Agent Driven Diagnosis 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 methodologies for designing MultiAgent Systems (MAS), there is no methodology suitable for the specification and design of MAS in complex domains where both the agent view and the organizational view can be modelled. Current multi-agent approaches 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 behavior of the agent society as a whole and/or the actions of individuals. In this paper, we propose a framework for modelling agent organizations, and we illustrate the different components of a society with one modality, the Axial Computed Tomography scenario, combining two methodologies for problem solving, the Artificial Neural Networks and the Case Based Reasoning ones.

Key-Words: - Artificial Intelligence, Agent Based Decision Support Systems in Medicine, Artificial Neuronal Networks, Extended Logic Programming.

1 Introduction

Artificial Intelligence 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.

Artificial Intelligence 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. 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 to Clinical Historic Databases, agent technology may provide answers to those who give assistance to patients with a maximum of quality and medical evidence. Agents can help physicians at this level. This is the aim of MEDsys, here used in computer tomography based diagnosis.

1 The MEDsys Framework

The use of Artificial Intelligence (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 methodologies, 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[6]. 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 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 decision support systems in the area of image interpretation

3 In the Search for an Answer

One modality was used, the Axial Computed

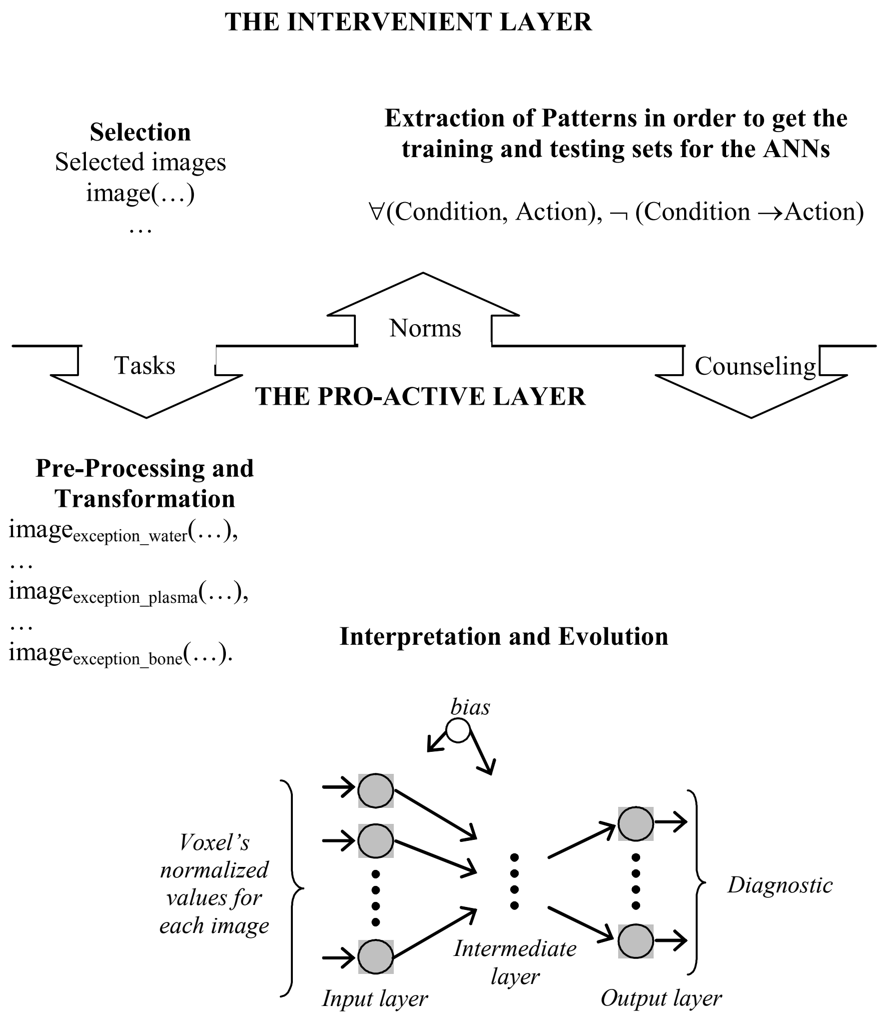

Figure 1 – From ontologies to logical theories

Tomography. The images were in raw data (DICOM) 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. The knowledge agent was configured as a multilayered feed forward ANN with one hidden layer, bias connections, the logistic activation function and RPROP training. 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). 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.

This process will be accomplished in terms of insights into the most similar case, an interval of values and generalization of pathologies, and the generalization of pathologies with similarities. 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.

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.

