LINKING O.O.P. AND FUZZY LOGIC FOR BUILDING AN EXPERT SYSTEM

Antonio Gisolfi & Giuseppe Moccaldi
Dipartimento di Informatica ed Applicazioni
Università di Salerno (Italia)

ABSTRACT.

The aim of our work is to design a system in such a way that it can be an example as to how it can be possible to use such methodologies as fuzzy logic and frames, for facing a special problem in the most convenient way. Moreover, we will recall the role a quite new programming methodology, O.O.P. (Object Oriented Programming), played in it, and the reasons that drove us to turn to it, rather than to the well-known structured programming.
The case of study we carried out, consists in an expert system, performing medical diagnoses relavant to the training activity of a group of athletes.

INTRODUCTION: EXPERT SYSTEMS AND MEDICINE

Medicine field is one of those in which problem solving (diagnosis) by a human being, mostly remains entrusted to insight (in this case, physician's insight).
In fact, if on one side there are quite well defined rules, to which one can entrust himself for performing a diagnosis, on another, they are so many, and such, that they don't permit an "automatic" determination allowing no margin to errors: every diagnosis will have vagueness characteristics, as we will see. In reality, it's the physician who always telles the last word, that's usually right, thanks to his theoretical knowledge, to patient supplied information, to experience and insight. We can easily supply a computer with knowledge, but it's more difficult to supply it with the just mentioned characteristics. Therefore, a diagnostic system, however "expert", will essentially play the function of an assistant. It supports the physician by supplying him with the information that might have slipped his mind, helping him in deductions, and letting him get a general view on the situation, before probing deeper into the search.

MEDICINE AND FUZZY DIAGNOSES

We've just mentioned the vagueness of diagnosis. As a matter of fact, different diseases may show themselves by the same symptoms. Such symptoms, on their turn, are highly subjective; for instance, they could just be imaginary, in the sense that a pre-existent malaise situation, might be put into connection, by patient's mind, to a more recent pathology, taking the physician far away from the ascertainment of the real situation. Traditional logics are not fit for managing a "vague" knowledge such this. That's why we rely on "fuzzy" logic, which lets us make qualitative, rather than quantitative, expert's knowledge, and supply fuzzy diagnoses, that is approximate diagnoses, but giving a clear view on the real situation.
We recall that, according to the Zadeh theories the belongings to a fuzzy set is not defined sharply, as in traditional binary logic, but more "vaguely". [1,2]

RULES AND FRAMES

Because of its structure, the particular problem we studied, can be efficiently faced, through the use of "frames" and " production rules". Through frames, knowledge is divided into organized structures with specific properties, connected between themselves in a hereditary transmission hierarchy, which lets common properties to be tranferred between them. On the other hand, rules are essential for making systematic the typical reasoning of human beings.
Therefore, a hybrid architecture showed itself to be fit for our aims. It lets rules be organized in a hierarchy, too, by "attaching" them to the nodes representing the objects they refer to.

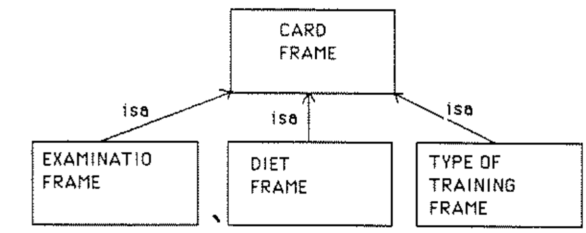
O.O.PROGRAMMING AND SMALLTALK/V

O.O. languages allow us to implement such a structure in an excellent way, as there's a simple and natural correspondence between "frames" and "objects". In fact, one of their properties is the possibility to create easily, hierarchically organized structures. The possibility of creating objects is of fundamental interest, as such objects identify themselves with the frames making up the structure of the system. The O.O. language we used is Smalltalk/V; according our opinion, it's the language most completely possessing the characteristics of O.O. languages. It has showed itself to be extremely efficient, as we expected, in giving the system modularity, and, above all, to be extremely readable. [3,4]

A CASE OF STUDY: AN EXPERT SYSTEM FOR MEDICAL DIAGNOSES

Now, let's show the way theoretical supports we dealt with

till now, are used for carrying out an actual expert system. In the meanwhile, we want to stress again the fact that ours is not a "complete" system, but a demonstration of application in this field, of comparatively new techniques.
We know that a physician must avail himself with a great deal of various information, to obtain a diagnosis with an uncertainty margin, therefore, a "fuzzy" diagnosis. As a consequence, it's immediate to resort to fuzzy logic. The diagnosis will be obtained through production rules, and the problem field is described by frames, implemented as Smalltalk/V objects. [5,6,7,8,9,10]
As to the description of the problem, every patient is associated with a personal card, containing his characteristics, and a description of his health situation, obtained from a medical examination. If we analyse the situation for nearer, we realize that, in reality, an "examination" is a "card"; that is, an "examination" object is nothing more than a particularization of a "card" object. Therefore, we create two frames: "card" and "exam", implemented by a Smalltalk class, and a subclass of such class. The slots of CARD frame (in our case, instance variables of the class bearing the same name, as the concepts coincide) are quite general: NAME, SURNAME, AGE, HEIGHT, WEIGHT. Frame EXAM, instead, as it is a particularization of CARD, possesses its attributes as an inheritance, and moreover, its own attributes, describing patient's symptoms (fig.1).



