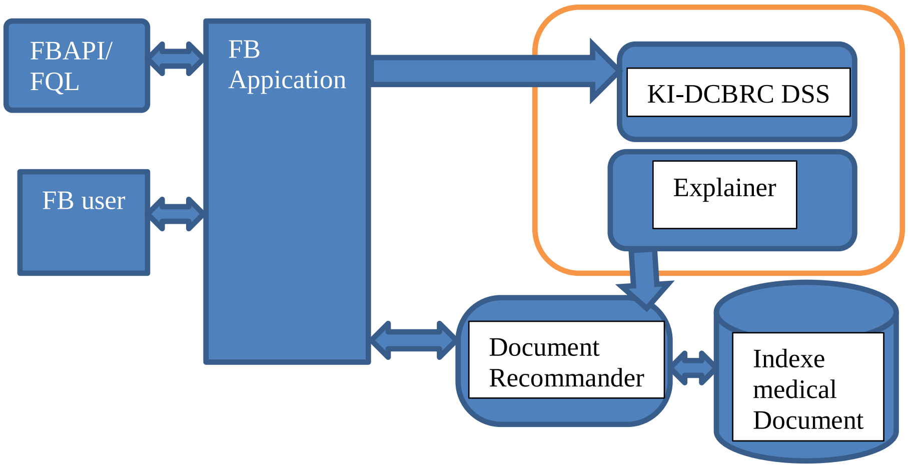


Figure III.5. The architecture of reasoning system

The medical actors as developers, novice and doctors use the system in their Facebook sessions for an ordinary online diagnosis. The system take the user's provided symptoms and measures, introduced interactively in the online diagnosis system, with the needed information from the Facebook user profiles (with permission for ensuring the privacy of users). Following this the system request the diagnosis of this case with the KI-DCBRC and categorize the user by the UC component this categorization is done by another CBR system. The Facebook application makes a tie between the users and the intelligent system by affecting the associated explanation and documents to the appropriate user. The response of the online DSS should be adaptive to the knowledge level of the users which is defined by the UC component. In our context, in which introduce the mass uses of intelligence we deal with an adapted interface which make the deference between a doctor which need the degree of uncertainty and the reasoning trace when he detect a doubt and some journals paper which will increase his knowledge in the detected disease and the patient who need some information about his disease and therapy complements (diet nutritional program, prevention and home intervention).

Feedback collection for future uses

The problem of information quality and relevance will be resolved by the recommendation component which will store the feedback of the categorized users introduced by the interactive explanation interface. The recommendation component will store the users recommendations with the weighting affected via their categories. The recommendation will be stored in a case base inferred by the recommendation component.

User categorization

The user model contains the useful information about his work, his education and his contacts. The existing social networks as Facebook, Linkedin and Viadio provide an access for this information if the user permitted but not all users put the real and the useful information for the categorization. For this there are additional information extracted from their behaviors and network. The case based reasoning can generates an estimated model of user where we can find the needed features as age, title etc by using some stored cases.

In medical applications we can find three class of actors1) the doctor 2) the patient chronic or not 3) the ordinary users who need some information for preventions. Each one of these actors have appropriates needs when exploring a response of the DSS. For example the developer the quality of the application is his aim the causes of decision, the doctor need more arguments in the DSS response and recent professional documents which is connected with the response. The patient also needs to understand the response and the home caring information.

4. Evaluation

Social scientists have also pointed to new issues that can be especially relevant for use of web 2.0 applications in health care. Specific points of renewed concern include: disclosure of authorship and information quality, anonymity and privacy, and the ability of individuals to apply information to their personal situation.[2] all of these criteria touch the information inconsistency. The evaluation of this project will focus on responding if our realized project will ensure these criteria.

4.1 Privacy protection

The Request for Permission in Facebook applications for the access to the basic information including name, profile picture, gender, networks, user ID, list of friends, and any other information made public by the users. Also nearly 60 permissions can be given by the users as email, likes, photos,...etc.

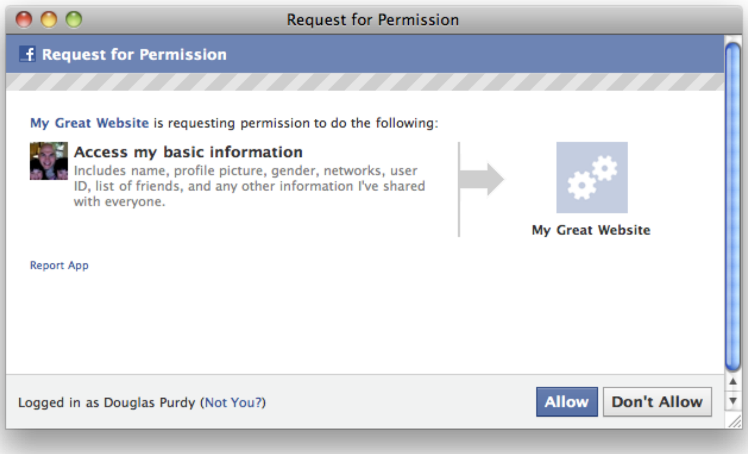


Figure III.6 privacy protection by giving permission by the users in Facebook.

The privacy of the users is offered in the setting of their sessions by defining the public and the private information, but when they use our application a request for permission (as in figure III.6) is appeared for access to their information. Also we can use the information in the graphic network in the case of missed information.

4.2 The information inconsistency

By considering the kind of recommender and the level of abstraction of explanations and the indexed documents the problem of information inconsistency is not appeared in the developed application also the authorships and contradictory information where the professional supervising exist in the system.

5. Conclusion

In this chapter a summery about the realized health 2.0 applications and an original proposal of reasoning system for medical explanation and diagnosis is presented. The developed system implements a strong approach for diagnosis: the Case Based Reasoning enriched by an explanation component and document recommendation component for ensuring the suitable information for all kinds of users (the patient and doctors recognized via their social network information). This proposal aims to reuse the health 2.0 technologies for ameliorating the newest issue in the health 2.0 applications.

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Part 3 Publications

Part III Publications

Introduction and acknowledgments

The research works should be validated and needs an improvement and interchange of experiences between researchers for ensuring a high level of quality and for continues capitalization of knowledge. The following part contains all publications in referee international conferences. Each publication is presented by the title, abstract results and bibliographic information of the article.

I would like to give a thanks for all reviewers, mentors and organizers of each conference which we have published our research works in their proceedings

Paper A: Distributed Case-Based Reasoning classifier for cardiac arrhythmia diagnosis

Authors: Abdeldjalil KHELASSI, Mohamed Amine CHIKH

Abstract

The Case Based Reasoning CBR is an intelligent approach inspirited from many disciplines. It draws the human reasoning model. It consists to use the prior expertise to resolve a new problem. In this work we have used the distributed variant of this paradigm to construct a cardiac arrhythmia classifier. The most important resource of information used by our classifier is the Electrocardiogram (ECG) signal. In this paper we will present the CBR paradigm and its variant called Distributed Case-Based Reasoning which integrates the multi-agent system, the patient model which is the input parameters vectors of our classifier. And finally we will present the classifier architecture, learning and evaluation.

Key words: Distributed Case-Based Reasoning, ECG signal, Automatic cardiac arrhythmias diagnosis.

