Agent Based Decision Support Systems in Medicine

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Abstract: - Embedding Machine Learning technology into Agent Driven Diagnosis Systems adds a new potential to the realm of Medicine, and in particular to the imagiology one. However, despite all the research done in the last years on the development of new methodologies for problem solving, in terms of the design of MultiAgent Systems (MAS) there is none where both the agent and the organizational view can be modelled. Current multi-agent approaches to problem solving either take a centralist, static approach to organizational design or take an emergent view in which agent interactions are not pre-determined, thus making it impossible to make any predictions on the behavior of the whole systems. Most of them also lack a model of the norms in the environment that should rule the behaviour of the agent society as a whole and/or the actions of the individuals. In this paper, it is proposed not only a framework for modelling and run agent organizations, but also to depict the different components of such societies. To illustrate these premises, we will evoke a society with one modality, the Axial Computed Tomography one, where two different but complementary computational paradigms, the Artificial Neural Networks and the Case Based Reasoning are object of attention.

Keywords: - Artificial Intelligence, Agent Based Decision Support Systems in Medicine, Artificial Neuronal Networks, Case Based Reasoning, Extended Logic Programming.

1 Introduction

Artificial Intelligence (AI) is the realm of Medicine, either in diagnostic or educational, laboratorial or machine learning processes that may elaborate in new forms of knowledge. Indeed, contemporary Medicine has moved away from seeing disease in isolation, to understand that illness occurs at a complex system level, i.e. by seeing things at a meta level one come ever closer to understand what it really means to be diseased, and how that state may or may not be reversed.

AI may support both the creation and the use of medical knowledge, namely in generating alerts or reminders; providing diagnostic assistance; judging on therapy critiquing and planning. That is the case when it looks for inconsistencies, errors and omissions in existing treatment plans based upon a patient specific condition and accepted guidelines, using agents and agent-based technology for information retrieval and update[1][2]. A case that is triggered when an agent knows the patients preferences and needs and uses the Internet to search and retrieve information; or in image recognition and interpretation, a case that is relevant, for example, in mass-screenings, when the system can flag potentially abnormal images for human attention. Indeed the majority of computer vision applications used in diagnostic reporting in Medical Imaging involve real time analysis and description of object behavior from image sequences.

In the traditional clinical process, the physician elaborates on a pattern that matches the interpretation of the clinical data on a generic clinical model that emerges as a consequence of the education and experience of the expert. However, the reasoning process may be improved if the physician is able to:

- ask for support or an opinion;
- consult the evolution of the clinical past data and forecasts from it;
- visualize studies, clinical analysis and images.

With access granted to Clinical and Historical Databases, agent technology may provide answers to those who give assistance to patients with a maximum of quality and medical evidence.

2 The MEDsys Framework

The use of AI in Medicine is primarily concerned with the construction of AI programs that performs diagnosis and makes therapy recommendations.

Unlike medical applications based on other programming techniques, such as the purely statistical and probabilistic ones, medical AI programs are based on symbolic descriptions of diseases, and their relationship to patient factors and clinical manifestations [3]. The strategy is to compare a modality independent model with the image via an intermediate symbolic feature space. The system is characterized by the use of explicit anatomical models for the visualization of the anatomical structures identified in the image segmentation. The anatomical model makes a major component of the system, and is organized in terms of a semantic network. The inference engine handles the decision making praxis during the process of segmenting major anatomical landmarks. It is at this point that enters MEDsys, a formal specification framework that focuses on the organizational dimension, properly modeling not only organizational structures in an agent society (structuring the global behavior of the society) but also the aims and the behavior of the agents from the agent perspective, in terms of logical theories. It also explicitly provides for ontological descriptions of agent interactions, i.e. it focuses on the organizational dimension, properly modeling not only organizational structures in an agent society (structuring the global behavior of the society) but also the aims and behavior of the agents from the agent perspective. It not only explicitly provides for ontological descriptions of agent interactions but, as a formal framework, it facilitates the modeling of especially highly regulated organizations from the abstract level where norms usually are defined to the final protocols and procedures that implement those norms. It also incorporates ontologies to describe and connect the different levels (layers) of norms (Figure 1). It will be used in the development of agent based decision support systems in the area of image interpretation.