When assigning values to attributes, fuzzy logic intervenes. Attributes are not constants (like HEIGHT=180 cm., for instance), but "linguistic variables", with the exceptions of NAME and SURNAME. For each of them, a set of values is supplied, the possibility distributions of which are determined "a priori" with the help of the domain expert. When we say "linguistic variables", we mean that the values they take on, are expressions from natural language, which can't find an exact correspondence to numeric values. A correspondence is fixed by assigning such "fuzzy" values, the possibility distribution determined by the domain expert for the fuzzy values. In pratice, for every value of a linguistic variable, there exists a possibility distribution P, and a fuzzy set F, induced by P, defined by Mf(x)=P(x), where x is a "precise" value of the attribute. For instance, the attribute HEIGHT can be considered a linguistic variable, with values "short", "middle", "tall", and so on, for each of which a fuzzy set is defined. If we take into consideration the discrete set of heights (170 175 180 185 190 195 200 205 210 215), the possibility distribution P(0 0 0 1/4 1/2 3/4 1 1 1) corresponds to the value "tall" of attribute HEIGHT, and induces a fuzzy set, according to the rules we mentioned before. [11]
By using of linguistic variables, several advantages arise:
1)Man-machine dialogue becomes more natural and simple, as the former has the possibility to express himself according to his ordinary language;
2)If the value associated with linguistic variable is changed, rules in which it is present don't have to be changed, but we just have to change the possibility distribution associated to it.
The possibility distributions and fuzzy sets we have talked over, are used for inferring fuzzy diagnoses through prodution rules, in the way we are going to describe.
Some of the rules are associated to CARD frame, and are of use for inferring default values. Others, associated with EXAM frame, for inferring a fuzzy diagnosis. All of these rules are of the kinds:

"if (V_1 is A_1) and ... ... and (V_n is A_n) then U is B",

where the V_i's are linguistic variables, and the A_i's are fuzzy sets defined over the base sets associated with the V_i's.
Three numeric values, included in the interval [0,1], and called "a priori confidence", "a posteriori confidence" and "matching", are associated with each rule.
The a priori confidence value is defined by the domain expert suggesting the rule, and expresses the validity of the rule, not depending on the facts in system knowledge.
The matching value expresses how much the conditions of the rule meet the facts in the frame to which the rule is being applied.
It is computed in the following way:
given the rule

"if (V_1 is A_1) and ... ... and (V_n is A_n) then U is B"

and given the facts

"V_1' is A_1' ...... V_n' is A_n' ".

Compute $S = (S_1,...,S_n)$ where $S_i = \max (A_i \cap A_i')$
and give matching = $1/n \ \Sigma_{i=1,..,n} S_i$
When the conditions in the rule completely meet the facts, we have: matching = 1.
The a posteriori confidence value expresses the validity of the rule, after comparing it with the facts. It is given by the formula pos.c. = pri.c. - (1 - matching),
where pos.c. is the posteriori confidence, and pri.c. is a priori confidence.
They coincide when the conditions of a rule completely meet the facts. The rule supplying the greatest a posteriori confidence is the one that most limely should be applied for a right diagnosis.

CONCLUSIONS

The expert system we carried out, can't be surely defined complete, nor it can perform completely sure diagnoses. Actually, it can diagnose, as we can see in the appendix, non-multiple pathologies, and takes into consideration an extremely little set of symptoms and diagnoses. Sure, the diagnosis nearest to truth, is the one supplied by the physician, who almost gets it by a glance. However, with our system, we stated the possibility of breaking away from the traditional two-value logics, when the problem to be faced asks for managing uncertainty and its propagation while reasoning. In fact, we want to stress the fact that fuzzy logic allows us to make system knowledge qualitative rather than quantitative, and to manage quite hazy medical entities. A remarkable advantage it brings is that facts don't have necessarily to meet completely the conditions of the rules, for their applicability. This brings, as a consequence, a considerable reduction of the rules present in the knowledge base.

In the end, we want to confirm the qualities of O.O.P. programming, which supplied an optimal support for a work of this kind, and for creation of a really friendly man-machine communication channel.