Results

The main aim of this paper is to explain the developed reasoning system with the aspect of distributed reasoning. Many investigations are done for explaining the engineering process with the implementation choices. As a second result we have introduced the cardiac arrhythmias diagnosis and the contribution of pattern classification for medical diagnosis. The benchmark in this paper have proven a local efficiency for normal and VEB classes but a bad results for the other classes many observation and justifications are inferred from these experiments which help us for starting the new steps.

Published in: proceeding of 10th magrebian conference on software engineering and artificial intelligence MCSEAI'08; April 28-30, 2008 – Oran, Algeria. http://mcseai.simpa-usto.net

Paper B: Automatic recognition of cardiac arrhythmias using a Distributed Case-Based Reasoning classifier

Authors: A.Khelassi, MA Chikh

Abstract.

The automatic cardiac arrhythmias diagnosis using the classification techniques is a complex task and in the same time an important research field which can help to save, in some cases, the human life. The aim of this study is to explain an original architecture of distributed case based reasoning classifier and how we have used it for the identification of Ventricular Ectopic Beats (VEB) and the normal beats. In this paper we present the Case Based Reasoning (CBR) paradigm and its variant called Distributed Case-Based Reasoning (DCBR), the electrocardiogram characteristics and the patient model. Finally we present the classifier architecture and evaluation.

Keywords: Distributed Case-Based Reasoning, ECG signal, automatic cardiac arrhythmias diagnosis, VEB.

Results

In this paper we introduced the aim of using some trends in our reasoning system, as the multi agent system and the case based reasoning. In the other hand we have introduced the usability of our system in the automatic recognize of patterns. Also we have done another experiments with deferent data set for validating and improving the system the system

Published in: Actes du 5ème édition du Colloque sur L'Optimisation et les Systèmes d'Information **COSI 2008, 8-10** juin 2008 Tizi-ouzou Algérie.

Paper C: Distributed classification using Intensive-knowledge Case-Based Reasoning

Authors: A.Khelassi, MA Chikh

Abstract

The intensive knowledge Case Based Reasoning IKCBR consists to use a partial domain knowledge added to the similarity measures between the query and the stored cases. The distributed case based reasoning DCBR consists to distribute the reasoning through a set of agents. To increase the performance and to develop a strong and smart case based reasoning classifier we have used both CBR variants (IKCBR and DCBR). To evaluate our hybrid classifier we have used as a case study the automatic cardiac arrhythmia recognition which consists to classify an input vector extracted from the patient Electrocardiogram. In this paper we will present the approaches used: CBR DCBR, ICBR, our application and the obtained results.

Key words: Distributed Case-Based Reasoning, intensive knowledge case based reasoning, automatic cardiac arrhythmias recognition.

Results

In this paper we have presented a nutshell of some variants of case based reasoning with the novel extension of our reasoning system where we can reinforce the reasoning process by using some production rules written with XML. This extension was validated with deep experiments and comparison with rule based reasoning and similarity based classification. These benchmarks are done using the cardiac arrhythmias data sets. The proposed technique has improved significantly the accuracy of our system

Published in: Recueil des résumés Conférence International des Technologies de l'information et de la communication, P4, CITIC 09 4-5 mai 2009, Setif, Algérie

Paper D: Fuzzy similarity based classification VS intensive knowledge CBR classification applied in the automatic recognition of cardiac arrhythmia

Authors: A.Khelassi

Abstract
The case based reasoning is a paradigm inspired from a human reasoning model it consists to use a stored experience, structured as a cases, to resolve a new problem. This paradigm has a large use in many domains. Also there are many developed variants which give the possibility to solve many kinds of problem as the classification. In this work we have applied the CBR approach in the classification to resolve the problem of automatic cardiac arrhythmias recognize by using two variants: fuzzy similarity based reasoning and intensive knowledge case based reasoning. And we have compared the results given by these variants. In the learning and the evaluation step we have used a training base extracted from the MIT-BIH database which contains a classified and commented cardiac beats by the BIH doctors.
Key words Fuzzy similarity based classification, intensive knowledge CBR, Automatic cardiac arrhythmias recognize.

Results

In this paper we have realized a comparison between the intensive knowledge case based reasoning and the fuzzy similarity based classification. First of all we have introduced the theoretical deference by explaining each approach. After that we have presented the empirical experiments by applying the approaches on the classification of cardiac arrhythmias diagnosis. The result of this study has makes clear that both of these approaches is good but the fuzzy similarity based classification prove more accuracy than the other approach.

Published in: Proceding de la 1ère colloque international sur les Nouvelles Techniques Immuno-cognitives dans les réseaux informatique, NTICRI'09, 10-11 mais 2009 ORAN Algérie.

Paper E: Fuzzy case based classification applied in the classification of breast cancer pattern

Authors: A.Khelassi

Abstract

The case based reasoning is a paradigm inspired from a human reasoning model, it consists of using a stored experience, structured as cases, to resolve new problems. This paradigm has a large use in many domains as planning, information retrieval, classification and other important domains. This work describes a medical application in which we have used the case based reasoning approach with a novel and personalized fuzzy similarity measures function for recognizing the breast cancer class (malignant or benign) from a pattern extracted from the microscopic image of a tissue taken from the patient breast which contains a cancerous cells.

Keywords- *Classification, Case Based Reasoning, Fuzzy sets, Breast cancer diagnosis.*

Results

In this work an original application was applied for the recognize of malgnant breast cancer by enriching the traditional global-local similarity measures by a fuzzy sets adapted to the proposed multi-agnet architecture. An overview about the novel approaches and the related works was presented. The benchmark was done by using an international tested data set published in the UCI deposetory. A positive results descovred in the realized benchmark comparing with the aplied paradigms (linear programin and K Nearest Neigboard).

Published in : Actes du 2ème doctoriales Siences et technologies de l'information et de la communication STIC'11, 20-21 avril 2011, Tébessa, Algérie**.**

Paper E: Title: Fuzzy knowledge-intensive case based classification applied in the automatic cardiac arrhythmias diagnosis

Authors : A. Khelassi, MA Chikh

Abstract. *Case Based Reasoning CBR is an intelligent approach inspired from many disciplines. It draws the human reasoning model. It consists to use the prior expertise to resolve a new problem. In this work we have developed an original fuzzy knowledge intensive case based reasoning system dedicated for the automatic cardiac arrhythmias diagnosis. This application combines between many intelligent approaches and algorithms for satisfying the biomedical needs which are the accuracy and the performance. Through the system criteria and some empirical experiments we can concludes that the classification system achieves such average accuracies and performance better than most of the current state-of-the-art approaches.*

Results

In this paper we have introduced many theoretical aspects of the combined approaches for explaining the advantages of the proposed fuzzy model. After that we have detailed the novel similarity measures model by using a mathematical model which describes the similarity function enriched by fuzzy sets for more semantics. We have applied this technique in cardiac arrhythmias diagnosis and we have observed an important and very significant result not just in the learned classes but also for detection of other classes not learned and not characterized. This conclusion improve the importance of the used technique introduction of unknown response by the similarity agent.

