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Fuzzy Expert System Design for Medical Diagnosis

Man Diana Ofelia

Abstract

In recent years, the methods of artificial intelligence have largely been used in the different areas including the medical applications. In the medicine area, many fuzzy expert systems (FES) were designed.

We study the possibilities of using fuzzy logic in building agent software assuming the role of an experienced medical person, which benefits of a vast medical knowledge regarding symptoms and diseases and has the role to orientate the young resident doctors in the process of diagnosis establishment.

1 Introduction

Fuzzy expert systems have been successfully applied in fields such as automatic control, data classification, decision analysis, expert systems, and computer vision.

Fuzzy expert systems can be used to aid in diagnosing medical cases. Symptoms and test results can be given to the expert system, which then searches its knowledge base in an attempt to match these input conditions with a particular malady or disease. This results in a conclusion about the illness and some possible suggestions on how to treat it. Such an expert system can greatly aid a doctor in diagnosing an illness and prescribing treatment. It does not replace doctors, but helps them confirm their own decisions and may provide alternative conclusions.

The Medical Diagnostics System is intended to be a software application mainly destined to orientate the resident doctors in the diagnostic process for patients‟ examinations. The system will be implemented for psychiatry diseases, but the architecture will try to make it flexible for further modules covering other medical areas.

The knowledge base of the system contains a few main entities: symptom with associated symptom values, disease and disease symptom value.

A *symptom* in our model is not equivalent with a medical symptom; it is an independent characteristic, like temperature, pulse, etc. The symptom has associated a name, a description - attribute that will be used to formulate the questions, and a list of two or more symptom values.

The symptom value in conjunction with a symptom on the other hand is similar with a medical symptom e.g. temperature of 38 degrees, pulse of 80, etc. For symptom "temperature" the symptom values would be a list of values: "36 degrees", "37 degrees", etc. Some of the symptom may have only the yes/no values.

A disease symptom value represents a symptom value associated to a disease. It contains a symptom and a symptom value associated. The diseases are stored under a hierarchical form following the model already defined in medicine. Important attributes are a list of disease symptom values for that disease. A patient should have most if not all the disease symptom values associated with a disease (at least all the mandatory ones) to be diagnosed with that disease [1].

2 Theoretical backgrounds

2.1 Fuzzy logic

Fuzzy logic is a form of multi-valued logic derived from fuzzy set theory to deal with reasoning that is approximate rather than precise. In contrast with binary sets having binary logic, also known as crisp logic, the fuzzy logic variables may have a membership value of not only 0 or 1.

Just as in fuzzy set theory with fuzzy logic the set membership values can range (inclusively) between 0 and 1, in fuzzy logic the degree of truth of a statement can range between 0 and 1 and is not constrained to the two truth values {true (1), false (0)} as in classic propositional logic.

Paradoxically, one of the principal contributions of fuzzy logic is its high power of precisiation of what is imprecise. This capability of fuzzy logic suggests, as was noted earlier, that it may find important applications in the realms of economics, linguistics, law and other human-centric fields [2].

2.2 Fuzzy sets

In fuzzy sets an object can belong to a set partially. The degree of membership is defined through a membership function: $\mu_A : U \rightarrow [0,1]$

where U is called the universe, and A is a fuzzy subset of U. Each value of the function is called a membership degree [3].

2.2.1 The basics notions of fuzzy sets

A support of a fuzzy set A is the subset of the universe U, each element of which has a membership degree to A different from zero

supp(A) = {u|u U, μA(u) > 0} (1)

Cardinality of a fuzzy set M(A) is defined as follows:

M(A)= $\sum \mu_A(u), u \in U$ (2)

Power set of A is called the set of all fuzzy subsets of A.

Normal fuzzy set if the membership function of the fuzzy set has a grade of 1 at least for one value from the universe U.

x-cut of a fuzzy set A is a subset Aa of the universe U which consists of values that belong to the fuzzy set A with a membership degree greater (weak cut), or greater or equal (strong cut) than a given value x from [0,1]

Subsethood (introduced by Kosko in 1992). It measures the degree to which the whole universe U belongs to any of its fuzzy subsets [3].