APPENDIX

We maintained before that our system is an hybrid, because its knowledge base is built both on frames and rules. We have already described the organization of our frames, and their attributes, and we are not going to see it more in detail. We will just have a look at the way initial values are assigned (fig.2).

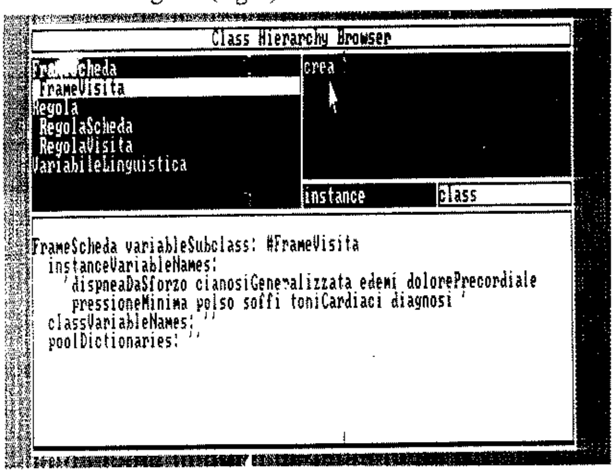


fig.2

It's more interesting for us to see the way rules are applied. We have defined a class RULE, with subclasses CARDRULE and EXAMRULE, whole elements are rules to be applied to frames CARD and EXAM, respectively (fig.3).

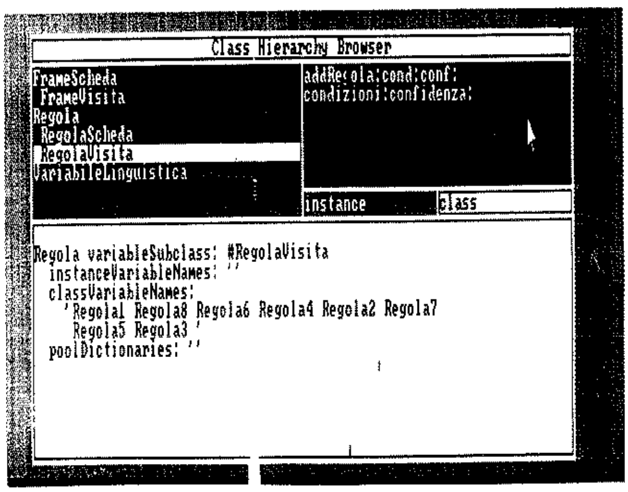


fig.3

Linguistic variables are defined as one more class, a subclass of DICTIONARY. Most of global variables belong to this class. They are dictionaries in which possibility distributions are associated to the linguistic variables they refer to (fig.4,5a,b).

```
linguistic variables class

Dictionary variableSubclass: #VariabileLinguistica
   instanceVariableNames: ''
   classVariableNames: ''
   poolDictionaries: ''
```

fig.4

```
Linguistic variables

          WEIGHT
BASIC SET     (60 65 70 75 80 84 87 91 95 100)
about 90 Kg.  (0 0 0 0 0.3 0.6 0.8 1 0.7 0.3)
about 85 Kg.  (0 0 0 0.3 0.7 1 0.9 0.7 0.3 0)
about 95 Kg.  (0 0 0 0 0 0 0.3 0.8 1 0.7)
about 80 Kg.  (0 0 0.3 0.7 1 0.7 0.4 0 0 0)
about 75 Kg.  (0 0.3 0.7 1 0.7 0.3 0 0 0 0)
```

fig.5a

```
          MINIMUM PRESSURE
BASIC SET    (40 50 60 70 80 90 100 110 120 130)
hight        (0 0 0 0 0 0.7 0.9 1 1 1)
normal       (0 0.2 0.8 0.9 1 0.9 0.4 0 0 0)
low          (1 1 0.5 0.3 0 0 0 0 0 0)
```

fig.5b

This is how a diagnosis is performed:
-an EXAM frame is created and inizialized. Data and symptoms are assigned through PROMPTER's, following the indications supplied by the system. Values for attribute WEIGHT are obtained through application of rules.
-methods "matching:" (fig.6), in class RULE, and "infDiagnosis" (fig.7) in class EXAM, carry out the DIAGNOSIS (global variable) process, as described before.

a)Method "matching:" computes the posteriori confidence value for any rule;
b)Method "infDiagnosis" applies systematically to all the rules present in the system.
-In the end, the DIAGNOSIS is shown by the method "fuzzyDiagnosis".
It consists in a possibility distribution over the set of all possible diagnoses. Through this distribution, the diagnosis which is through to be nearest to truth, can be chosen.
The methods we've just described make up the inferential engine of our expert system.