Published in: Proceeding de la 8ème édition du Colloque sur L'Optimisation et les Systèmes d'Information COSI 2011P460, 24 -27 Avril, Guelma, Algérie

Paper F: Data mining application with case based reasoning classifier for breast cancer decision support

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Abstract:

Cytology is a complex diagnosis task which requires both expertise and experience of an oncologist for providing the cancer class and stage which is very useful in the therapy and in the surgery intervention. A case based reasoning classifier is developed with specialized agents for recognizing the malignant breast cancer. The proposed application implements a data mining method for the knowledge extraction and discovery by mining a medical database, which contains classified instances characterized by some features extracted automatically from the cytological image of the patient cancer. An original technique is implemented for enriching the retrieving process on the developed CBR system; this technique is based on the combination of global-local similarity measures and fuzzy sets for modeling the unknown response generated from the agents which increase significantly the accuracy of the system. The features selection and weighting is done by a machine learning algorithm. The efficiency of the proposed methodology has been validated through some empirical experiments applied in the cited data set which demonstrates that the developed approach achieves such average accuracies better than the current state-of-the-art approaches.

Results

In this article a data mining application is described with the developed classifier and the novel fuzzy similarity measures function for knowledge extraction from medical data. The possess of data mining based on classification is defined and evaluated via an international database for breast cancer decision support.

Published in:

Proceedings of MASAUM International Conference on Information Technology 2012 (MICIT'12) ,Liverpool, UK

Paper G: Cognitive Amalgam with a Fuzzy sets and case based reasoning for accurate cardiac arrhythmias diagnosis

Authors: Abdeldjalil Khelassi, Mohammed Amine CHIKH

Abstract. In This paper a cognitive amalgam for inferring from distributed and heterogeneous knowledge bases by using a set of cognitive agents is presented. This cognitive amalgam is developed by combining some intelligent approaches and algorithms, as well as case based reasoning, rule based reasoning, distributed reasoning and fuzzy sets to meet the needs of medical applications and improve their efficiency and transparency. Through the system criteria and some empirical experiments, applied to a data set extracted from the international MIT-BIH Electrocardiogram (ECG) records, it is concluded that the developed system achieves such average accuracies and performances better than most of the cited state-of-the-art approaches.

Keywords: Case Based Reasoning, Distributed reasoning, Fuzzy sets cardiac arrhythmia recognition, ECG.

Results: In this paper a proposal for resolving the problem of inconsistency when multiple source of knowledge is integrated. Several experiments for evaluation are successfully realized.

Published in: Proceedings of the 5th international workshop of Case Based Reasoning On Health Sciences, September 2012 Lyon France Co-located with ICCBR'12.

Synthesis and Conclusion

This thesis is focused on applying the artificial reasoning systems theory for health sciences purposes and by reusing some newest sophisticated technologies for mass and adapted uses. In this thesis a diversity of common problems are treated in the context of medical application as Uncertainty, distributed reasoning, knowledge integration, explanation aware computing, participative applications, health 2.0 and recommender systems.

In this conclusion, we will highlight the main realized contributions in this research project. We address also the proses and the limitations of these contributions. A short evaluation will be given, before we conclude with the future perspectives related to the presented works.

1. Contributions

The main research contributions in this thesis are:

1. Developing a strong case based reasoning system decision support system for medical application where some software criteria are crucial as well as accuracy, efficiency, transparency, interpretability and flexibility. By developing this complex reasoning system some problem was challenged as uncertainty, inconsistency and distributed reasoning.
2. Integrating heterogeneous Knowledge sources for an accurate decision support system, inferring knowledge via a hybrid and distributed approach, enriching the retrieving process in the case based reasoning system with a flexible fuzzy model.
3. Enriching the reasoning system with a cognitive agent for explanation with level of abstraction for a relevant affectation of the explanations kind to the users.
4. Reusing of the terminological explanation and the social information of the users for an adaptive participative document recommendation system which

vises the prevention for the novice users, debugger for the developers and knowledge enrichment for the professional users.

2. Pros and Limitations

There are several applications and researches axes focused on the health sciences as decision support system and home care applications which integrates the information technologies for serving the health. Health sciences applications become pioneer axes of research and investigations. These kinds of applications have critical needs as precision, efficiency, adaptability and information quality.

The presented integration of multiple approaches for ensuring the efficiency of the reasoning systems becomes a major need for many critical domains as the medical domain. The case based reasoning is successfully and widely applied for solving several kinds of complex applications as information retrieval, recommender systems and a diversity of health science application. The rule based system from many years participates in the problem resolving and knowledge presentation but the complexity of knowledge modeling and conflicts is confronted frequently with this paradigm. The nature of environment were the uncertainty with all causes decrease the accuracy of the reasoning system and present an important source of faults in the critical domains as health sciences. The fuzzy paradigm is solicited in this contribution for decreasing the risk and ensuring a flexible and accurate model which increase the transparency by a linguistic variable understand by the explanations' users.

Although, the impact of our contribution ensures many aimed criteria as accuracy, high performance and explanation with a newest reuse of web 2.0 technologies some minor limitation is confronted as the complexity of the partial domain knowledge inherited from the rule based systems, also the medical applications touch human life which is a critical things to serve but the error prevention not yet exist in our reasoning system, the messing information of the social networks platforms presents some risks which decrease the information quality for the recommender system.

3. Perspectives

Due to the limitations cited above some perspectives and propositions will be integrated in the developed reasoning system in the futures versions as well as the integration of uncertainty measures for each decision of the system for the risks problems reusing the probability theory for the prevention of errors, reusing the developed textual CBR application for knowledge extracting from text and reusing the global information model of the users and their traces for an efficient recommendations and affectation of documents.

Another perspective for the future development is to applying this reasoning system for other diseases and for other more complex data as videos of the gastro capsules. For this we invite collaboration of interested researchers and research organisms.