3 In the Search for an Answer

One modality was used, the Axial Computed Tomography (CT). The images were in raw data

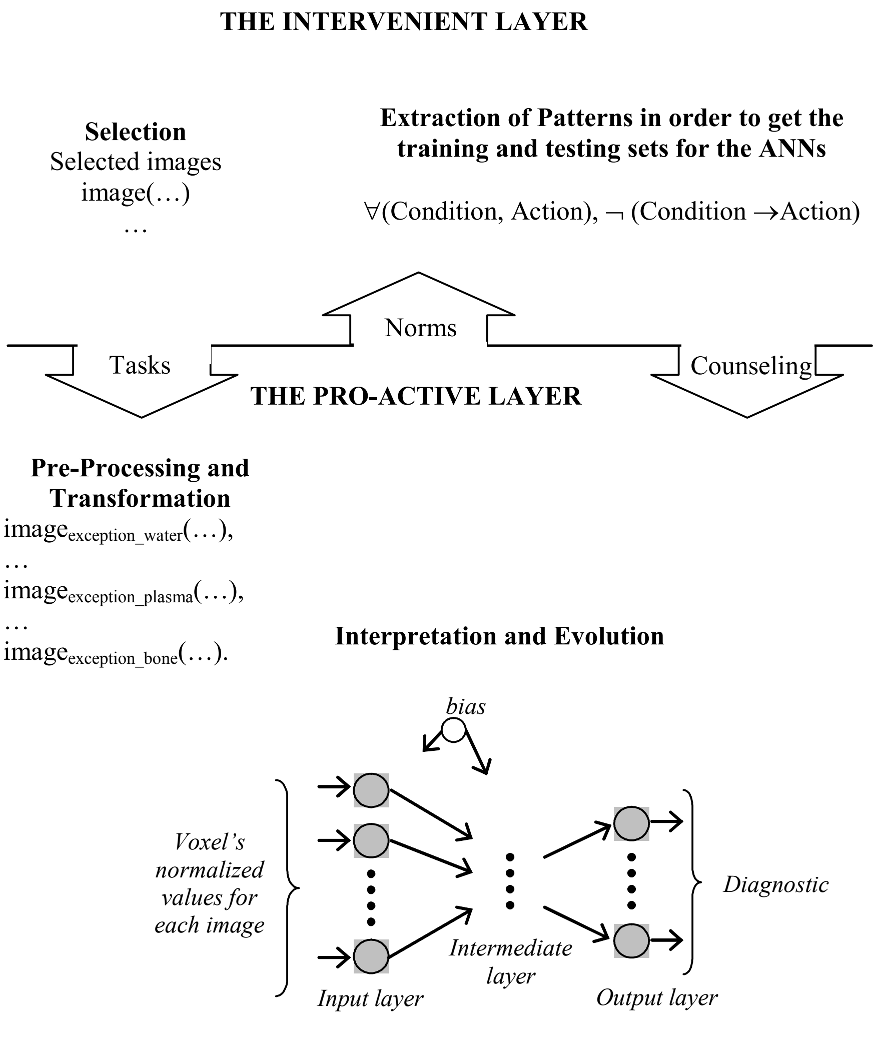

Figure 1 – From ontologies to logical theories

format, and 188 images were selected. The selected images refer to the section of the head that passes through the apex of the squamous part of the occipital bone and the frontal sinus. CT has some advantage over other imaging modalities, once it can provide images of tissue with a variety of contrast levels based on a simple adjustment of the window width and level of the image's raw data, i.e. it provides information that is not seen on film. The images, the patients gender and age were presented to two physicians that pronounced their own judgment according to what is depicted in Table 1 (notice that some of the images point to more than one pathology). It is interesting to notice that under the same circumstances and based on the same information, judgments of the two physicians only match on 78% of the cases (Table 2), which points to the necessity of further judgments, something that can be at the doorstep. The knowledge agent was configured as a multilayered feed forward Artificial Neural Network (ANN) with one hidden layer, bias connections, the logistic activation function and RPROP training [4][5]. 25% of the selected images were used as test cases. The input layer of the ANN is made of the normalized values for each image, plus the patient's gender and age. The output layer is made of its diagnosis (Figure 1).

Table 1 - The physician's judgments.

	Cases	
Agree	147	78%
Partially agree	15	8%
Disagree	26	14%

Table 2 - The physician's match or agreement.