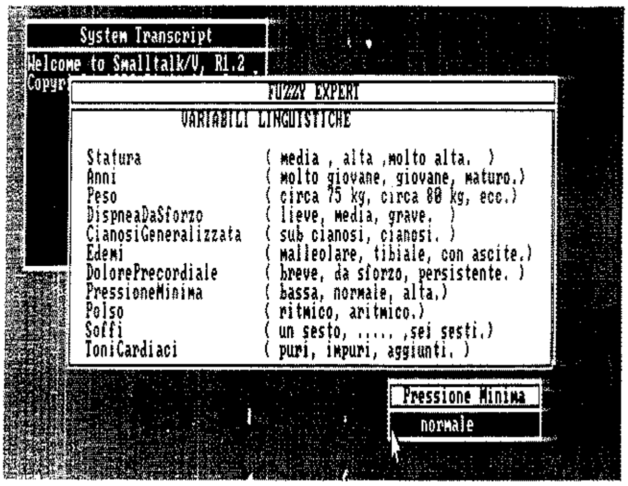
```
matching: aFrameScheda
   "confronta i valori dei sintomi nel FrameScheda con i
    valori dei corrispettivi sintomi nella parte 'condi-
    zioni' della regola che riceve questo messaggio"

    : cond a b d i f :
    cond:=self condizioni.
    d:=Array new:cond size.
    i:=1.
    cond KeysDo:[:c:
     a:=(Smalltalk at:c) valoreFuzzy:(aFrameScheda at:c)
     b:=(Smalltalk at:c) valoreFuzzy:(cond at:c).
     d at:i put:(a maxmin:b).
     i:=i+1.].
   f:=d media.
   matching:=f.
   confidenzaPost:=(confidenza - (1-f)).
   ^self confidenzaPost
```

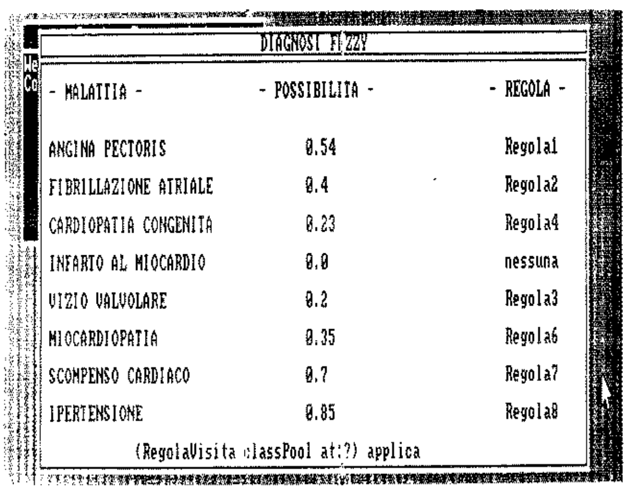
fig.6

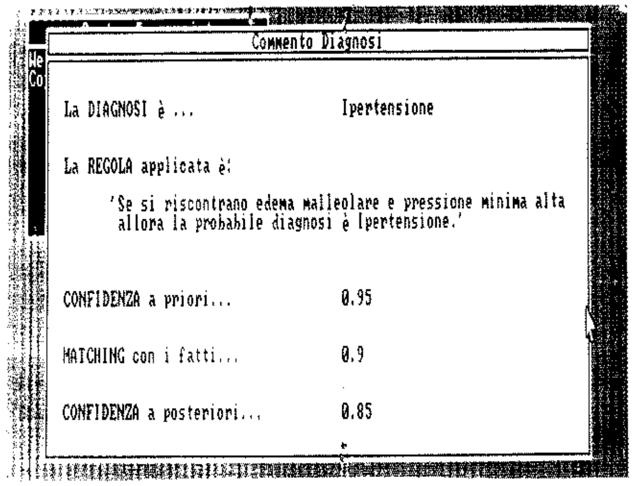
```
infDiagnosi
   "applica le regole associate alla classe FrameVisita
     per inferire una diagnosi fuzzy sul frame visita a
    cui tale messaggio è inviato"

   : match chiave valore :
   Diagnosi KeysDo:[:c:(Diagnosi at:c) at:1 put:0.00;
                                       at:2 put:'nessuna'.].
   match:=0.
   RegolaVisita classPool KeysDo:[:c:
           match:=((RegolaVisita  classPool  at:c)
matching:self)
     chiave:=(RegolaVisita classPool at:c) conclusione.
     valore:=Diagnosi at:chiave.
     (valore at:1)< match
       ifTrue:[ valore at:1 put:match;
                        at:2 put:c.].].
   ^Diagnosi diagnosiFuzzy
```

fig.7

An esample of diagnosis.







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