List of figures

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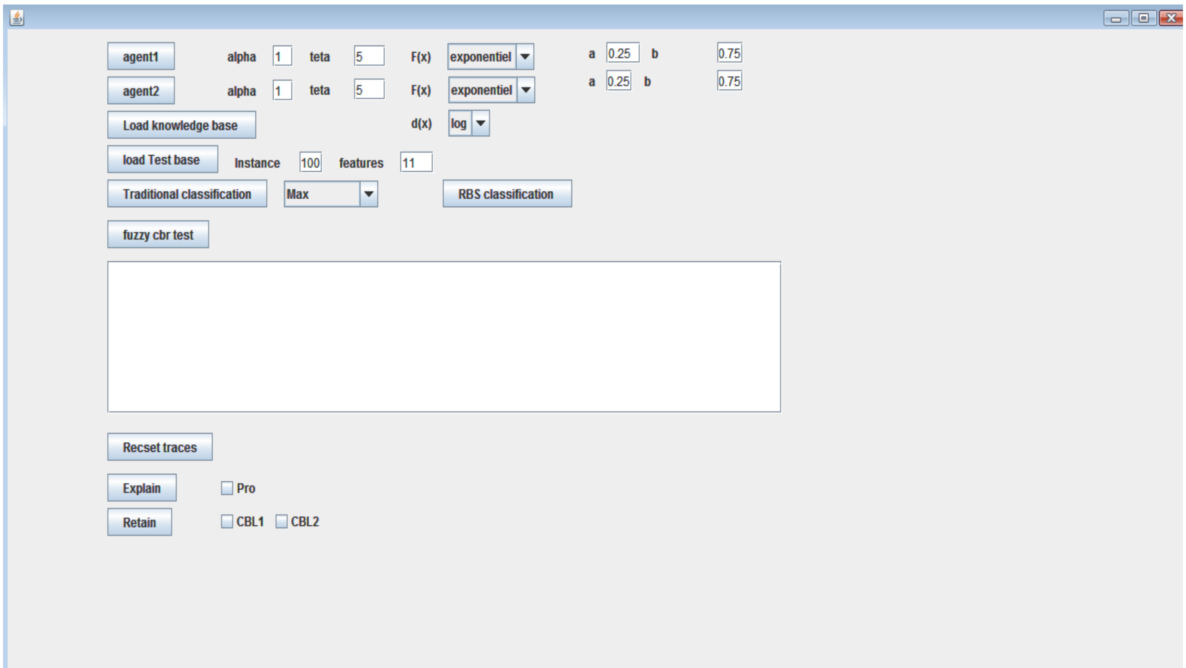
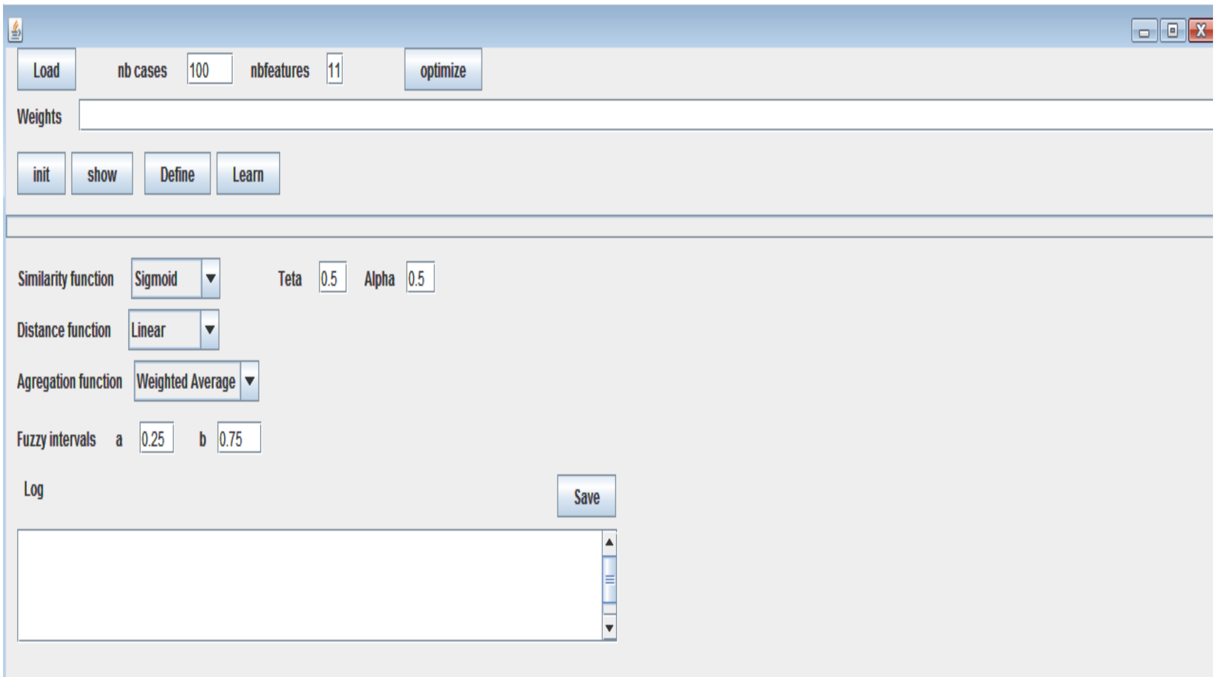
Annex A: Graphical User Interfaces