	Physician A		Physician B	
Normal	125	125	111	111
Atrophy	48		62	
Isquemic Lesions	12		24	
Hemorrhagy	6	73	7	101
Malign Tumor	3		3	
Normal Variants	4		5	

In the search for an answer, we look also into the Case Based Reasoning (CBR) techniques for problem solving[6], and postulate that each case is to be given in terms of the extensions and the exceptions of the predicates that make their realm, i.e. for all cases in the case's memory and for each pathology, a set of parameters were selected, and their relevance to the diagnostic evaluated. This process will be accomplished in terms of insights into the most similar case plus the generalization of pathologies with similarities.

- **The most similar case**

When one goes out in the search for an answer, it is usual to look at the simplest form of CBR, i.e. starting from a first case, the process continues with the remaining ones in the search for the most similar case. The CBR life cycle in this situation may be stated as:

- The new case is set, in terms of the patient's data (i.e. the patient's medical records and the new data;
- A comparison between this data and the one in the archive, is accomplished. The similarity between cases is computed in terms of its attributes, following an evaluation function given in the form:

$$\textit{similarity} = \sum_{j=1}^{n} w_j v(x_j) * \textit{quality-of-information}(\textit{case}_i)$$

where w_j and $v(x_j)$ denote, respectively, the weight of attribute x_j in the whole set of the case's attributes and an attribute's valuation measure taken from the interval [0,1]. The assessment of *quality-of-information(case$_i$)* is treated below[7].

- **The interval of values and generalization of pathologies**

For all the cases in the case's memory and for each pathology, a set of parameters were selected [8][9], and their relevance to the diagnostic was evaluated [7][10]. This process is called of pathology generalization. The similarity measure is given, as before, in the form:

$$\textit{similarity} = \sum_{j=1}^{n} w_j v(x_j) * \textit{quality-of-information}(\textit{case}_i)$$

however, under this specific conditions, and in order to evaluate the contribution of each parameter to the diagnostic, their domains are set in advance.

- **The Generalization of pathologies with similarities**

It follows the same approach to problem solving presented in the previous sections, but the similarity measures are considered not in terms of individual cases taken from the cases' memory, but with relation to the most general pathology case. The pathology selected is the one that presents the highest similarities values with respect to all pathologies.

The CBR life cycle is defined as follows:

- A new case is set, in terms of the patient's data (i.e. the patient's medical records and the new data, and given as the extension of suitable predicates and the exceptions to these extensions;
- The new case is re-defined in terms of the extension of an unary meta-predicate $L_p/1$ that evaluates the quality-of-information of each parameter (predicate) (here given in terms of the subscript), a measure of its contribution to the diagnostic;
- Using L_p, a mapping into an hyperspace is built, and the area delimited by the arcs that surround the hyperspace gives a measure of the quality of information carried out by each case under consideration (Figures 2,3,4,5).

In order to model the system, it were considered extended logic programs with two kinds of negation, classical negation ¬ and negation-by-failure *not*. Intuitively, *not a* is *true* whenever there is no reason to believe *a*, whereas ¬*a* requires a proof of the negated literal. An extended logic program (program, for short) *P* is a finite collection of rules *r* of the form:

$$c \leftarrow a_1,\ \ldots,\ a_n,\ not\ b_1,\ \ldots,\ not\ b_m$$

where the a_i, b_j, and *c* are classical ground literals, i.e. either positive atoms or atoms preceded by the classical negation sign ¬ .

One may now obtain, considering the case's parameters (predicates) referred to above, as *gender*/2, *age*/2, *isquemic-lesions*/2, *malign-tumor*/2, and *hemorrhage*/2, the logical theories or programs:

For the *gender/2* predicate:

gender(female,filipa).
gender(gender,luis).

$\neg gender(X,Y) \leftarrow$
    $not\ gender(X,Y),$
    $not\ exception_{gender}(X,Y).$

$exception_{gender}(X,Y) \leftarrow$
    $gender(gender,Y).$

$exception_{gender}(male,pedro).$
$exception_{gender}(female,\ Pedro).$

$exception_{gender}(female,\ joao).$
$exception_{gender}(male,\ joao).$
$exception_{gender}(unknown,\ joao).$

where *gender/2* denotes that predicate *gender* has two arguments. This program is now rewritten in terms of the meta-predicate L_p, taking the form:

$L_{filipa}(female) = 1$
$L_{luis}(gender) = 1/N \approx 0\ (N \gg 0)$
$L_{joão}(female) = L_{joão}(male) = L_{joão}(unknown) = 0.3(3)$
$L_{pedro}(female) = L_{pedro}(male) = 0.5$

For the malign-tumor/2 predicate:

malign-tumor(malign-tumor,filipa).
malign-tumor(lung-tumor,luis).
malign-tumor(melanoma,pedro).