2.2.2 Operations with fuzzy sets

Union, A∪B:

$$\mu_{A\cup B}(u) = \mu_A(u) \vee \mu_B(u)$$ for all u from U, where $\vee$ means MAX (3)

Intersection, A ∩B:

$$\mu_{A\cap B}(u) = \mu_A(u) \wedge \mu_B(u)$$ for all u from U, where $\wedge$ means MIN; (4)

The De Morgan's laws are valid for intersection and union.

Equality, A = B:

$$\mu_A(u) = \mu_B(u)$$ for all u from U (5)

Set complement, notA, ¬ A:

$$\mu_{notA}(u) = 1 - \mu_A(u)$$ for all u from U (6)

Concentration, CON(A):

$$\mu_{CON(A)}(u) = (\mu_A(u))^2$$ for all u from U; (7)

This operation is used as a linguistic modifier "very"

Dilatation, DIL(A):

$$\mu_{DIL(A)}(u) = (\mu_A(u))^{0.5} \text{ for all u from U;} \quad (8)$$

This operation is used as a linguistic modifier "more or less" [3].

2.2.3 Fuzzy terms

A linguistic variable denote a variable which takes fuzzy values and has a linguistic meaning.

Linguistic variables can be:

- *Quantitative*, for example, "temperature" (low, high); time (early, late); spatial location (around the corner);
- *Qualitative*, for example, "truth," "certainty," "belief."

The process of representing a linguistic variable into a set of linguistic values is called fuzzy quantization.

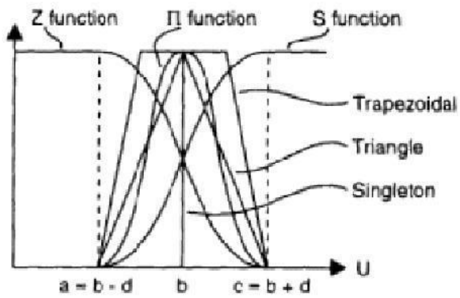

Figure 1- The types of membership function

2.3 Fuzzy propositions

Fuzzy propositions are propositions which contain fuzzy variables with their fuzzy values. The truth value of a fuzzy proposition "X is A" is given by the membership function .

<u>Examples</u> A person is a "heavy smoker." The temperature is "high." The speed is "moderate.“

The fuzzy connectives are the same as in propositional logic, but here applied differently

AND: $\mu_{AandB} = \mu_A \wedge \mu_B$ (9)

OR: $\mu_{AorB} = \mu_A \vee \mu_B$ (10)

NOT: $\mu_{\neg A} = 1 - \mu_A$ (11)

2.4 Fuzzy rules

The concept of “computing with words”(CW) is rooted in several papers, starting with Zadeh paper in 1973 – “Outline of a New Approach to the Analysis of complex Systems and Decision Processes”, where the concepts of linguistic variable and granulation were introduced.
Computing with words evolved in a distinct methodology during time and it reflects many advantages of fuzzy logic and soft computing, advantages that took place within the past few years. A key aspect is that it involves a fusion of natural languages and computation with fuzzy variables [4].

The machinery of linguistic variables and fuzzy if–then rules is unique to fuzzy logic. This machinery has played and is continuing to play a pivotal role in the conception and design of control systems and consumer products.

- *Zadeh-Mamdani's fuzzy rules*:

IF x is A, THEN y is B, (12)

A generalized form of the fuzzy rule is the following:

IF x1 is A1 AND x2 is A2 AND . . . AND xk is Ak, THEN y is B, (13)

A set of fuzzy rules has a general form:

Rule 1: IF x1 is A1,1 AND x2 is A2,1 AND . . . AND xk is Ak,1, THEN y is B1, ELSE

Rule 2: IF x1 is A1,2 AND x2 is A2,2 AND . . . AND xk is Ak,2, THEN y is B2, ELSE

. . .