1. Adaptation agent

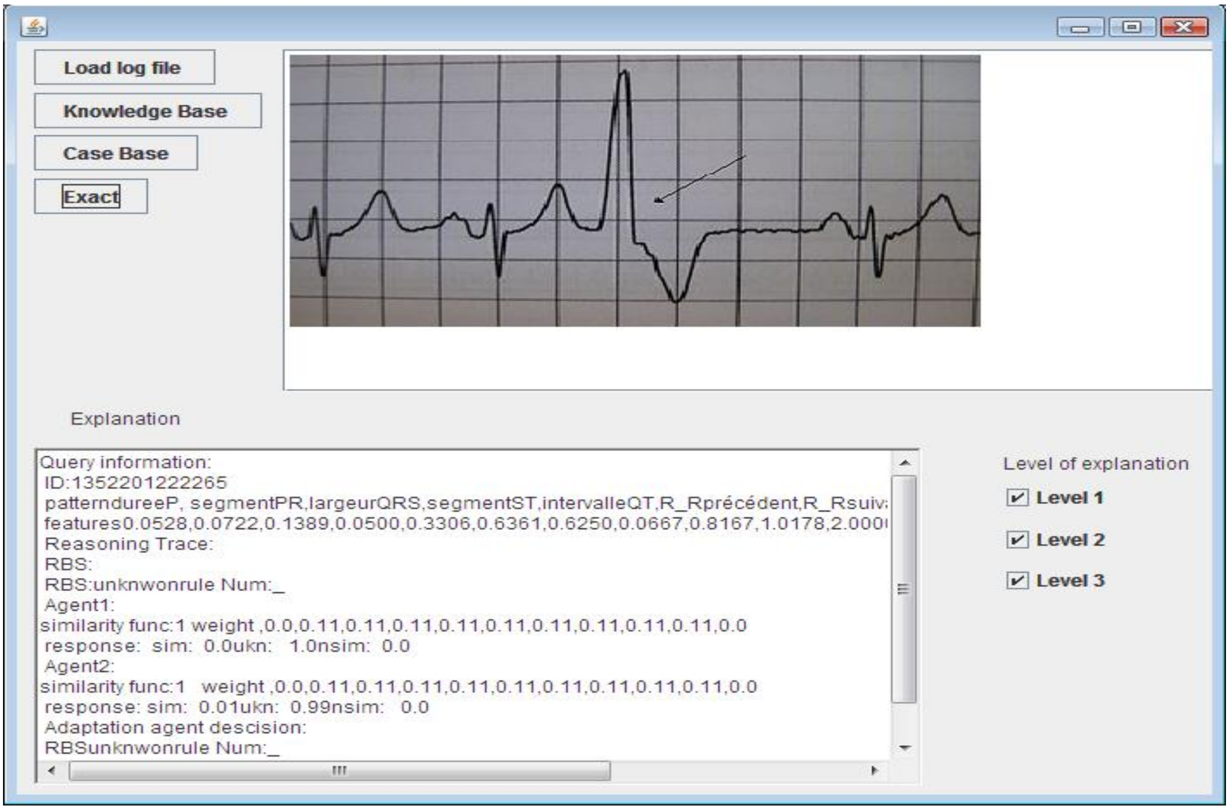


2. Similarity agent

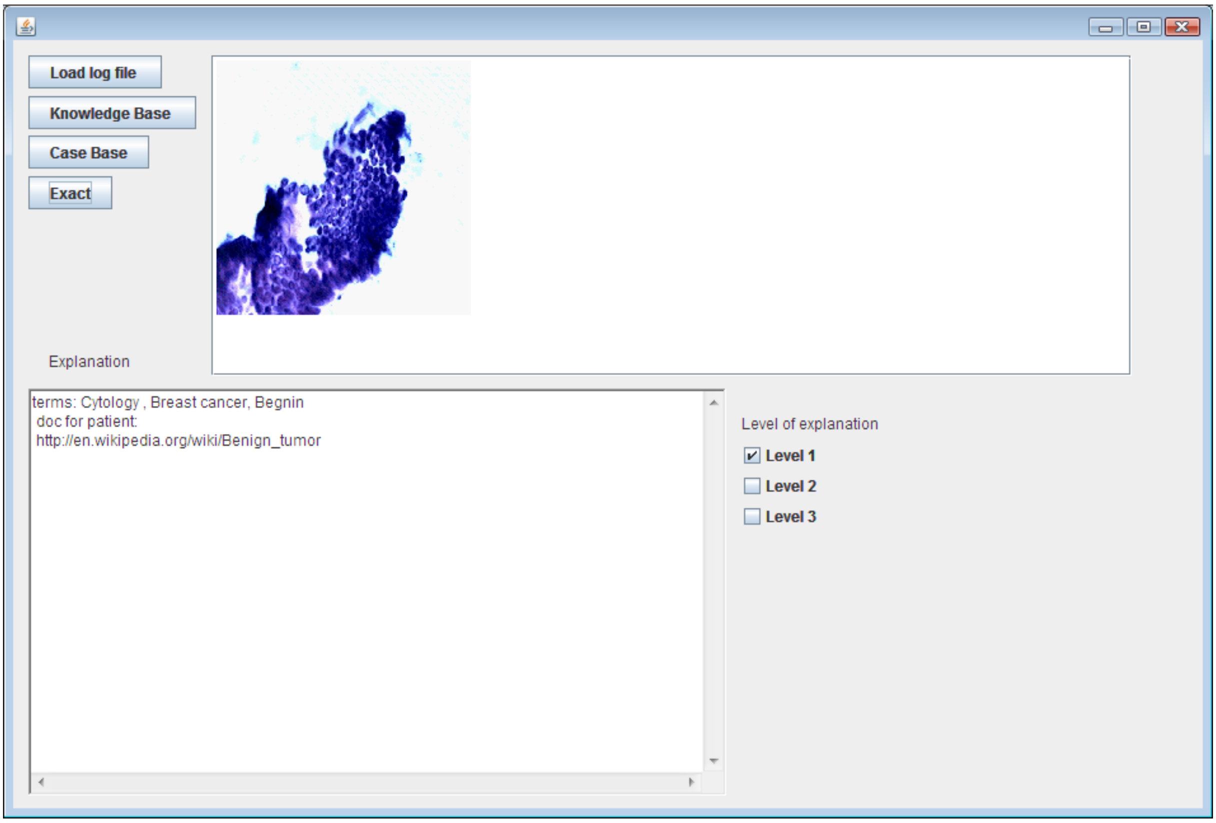


3. Explanation agent

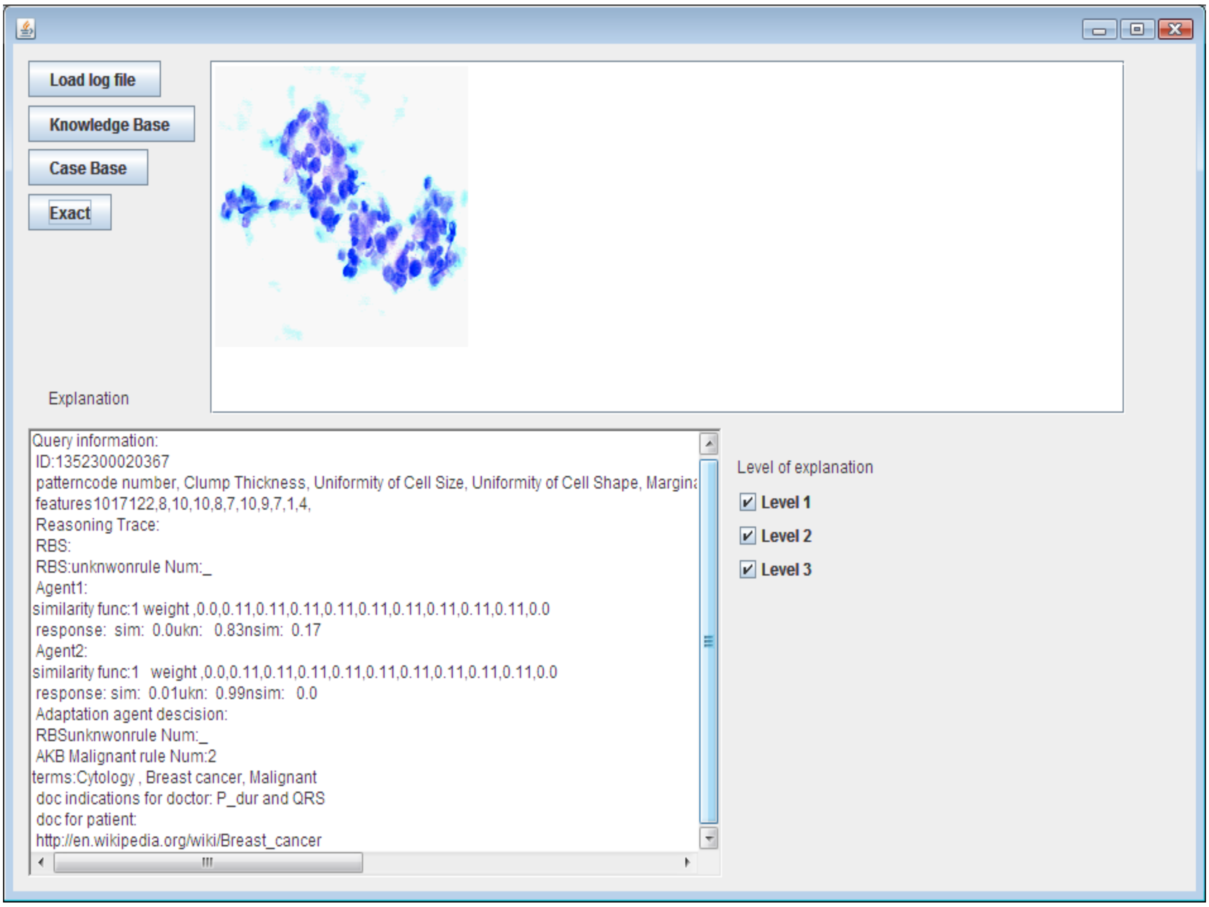
a. PVC



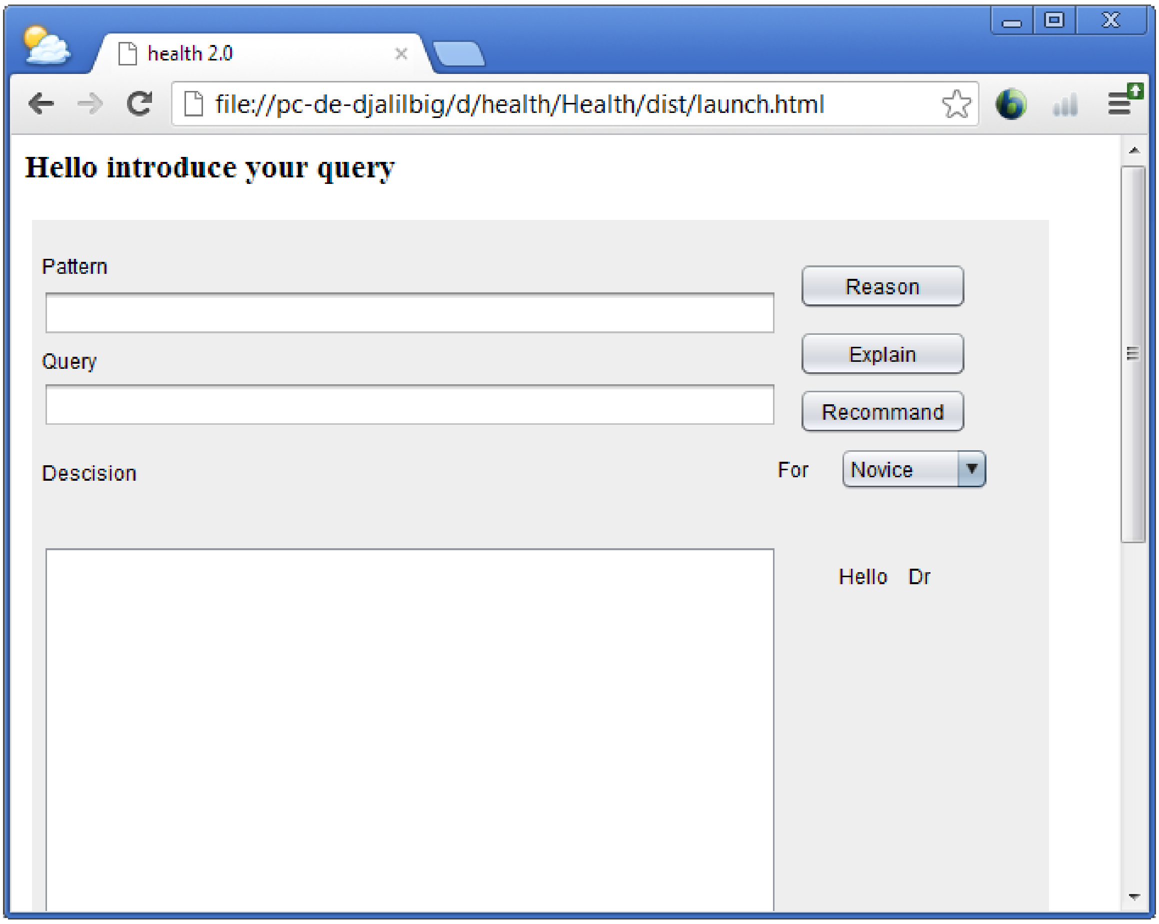
b. Breast Cancer Benign



c. Breast Cancer Malignant



4. Online health 2.0 DSS interface



Annex B Similarity measures functions

1. Traditional similarity measures

$$dist_H(\bar{x},\bar{y}) = \frac{1}{n} \cdot \mid \{i \mid x_i \neq y_i\} \mid \qquad \text{(Hamming Distance)}$$

$$sim_H(\bar{x},\bar{y}) = \frac{1}{n} \cdot \mid \{i \mid x_i = y_i\} \mid \qquad \text{(Simple Matching Coefficient, SMC)}$$

$$sim_{H,\bar{w}}(\bar{x},\bar{y}) = \sum_{i=1,\ x_i=y_i}^{n} w_i \quad \text{with} \quad w_i \geq 0 \quad \text{and} \quad \sum_{i=1}^{n} w_i = 1$$

(Weighted SMC)

$$sim_{H,\alpha}(\bar{x},\bar{y}) = \frac{\alpha \cdot sim_H(\bar{x},\bar{y})}{(\alpha \cdot sim_H(\bar{x},\bar{y})) + (1-\alpha)\cdot(1 - sim_H(\bar{x},\bar{y}))} \qquad \text{(Non-linear SMC)}$$

$$\begin{aligned} sim_{T,f,\alpha,\beta,\gamma}(\bar{x},\bar{y}) \quad = \quad & \alpha \cdot f(\{i \mid x_i = y_i = 1\}) - \\ & \beta \cdot f(\{i \mid x_i = 1 \wedge y_i = 0\}) - \\ & \gamma \cdot f(\{i \mid x_i = 0 \wedge y_i = 1\}) \end{aligned} \qquad \text{(Tversky Contrast Model)}$$

$$dist_{|\cdot|}(\bar{x},\bar{y}) = \frac{1}{n} \cdot \sum_{i=1}^{n} \mid x_i - y_i \mid \qquad \text{(City Block Metric)}$$

$$dist_{Euklid}(\bar{x},\bar{y}) = \sqrt{\frac{1}{n} \cdot \sum_{i=1}^{n} (x_i - y_i)^2} \qquad \text{(Euclidean Distance)}$$

$$dist_{Max}(\bar{x},\bar{y}) = max_{i=1}^{n} \mid x_i - y_i \mid \qquad \text{(Maximum Norm)}$$

$$dist_{Minkowski,p}(\bar{x},\bar{y}) = (\frac{1}{n} \cdot \sum_{i=1}^{n} \mid x_i - y_i \mid^p)^{\frac{1}{p}} \qquad \text{(Minkowski Norm)}$$