$\neg\ malign\text{-}tumor(X,Y) \leftarrow$
    $not\ malign\text{-}tumor(X,Y),$
    $not\ exception_{malign\text{-}tumor}(X,Y).$

$exception_{malign\text{-}tumor}(X,Y) \leftarrow$
    $malign\text{-}tumor(malign\text{-}tumor,Y).$

$exception_{malign\text{-}tumor}(lung\text{-}tumor,\ joão).$
$exception_{malign\text{-}tumor}(melanoma,\ joão).$

This program is now rewritten in terms of the operator L_p, taking the form:

$L_{filipa}(malign\text{-}tumor) = 1/N \approx 0\ (N \gg 0)$
$L_{luis}(lung\text{-}tumor\ ) = 1$
$L_{pedro}(melanoma) = 1$
$L_{joão}(lung\text{-}tumor)=L_{joão}(melanoma)=1/2 = 0,5$

For the *age/2* predicate:

age(24, filipa).
age(35, luis).

$\neg\ age\ (X,Y) \leftarrow$
    $not\ age(X,Y),$
    $not\ exception_{age}(X,Y).$

$exception_{age}(X,Y) \leftarrow age(age,Y).$

$exception_{age}(28,\ pedro).$
$exception_{age}(33,\ pedro).$

$exception_{age}(50,\ joão).$
$exception_{age}(55,\ joão).$
$exception_{age}(60,\ joão).$
$exception_{age}(65,\ joão).$

This program is now rewritten in terms of the operator L_p, taking the form:

$L_{filipa}(24) = 1$
$L_{luis}(35) = 1$
$L_{pedro}(28) = L_{pedro}(33) = 1/2 = 0,5$
$L_{joão}(50) = L_{joão}(55) = L_{joão}(60) = L_{joão}(65) = 1/4 = 0,25$

For the *hemorrhagy/2* predicate:

hemorrhagy(yes, filipa).
hemorrhagy(no, joão).

¬ hemorrhagy(X,Y) ←
not hemorrhagy(X,Y),
not exception$_{hemorrhagy}$(X,Y).

exception$_{hemorrhagy}$(X,Y) ←
hemorrhagy(hemorrhagy, Y).

exception$_{hemorrhagy}$(yes, luis).
exception$_{hemorrhagy}$(no, luis).
exception$_{hemorrhagy}$(unknown, luis).

exception$_{hemorrhagy}$(yes, pedro).
exception$_{hemorrhagy}$(no, pedro).
exception$_{hemorrhagy}$(unknown, pedro).

This program is now rewritten in terms of the predicate L_p, taking the form:

$L_{filipa}(yes) = 1$
$L_{luis}(yes) = L_{luis}(no) = L_{luis}(unknown) = 1/3 = 0,33(3)$
$L_{pedro}(yes) = L_{pedro}(no) = L_{pedro}(unknown) = 1/3 = 0,33(3)$
$L_{joão} = 1$

For the *isquemic-lesions/2* predicate:

isquemic-lesions(yes, luis).
isquemic-lesions(no, pedro).
isquemic-lesions(isquemic-lesions, joão).
isquemic-lesions(isquemic-lesions, joão).

¬ isquemic-lesions(X,Y) ←
not isquemic-lesions(X,Y),
not exception$_{isquemic-lesions}$(X,Y).

exception$_{isquemic-lesions}$(X,Y) ←
isquemic-lesions(isquemic-lesions,Y).

exception$_{isquemic-lesions}$(yes, filipa).
exception$_{isquemic-lesions}$(no, filipa).
exception$_{isquemic-lesions}$(unknown, filipa).

This program is now rewritten in terms of the predicate *Lp*, taking the form:

$L_{filipa}(\text{ isquemic-lesions}) =$
$L_{filipa}(\text{ isquemic-lesions}) =$
$L_{filipa}(\text{ isquemic-lesions}) = 1/3 = 0,33$

$L_{luis}(\text{ isquemic-lesions}) = 1$
$L_{pedro}(\text{ isquemic-lesions}) = 1$
$L_{joão}(\text{ isquemic-lesions}) = 1/N \approx 0 \ (N \gg 0)$

It is now possible to map the extension of the meta predicate L_p, when applied to predicates *gender/2*, *age/2*, *isquemic-lesions/2*, *malign-tumor/2*, and *hemorrhage/2* with respect to the individuals *filipa*, *luis*, *pedro* and *joão*. This is given in the Figures 2,3,4 and 5.