Rule n: IF x1 is A1,n AND x2 is A2,n AND . . . AND xk is Ak,n, THEN y is Bn, (14)

In general, every rule that has two condition elements in its antecedent part connected by an OR connective can be represented by two rules, for example, the rule

IF x1 is A1 or x2 is A2, THEN y is B (15)

is logically equivalent to the following two rules:

IF x1 is A1, THEN y is B and IF x2 is A2, THEN y is B. (16)

- *Fuzzy rules with confidence degrees*:

  If x is A, then y is B (with a CF). (17)

Example

IF (current economic situation is good) and (current political situation is good) and (the predicted value for tomorrow is up), THEN (action—buy) (CF = 0.9)

- *Takagi-Sugeno's fuzzy rules* (1985*)*:

Rule i: IF x is Ai and y is Bi, THEN z is fi(x, y) (18)

If the function is linear, the rule takes the following form:

Rule i: IF x1 is A1,i and x2 is A2,i and...xm is Am,i, THEN z = C0,i + C1,i· x1 + ··· + Cm,i · xm (19)

Example *IF x is A and y is B, THEN z = 5x -2y + 3.*

- *Gradual fuzzy rules*: These are rules of the Zadeh-Mamdani type, but instead of using fuzzy values for the fuzzy variables in the rule, they use fuzzy representation of gradual properties, for example, "the more a tomato is red, the more it is ripe“[5].

2.5 Fuzzy inference methods

Different reasoning strategies over fuzzy rules are possible. Most of them use either the generalized modus ponens rule or the generalized modus tolens inference rule.

(IF x is A, THEN y is B) and (x is A'), then (y is B') should be inferred.

Some of the main else-links between fuzzy rules are:

OR-link: Max operator is used

AND-link: Min operator is used

Truth qualification-link: A coefficient Ti' is calculated for the inferred fuzzy set Bi' by every rule Ri. The result obtained by a rule Rj with the maximum coefficient is taken as a final result:

$$T_j = MAX\{T_i\}, i = 1,2,...n$$
$$T_i = \sum \mu_{B_i'}(v) / \sum \mu_B(v), \forall v \in V \qquad (20)$$

Additive link: The fuzzy results Bi' inferred by the rules Ri are added after being multiplied to weighting coefficients:

$$\mu_{B'} = \sum \mu_{B_i'} \cdot w_i, i = 1,2,...n \qquad (21)$$

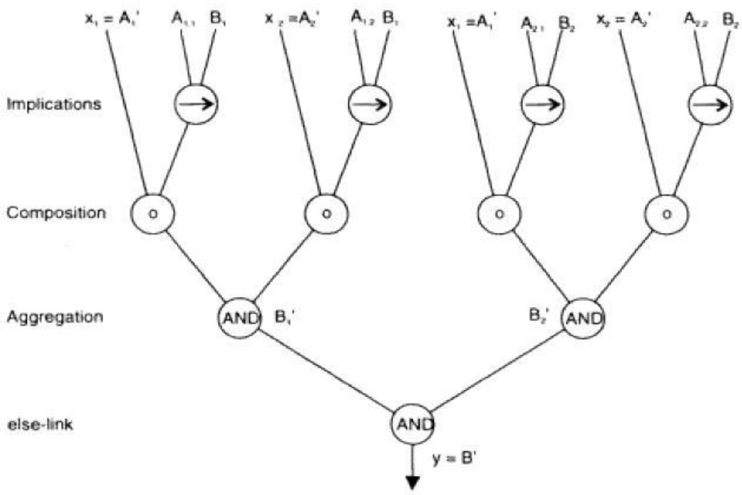

Figure 2- Fuzzy Inference Methods

2.6 Fuzzification, rule evaluation, defuzzification

Fuzzification is the process of finding the membership degrees and to which input data x'1 and x'2 belong to the fuzzy sets A1 and A2 in the antecedent part of a fuzzy rule.

Rule evaluation takes place after the fuzzification procedure. It deals with single values of membership degrees and produces output membership function B'. There are two major methods which can be applied to the rule above:

Min inference: $B' = B \cdot \min\{\mu_{A1}(x_1'), \mu_{A2}(x_2')\}$ (22)

Product inference: $B' = B \cdot \mu_{A1}(x_1') \cdot \mu_{A2}(x_2')$ (23)

where · denotes algebraic multiplication.