<table>
<tr><th></th><th colspan="2">Physician A</th><th colspan="2">Physician B</th></tr>
<tr><td>Normal</td><td>125</td><td>125</td><td>111</td><td>111</td></tr>
<tr><td>Atrophy</td><td>48</td><td rowspan="5">73</td><td>62</td><td rowspan="5">101</td></tr>
<tr><td>Isquemic Lesions</td><td>12</td><td>24</td></tr>
<tr><td>Hemorragy</td><td>6</td><td>7</td></tr>
<tr><td>Malign Tumour</td><td>3</td><td>3</td></tr>
<tr><td>Normal Variants</td><td>4</td><td>5</td></tr>
</table>

In the search for an answer, we look also into the Case Based Reasoning (CBR) methodology for problem solving, 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. 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 (i.e. image(s)));
- The new case is re-defined in terms of the extension of an unary predicate L_p that evaluates the contribution of each parameter (here given in terms of the subscript) 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 under consideration (Figures 2,3,4).

We consider extended logic programs with two kinds of negation, classical negation ¬ and default negation *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:

$$c \leftarrow a_1, \ldots, a_n, \mathit{not}\ b_1, \ldots, \mathit{not}\ b_m$$

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 referred to above, as we did with the ANNs referred to above, as gender, isquemic lesions, and hemorrhage, the logical theory or program:

gender(female, *filipa*).
gender(male, *luis*).
gender(*gender*, *pedro*).

¬ gender(X,Y) ←
not gender(X,Y),
not exception(gender,X,Y).

exception(gender,(X,Y) ←
gender(gender,Y).

exception(gender,male, joão).
exception(gender,female, joão).

$L_{filipa}(female) = 1$, $L_{luis}(male) = 1$, $L_{pedro} = 1/N \approx 0\ (N \gg 0)$, $L_{jo\tilde{a}o}(female) = L_{jo\tilde{a}o}(male) = 0.5$

insurance(*insurance*, *luis*).
insurance(100000, *joão*).
insurance(150000, *pedro*).

¬ insurance (X,Y) ←
not insurance (X,Y),
not exception(insurance,X,Y).

exception(insurance,X,Y) ←
insurance(seguro,Y).

*exception(insurance,*30000, *filipa).*
*exception(insurance,*50000, *filipa).*

$L_{filipa}(30000) = L_{filipa}(50000) = ½ = 0,5$,
$L_{luis} = 1/N \approx 0$ ($N \gg 0$), $L_{pedro}(150000) = 1$, e $L_{joão}(100000) = 1$

...

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 logical theory. The pathology selected is the one that presents the highest similarities values with respect to all pathologies (Figure 9).

4 System Architecture and Technologies

Logic is broadly concerned with studying inference and expressive power of formal languages with well-defined meanings. Computational logic emphasizes the design of finite inference procedures and analysis of complexity and proof search in them. 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(figure 5,6,7,8,9)[5].

To implement the MEDsys agents, like the diagnostic ones, it was used an extension to the language of Logic Programming [4]. They provide the via for the visualization and exploration of original DICOM 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 8), or to obtain diagnostics (Figure 9).

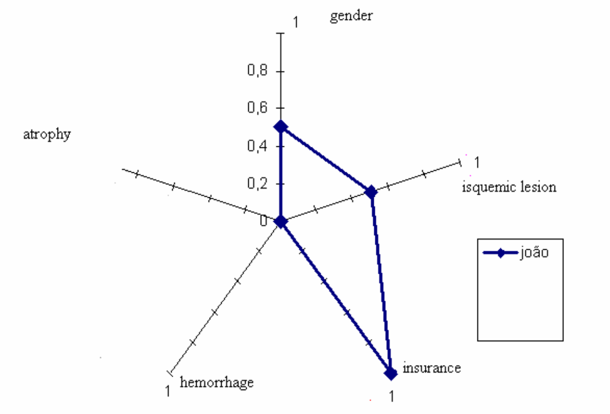

Figure 2 – An hyperspace representation of john's state of health, obtained in terms of operator L_p.

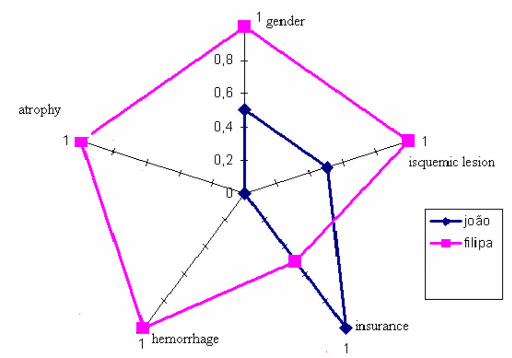

Figure 3 – An hyperspace representation of the john and filipa state of health, obtained in terms of operator L_p.