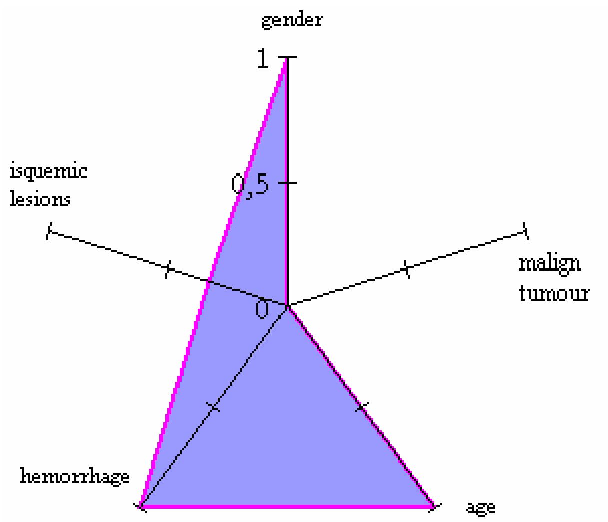

Figure 2 - The quality of information about filipa's state of health.

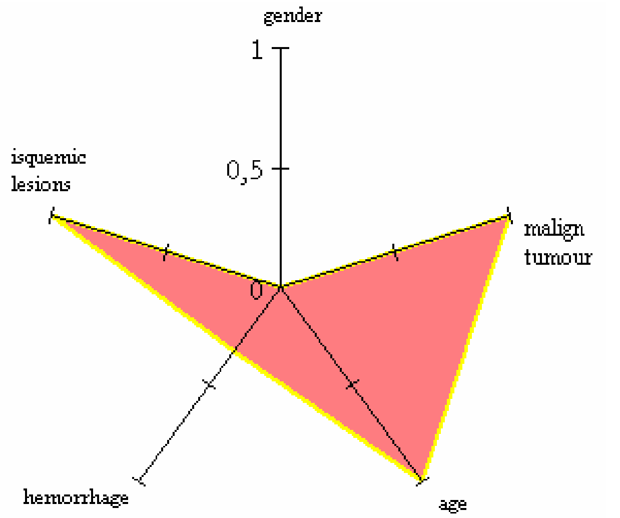

Figure 3 - The quality of information about *luis*'s state of health.

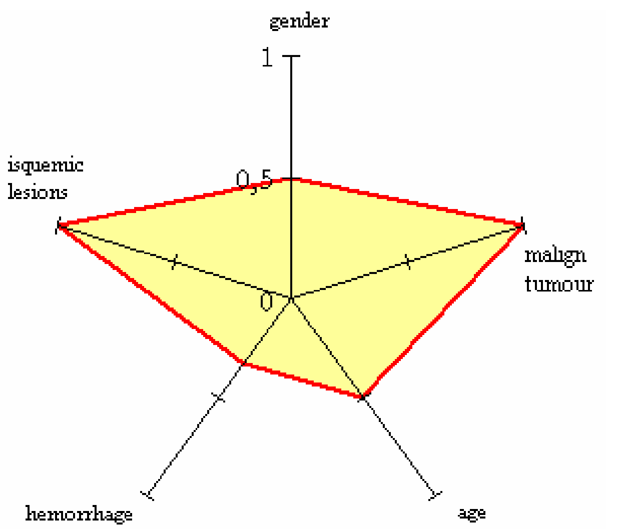

Figure 4 - The quality of information about *pedro*'s state of health.

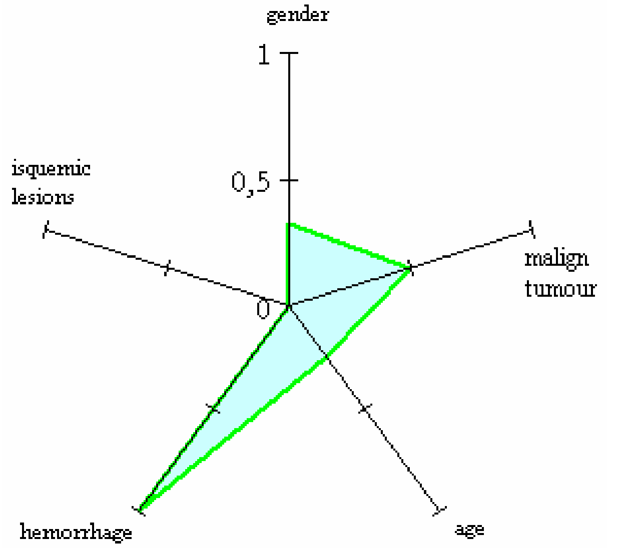

Figure 5 - The quality of information about *joão*'s state of health.