$$dist_{Minkowski,p,\vec{w}}(\bar{x}, \bar{y}) = (\sum_{i=1}^{n} w_i \cdot \mid x_i - y_i \mid^p)^{\frac{1}{p}} \qquad \text{(Weighted Minkowski Norm)}$$

2. Base function ($f1$, $f2$) for the Difference-Based Similarity Function

$$sim(\delta(q,c)) = \begin{cases} 1 & : \delta(q,c) < \theta \\ 0 & : \delta(q,c) \geq \theta \end{cases} \qquad \text{(Threshold Function)}$$

$$sim(\delta(q,c)) = \begin{cases} 1 & : \delta(q,c) < min \\ \frac{max-\delta(q,c)}{max-min} & : min \geq \delta(q,c) \geq max \\ 0 & : \delta(q,c) > max \end{cases} \qquad \text{(Linear Function)}$$

$$sim(\delta(q,c)) = e^{\delta(q,c) \cdot \alpha} \qquad \text{(Exponential Function)}$$

$$sim(\delta(q,c)) = \frac{1}{e^{\frac{\delta(q,c) - \theta}{\alpha}} + 1} \qquad \text{(Sigmoid Function)}$$

The **Jaccard distance**, which measures *dis*similarity between sample sets, is complementary to the Jaccard coefficient and is obtained by subtracting the Jaccard coefficient from 1, or, equivalently, by dividing the difference of the sizes of the union and the intersection of two sets by the size of the union:

$$J_\delta(A,B) = 1 - J(A,B) = \frac{|A \cup B| - |A \cap B|}{|A \cup B|}.$$

Tanimoto goes on to define a distance coefficient based on this ratio, defined over values with non-zero similarity:

$$T_d(X,Y) = -\log_2(T_s(X,Y))$$

Presented in mathematical terms, if samples *X* and *Y* are bitmaps, X_i is the *i*th bit of *X*, and $\land, \lor$ are bitwise *and*, *or* operators respectively, then the similarity ratio T_s is

$$T_s(X,Y) = \frac{\sum_i (X_i \land Y_i)}{\sum_i (X_i \lor Y_i)}$$

Annex C domain knowledge base

The used domain knowledge base for reasoning is represented in an XML fashion inferred by JRULEENGINE.