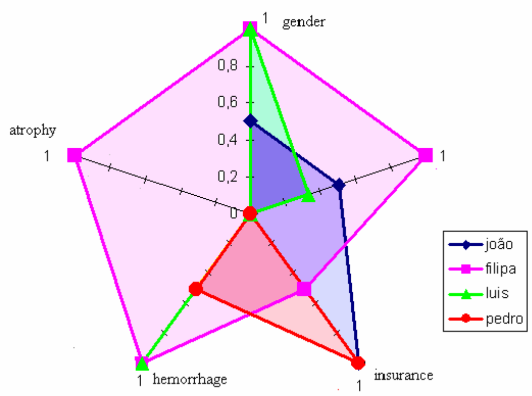

Figure 4 - An hyperspace representation of the john, filipa, luis and peter state of health, obtained

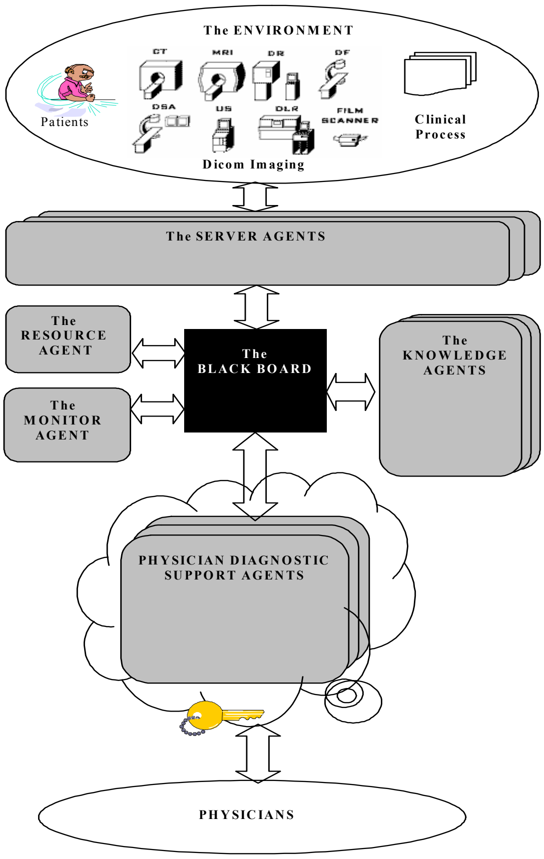

Figure 5- The Medical Diagnostic Support Agents

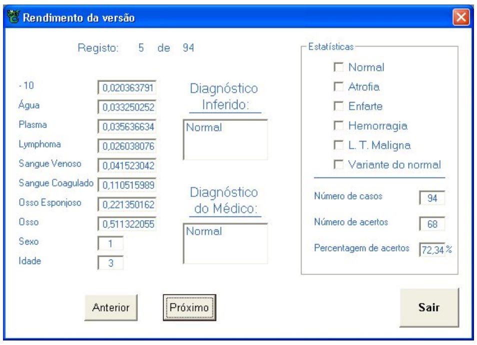

Figure 6 – Getting a Solution

Figure 7 - Data Acquisition

Figure 8 - The Diagnostic Support Agent – A Study request for Diagnostic Purposes.

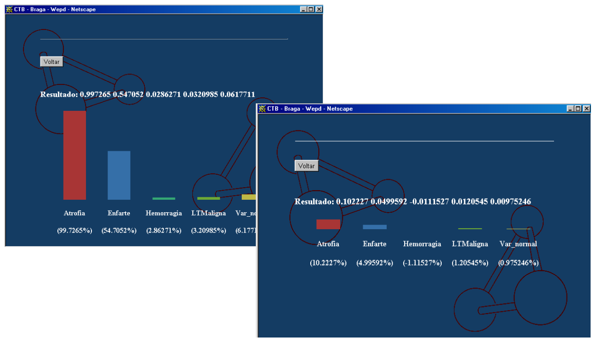

Figure 9 - The Diagnostic Support Agent – The diagnosis generated by the System.

5 Results analysis

In this work we had in mind to assess the possible inclusion of a CBR's based agent 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.

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

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% [3] (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% [1][2]. Once again the first solution gave the best results, with 89% of accurate outcomes.

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 1 and 2).

6 Conclusions

In order to obtain a solution to a particular problem, one looks at the 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 CBR based agents in the realm of Medicine, and it is believed that if more information had been made available, the results so far obtained would be more convincing [1][2]. 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.

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