The similarity measures are considered not in terms of individual cases taken from the cases' memory, but with relation to the most general pathology case, and given in terms of the quality of information carried out by each particular logical theory (i.e. the ones given in terms of the extensions and the respective exceptions to such extensions of the predicates *gender/2*, *malign-tumor/2*, *age/2*, *hemorrhagy/2*, *isquemic-lesions/2*. The pathology selected is the one that presents the highest similarities values with respect to all pathologies (Figure 6).

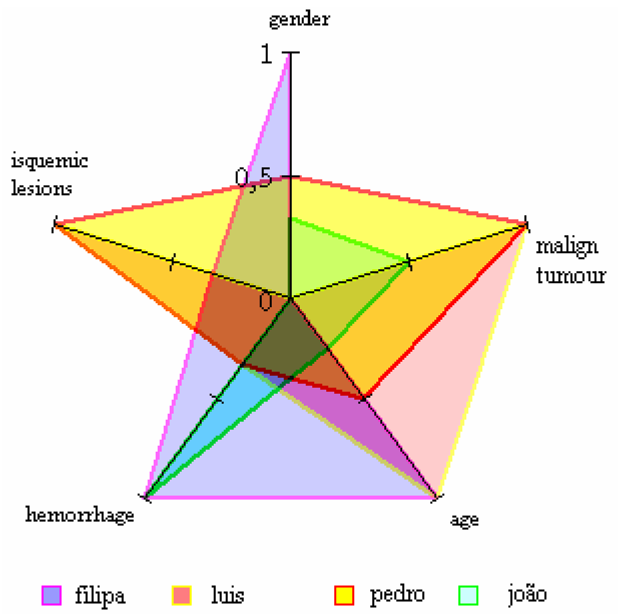

Figure 6 - The general mapping onto the hyperspace of the whole logic theory.

Figures 7 and 8 stand for, respectively, for the best and the worst situations that may arise in the process of measuring or quantifying the quality of the information to be used in the diagnostics.

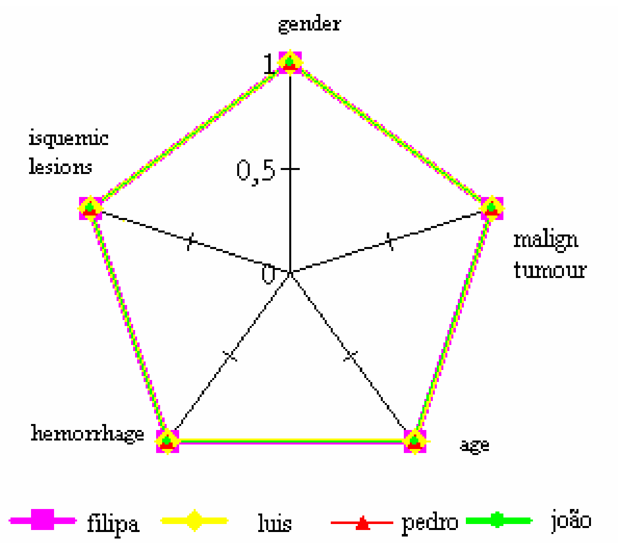

Figure 7 - The desirable (the optimal) mapping onto the hyperspace of the whole logical theory.

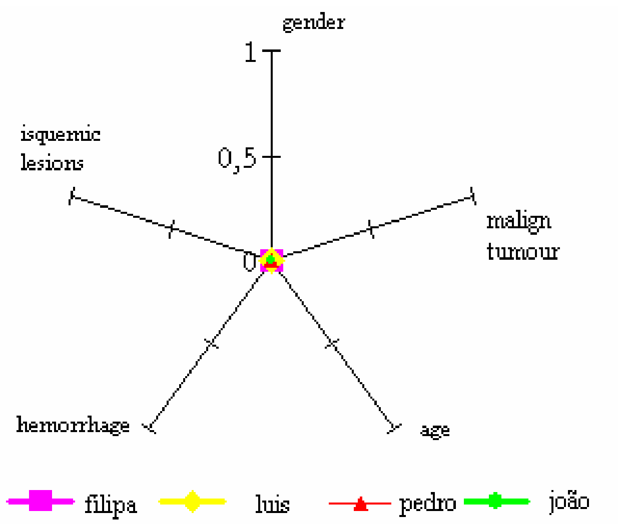

Figure 8 - The undesirable (the worst of all) mapping onto the hyperspace of the whole logical theory.