The following sample which is applied in the cardiac arrhythmias diagnosis contains a partial knowledge about the VEB and the normal classes.

```
<?xml version="1.0" encoding="UTF-8"?>
<rule-execution-set>
   <name>cardiac arrhythmias</name>
   <description>Rule Execution Set </description>
<synonymn name="prop" class="org.jruleengine.Clause" />
<!--
Rules for the detection of PVC and normal beat heart
-->
   <rule name="Rule1" description="PVC" >
<if leftTerm="q.c[0]" op="=" rightTerm=0 />
<if leftTerm="q.c[3]" op=">" rightTerm=0.14 />
<if leftTerm="q.c[3]" op="<" rightTerm=0.12 /> <then meth-
od="prop.setClause" arg1="PVC" />
   </rule>
   <rule name="Rule2" description="Normal" >
<if leftTerm="q.c[0]" op="<" rightTerm=0.11 />
<if leftTerm="q.c[1]" op=">" rightTerm=0.12 />
<if leftTerm="q.c[1]" op="<" rightTerm=0.20 /> <if leftTerm="q.c[2]"
op=">=" rightTerm=0.06 />
<if leftTerm="q.c[2]" op="<" rightTerm=0.10 /> <if leftTerm="q.c[4]"
op=">=" rightTerm=0.35 />
<if leftTerm="q.c[4]" op="<" rightTerm=0.39 /> <then meth-
od="prop.setClause" arg1="Normal" />
   </rule>
</rule-execution-set>
```

DTD for a Rule Execution Set XML file

Rules can be defined in an XML file. This file must respect the following DTD:

```
<!ELEMENT rule-execution-set (name, description, synonymn*, rule*)>
<!ELEMENT name (#PCDATA)>
<!ELEMENT description (#PCDATA)>
<!ELEMENT synonymn>
<!ATTLIST synonymn name CDATA #REQUIRED>
<!ATTLIST synonymn class CDATA #REQUIRED>
<!ELEMENT rule (if*, then*)>
<!ATTLIST rule name CDATA #REQUIRED>
<!ATTLIST rule description CDATA #REQUIRED>
<!ELEMENT if >
<!ATTLIST if leftTerm CDATA #REQUIRED>
<!ATTLIST if op CDATA #IMPLIED>
<!ATTLIST if rightTerm CDATA #IMPLIED>
<!ELEMENT then >
<!ATTLIST then method CDATA #REQUIRED>
<!ATTLIST then arg1 CDATA #IMPLIED>
<!ATTLIST then arg2 CDATA #IMPLIED>
...
<!ATTLIST then argN CDATA #IMPLIED>
```

Annex D XML-ACL messages

The following DTD specifies the encoding of the abstract FIPA specification as an XML message:

```
<!--
Document Type: XML DTD
Document  Purpose:  Encoding  of  FIPA  ACL  message  envelopes  (as  in
[FIPA0067]).
See http://www.fipa.org
Last Revised: 2000-08-16
-->
<!ELEMENT     envelope               ( params+ )>
<!ELEMENT     params                 ( to?,
                                      from?,
                                      comments?,
                                      acl-representation?,
                                      payload-length?,
                                      payload-encoding?,
                                      date?,
                                      encrypted?,
                                      intended-receiver?,
                                      received?,
                                      user-defined* )>

<!ATTLIST     params                  index CDATA #REQUIRED>

<!ELEMENT     to                     ( agent-identifier+ )>

<!ELEMENT     from                   ( agent-identifier )>

<!ELEMENT     acl-representation     ( #PCDATA )>

<!ELEMENT     comments               ( #PCDATA )>

<!ELEMENT     payload-length         ( #PCDATA )>

<!ELEMENT     payload-encoding       ( #PCDATA )>

<!ELEMENT     date                   ( #PCDATA )>

<!ELEMENT     intended-receiver      ( agent-identifier+ )>


<!ELEMENT     agent-identifier       ( name,
                                      addresses?,
                                      resolvers?,
                                      user-defined* )>

<!ELEMENT     name                   ( #PCDATA )>

<!ELEMENT     addresses              ( url+ )>

<!ELEMENT     url                    ( #PCDATA )>

<!ELEMENT     resolvers              ( agent-identifier+ )>

<!ELEMENT     received               ( received-by,
                                      received-from?,
                                      received-date,
```

```
                                              received-id?,
                                              received-via?,
                                              user-defined* )>

<!ELEMENT     received-by             ( url )>
<!ELEMENT     received-from           ( url )>
<!ELEMENT     received-date            EMPTY>
<!ATTLIST     received-date            value CDATA #IMPLIED>
<!ELEMENT     received-id              EMPTY>
<!ATTLIST     received-id              value CDATA #IMPLIED>
<!ELEMENT     received-via             EMPTY>
<!ATTLIST     received-via             value CDATA #IMPLIED>
<!ELEMENT     user-defined            ( #PCDATA )>
<!ATTLIST     user-defined             href CDATA #IMPLIED>
```

Here is a simple example of an envelope conforming to the DTD described above:

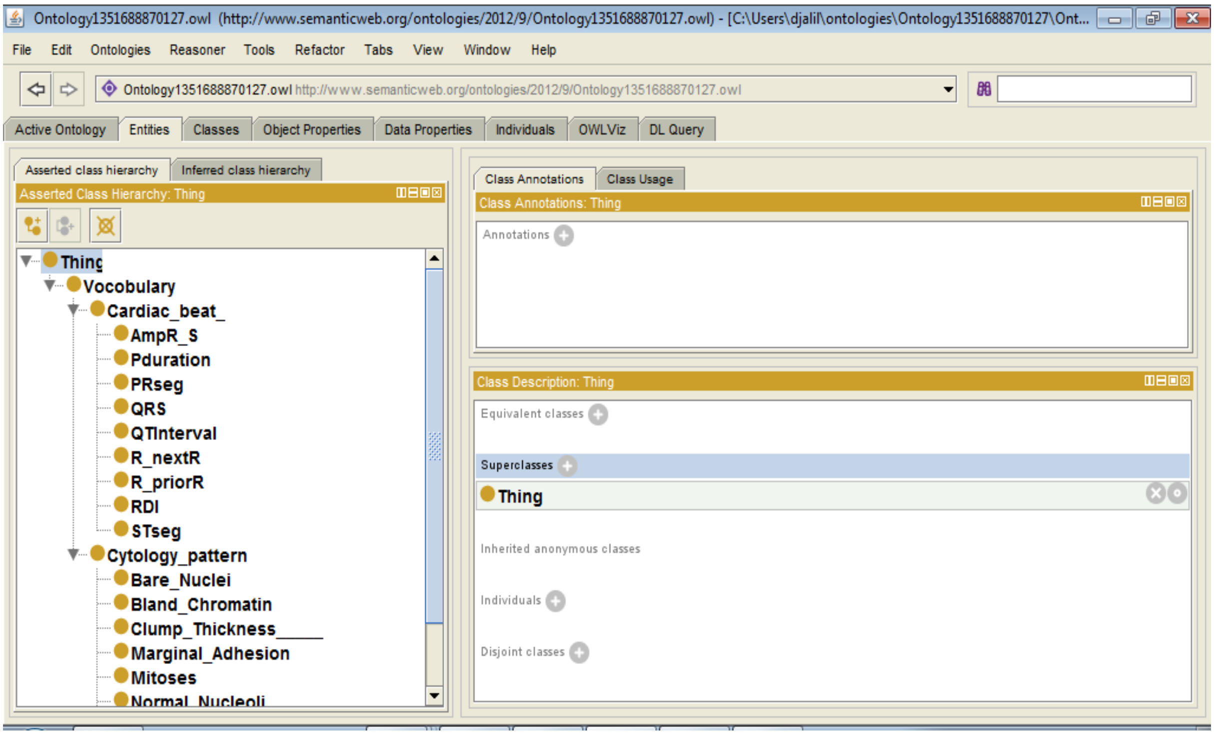
```
<?xml version="1.0"?>
<envelope>
  <params index="1">
    <to>
      <agent-identifier>
        <name>receiver@foo.com</name>
        <addresses>
          <url>http://foo.com/acc</url>
        </addresses>
      </agent-identifier>
    </to>
    <from>
      <agent-identifier>
        <name>sender@bar.com</name>
        <addresses>
          <url>http://bar.com/acc</url>
        </addresses>
      </agent-identifier>
    </from>

    <acl-representation>fipa.acl.rep.xml.std</acl-representation>

    <date>20000508T042651481</date>

    <received >
      <received-by value="http://foo.com/acc" />
      <received-date value="20000508T042651481" />
      <received-id value="123456789" />
    </received>
  </params>
</envelope>
```

Annex E the vocabulary ontology



Abbreviations

ACL	Agent Communication Language
AI	Artificial Intelligence
ANFIS	Artificial Neuronal Fuzzy Inference System
ANN	Artificial Neuronal Network
AUCF	Absolute Case Utility Feedback
AUF	Absolute Utility Feedback
CB	Case Base
CBL	Case base learning
CBML	Case-Based Mark-up Language
CBRS	Case Based Reasoning System
DAML-oil	DARPA Agent Markup Language-Ontology Interchange Language
DCBR	Distributed Case Based Reasoning
DSS	Decision Support System
DTD	Document Type Definition
EA	Evolutional Algorithms
EASD	Explanation-aware Software Design
ECCBR	European Conference on Case Based Reasoning
ECG	ElectroCardioGram
EXACT	*Explanation aware computing*
FAQ	Frequently Asked Questions
FL	Fuzzy Logic
FNA	Fine Needle Aspirates
FOL	First Order Logic
GA	genetic algorithms
GS	Global Similarity
GUI	Graphical User Interface
HPC	High Performance Computing
ICCBR	International Conference on Case Based Reasoning
IK-CBR	Intensive Knowledge-Case Based Reasoning
IR	information Retrieval
IT	*Information technologies*
JSR	Java Specification Requests
KBS	Knowledge Based System
KQML	Knowledge Query and Manipulation Language
LBBB	Left Bundle Branch Block

LS	Local Similarity
LSMC	Linear Simple Matching coefficient
MACE	The mining and analysis continuum of explaining
MAS	Multi Agents System
MIT-BIH	Massachusetts Institute of Technology-Beth Israel Hospital
ML	Machine Learning
OWL	Web Ontology Language
OWL-DL	Web Ontology Language-Description Logic
PSM	Probabilistic Similarity Models
PVC	Premature Ventricular Contraction
RBBB	Right Bundle Branch Block
RBS	Rule Based System
RCUF	Recursive Case Utility Feedback
RDF	Resource Description Framework
RSS	Rich Site Summary
SMC	Simple Matching coefficient
TBRS	Trace Based Reasoning Systems
TCBR	Textual Case Based Reasoning
UI	User Interface
UML	Unified Modeling Language
WSMC	Weighted Simple Matching coefficient
XML	Extensible Markup Language

تلخيص

نظم التفكير الاصطناعي اصبحت الآن قوية جدا لحل الكثير من المشاكل المعقدة في جميع المجالات وبالخصوص في العلوم الصحية. أيضا هناك العديد من التحقيقات في هذا المجال والتي تركز على الجمع بين النمذجة تنفيذ بعض الطرق الذكية لاستكشاف المعرفة المفيدة استخراج تلقائيا من مستودعات البيانات أو النمذجة من خبرات الخبراء والتي تمثل نتائج سنوات عديدة من الملاحظات التجريبية. في هذه الأطروحة حققنا في كثير من الجوانب النظرية لخدمة المجال الطبي التي تحمي حياة البشر عن طريق الكشف ورعاية وحماية الصحة.

كتطبيق اساسي في العلوم الصحية : التشخيص بمساعدة الحاسوب أو أنظمة دعم القرارتتخذ مكانة هامة في سوق البرمجيات وكذلك في المجتمع. مجموعة متنوعة من النظم اصدرت للاستجابة لتحديات واحتياجات العلوم الطبية لضمان مستوى عال من الرعاية الصحة من خلال ضمان الدعم والتسهيلات للجهات الفاعلة الطبية.

ExACt: الحوسبة بالتفسيير المدرك مع العديد من الأهداف وأنواع كثيرة من التفسيرات هو اتجاه مناسب لجميع مستخدمي تكنولوجيا المعلومات الطبية بما في ذالك الأطباء المطورين وحتى المرضى. لتطوير علاقة قوية تقوم على الثقة بين التطبيقات الطبية الذكية المعقدة والمستخدمين.

تركز هذه الأطروحة على قسمين الأول هو وصف للكثير من الجوانب النظرية في مجال التفكير الاصطناعي كالتفكير بحسب الحالات, و التفكير الموزع باستخدام النضم متعددة العملاء , والتفكير بوجود الارتياب باستخدام نظريات المجموعات المبهمة.أما الجزء الثاني فقد تضمن وصف مساهماتنا في العلوم الطبية: المساهمة الأولى تتعلق بتطوير نضام لتشخيص الطبي بمساعدة الكمبيوتر وقد تم تطبيقه في الكشف عن عدم انتظام ضربات القلب وسرطان الثدي باستخدام البيانات المأخودة من الإشارة الكهربائية للقلب و الصورة المكروسكوبة للنسيج الخلوي للسرطان و باستخدام ايضا مزيج من نظريات التفكير الاصطناعي و الطرق الذكية. المساهمة الثانية، وهي تكملة للجزء الأول، برنامج لشرح القرارات المتخدة من نضام التفكير المطور و اعادة استخدام التفسيرات الاصطلاحية لتوصية ذات فاعلية للوثائق و النصوص الملائمة لنوع المستخدم عن طريق التقنيات التشاركية من web2.0.