It is therefore possible, through the evaluation of a simple area, measured on a hyperspace, to quantify not only the quality of the information to be used in a diagnostic (with values taken from the interval [0,1]) undertaken under a CBR approach to problem solving, but also to get the pairs of training/testing cases to train an ANN to be used in forecasting.

4 System Architecture and Planning

Logic is broadly concerned with studying inference and expressive power of formal languages with well-defined semantics. As a representation, a plan guides the deliberation and action of an agent by describing the consequences of a series of actions that the agent can feasibly choose and carry out. Such plans have a variety of uses: agents need them to collaborate with other agents, to respond to changing goals and circumstances, and to narrow its deliberation based on its existing commitments. Plans are more than programs that an agent cooks up, blindly runs, and discards. We explore a representation of plans as proofs in a logical theory of action, time and knowledge. This view not only allows plans to be constructed by logical proof-search techniques, but also allows plans to be transformed and reused respecting proof-theoretic principles. It was under this umbrella that MEDsys was built (Figures 9,10,11,12)[11].

To implement the MEDsys agents, like the diagnostic ones, it was used an extension to the language of Logic Programming [12]. They provide the via for the visualization and exploration of original raw data from the imaging devices (e.g. CT, MR), and the physician front-end to the system, either for image consultation using interactive image visualization functions, namely graylevel windowing (Figure 9), or to obtain diagnostics (Figure 11).

Figure 9 - The Diagnostic Support Agent – A Study request for Diagnostic Purposes.

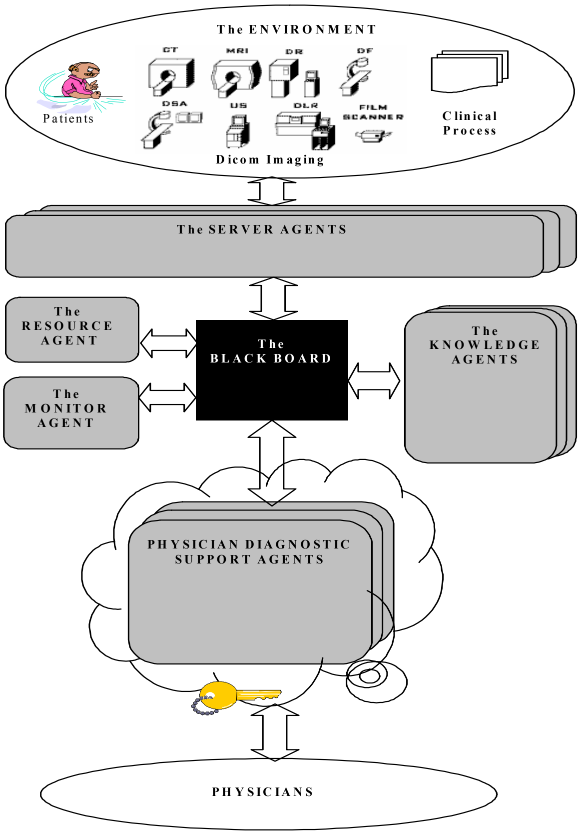

Figure 10- The Medical Diagnostic Support Agents

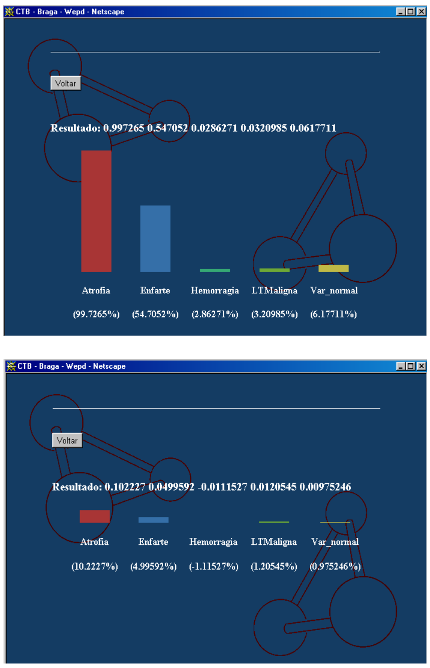

Figure 11 - The Diagnostic Support Agent – The diagnosis generated by the System.

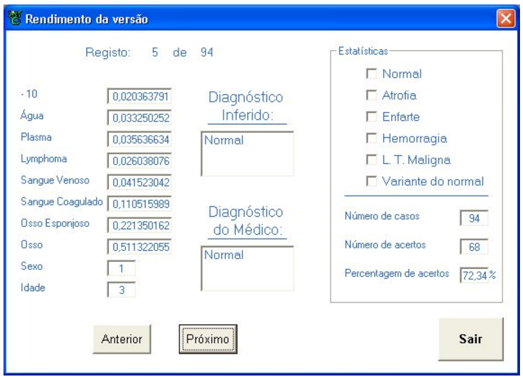

Figure 12 – Getting a Solution

5 Results analysis

In this work we had in mind to assess the possible inclusion of logic based CBR agents in medical diagnosis, being the problem addressed in terms of the most similar case based on the quality of information being carried by each case, interval of values and generalization of pathologies, and generalization of pathologies with similarities. The results are given in Table 3. On the other hand, since we had test cases, it was possible to look to the accuracy of each solution, in a pathology by pathology base, being in this case the results given in Table 4. Taking the results depicted by Tables 3 and 4, it is noted that the highest levels of accuracy happen when one's look at the pathologies individually, although the pattern may not be necessarily the same for all the pathologies. Therefore, it is possible to conclude that the CBR's approach has potential as a diagnosis tool. It is now possible to compare results obtained using ANN's and those gotten with the use of CBR, in order to consider the possibility of integrating CBR in medical diagnosis. The accuracy with ANN's is around 67% [13] (remember that with the same information, two different physicians agreed on 78% of the cases). From the tests referred to above, the first solution presents itself with a slightly better result (72%). When we try just to test if a medical image is "normal" or not, using ANN's we obtained results of 82% [14][15]. Once again the first solution gave the best results, with 89% of accurate outcomes.

Table 3 - Percentage of Accuracy between versions

Version	Accuracy
Most similar Case	72 %
Interval of values and Generalization of pathologies	65 %
Generalization of pathologies with similarities	58 %

Table 4 - Diagnosis accuracy between version and pathology.

Version	Normal	Atrophy	Isquemic	Hemorragy
Most similar Case	89%	60%	50%	0%
Interval of values and Generalization of pathologies	74%	80%	0%	0%
Generalization of pathologies with similarities	64%	65%	50%	33%

Table 5 - Diagnostic accuracy by pathology (ANNs)

Atrophy	Isquemic lesion	Hemorragy
80%	92%	94%

We are now in a position to compare the ANN's and CBR's agent's performances. ANN's shows to be particularly suited for single pathology diagnostics (Table 5), although one's objective, since the beginning, was far away to produce a system to outperform that based on ANN's. The results also show that with a CBR based approach to problem solving, it is possible to produce feasible diagnostics (Tables 3 and 4).

6 Conclusions

This paper shows how to construct a dynamic virtual world of complex and interacting cases and ANNs in which fitness is judged by one criterion alone: quality of information. The architecture underlying this system is versatile, creative and powerful enough to engender a practically infinite variety of data processing and analysis capabilities, adaptable to almost any conceivable intellectual tasks. This virtual world could witness the emergence of a learning, thinking machine, and foray into a vast, untapped technological market. In order to obtain a solution to a particular problem, one looks at a case based repository, in order to find similarities between those cases and the case that is being object of close examination. This praxis allows us to assess the impact of using logic based CBR agents in problem solving, and in particular in the realm of Medicine. It is believed that if more information had been made available, the results so far obtained would be more convincing [14]. It is also believed that we must come to a close integration of ANN's and CBR's technologies; they are not exclusive, but complementary. Usually important is that a logical system have associated with it a metatheory, which would address questions such as whether the system in question is sound, complete, decidable, and so on. Such meta-properties are determined by bringing mathematical tools to bear on the system in question. In this work such a meta-theory was defined in terms of the extension of an unary predicate $L_p/1$ that evaluates the contribution of each case`s parameter (predicate) in terms of the quality of information it carries (given in terms of an area delimited on a hyperspace) into the diagnostic.

7 Acknowledgements

We are indebted to the *SMIC – Serviços Médicos de Imagem Computorizada*, for their help in terms of experts, technicians and machine time.

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