A *T-norm* is a binary mapping T: [0, 1] x [0, 1] → [0, 1], which has the following properties: commutativity, associativity, monotonicity. A boundary condition is held: T(a,1) = a. The following T-norm operators have been used in practice:

T(a,b) = min{a, b}; (24)

T(a, b) = a * b (product); (25)

T(a, b) = max{0, a + b - 1}. (26)

A T-conorm S(a, b) differs from a T-norm in that it has the property of S(a, 0) = 0 instead of the boundary property of the T-norms. Widely used T-conorms are:

S(a, b) = max{a, b}; (27)

$$S(a, b) = a + b - ab; \qquad (28)$$

$$S(a, b) = \min\{1, a + b\} \qquad (29)$$

Defuzzication is the process of calculating a single-output numerical value for a fuzzy output variable on the basis of the inferred resulting membership function for this variable.

Two methods for defuzzication are widely used:

- *The center-of-gravity method(COG).* This method finds the geometrical centre y' in the universe V of an output variable y, which center "balances" the inferred membership function B' as a fuzzy value for y.

  The crisp value is calculated by the method center of gravity defuzzifier by the formula:

$$D^* = \frac{\int D_{\mu\ middle(D)}\, dD}{\int \mu_{middle(D)}\, dD}$$

- *The mean-of-maxima method(MOM).* This method finds the value y' for the output variable y which has maximum membership degree according to the fuzzy membership function B' [3].

3 The structure of the Fuzzy Expert System

We have developed a rule-based Fuzzy Expert System for determination of the possibility of the diagnosis of schizophrenia, that uses symptoms data and simulates an expert-doctor's behavior.

As symptoms, Anxiety and Terror (AT), Age (A) and Isolation (I) are used. Using this data the fuzzy rules to determine the risk factor was developed. The developed system gives to the user the patient possibility ratio of the schizophrenia.

For the design process AT, A and I are used as input parameters and schizophrenia risk (SR) is used as output.

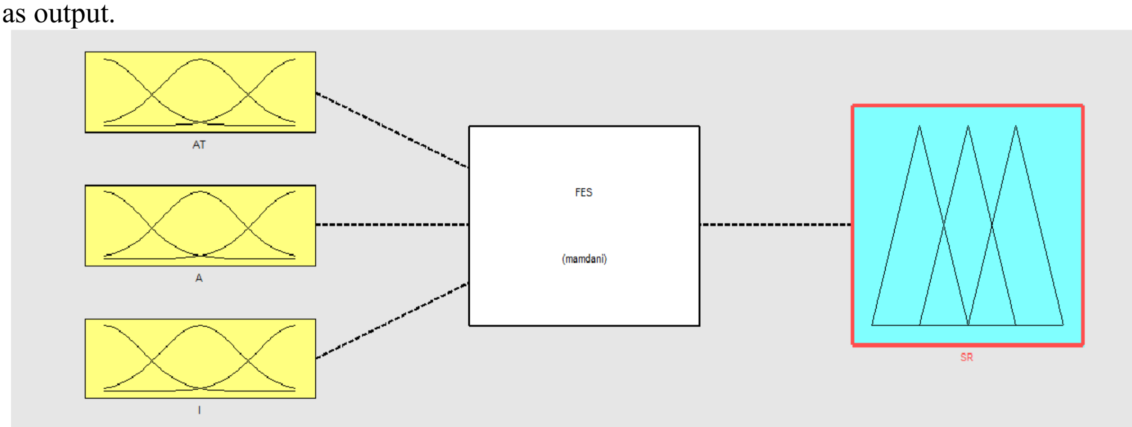

Figure 3- The structure of Fuzzy Expert System

Fuzzy inference process comprises of five parts: fuzzification of the input variables, application of the fuzzy operator (AND or OR) in the antecedent, implication from the antecedent to the consequent, aggregation of the consequents across the rules, and defuzzification.

The first step is to take the inputs and determine the degree to which they belong to each of the appropriate fuzzy sets via membership functions. The input is a crisp numerical value limited to the universe of discourse of the input variable (in this case the interval between 0 and 10 for AT and I, respectively the interval between 0 and 100 for A) and the output is a fuzzy degree of membership in the qualifying linguistic set (always the interval between 0 and 1).

For fuzzification of AT and I factors the linguistic variables Low, Medium and High are used and for fuzzification of A factor, the linguistic variables Very Young, Young, Middle Age and Old are used.

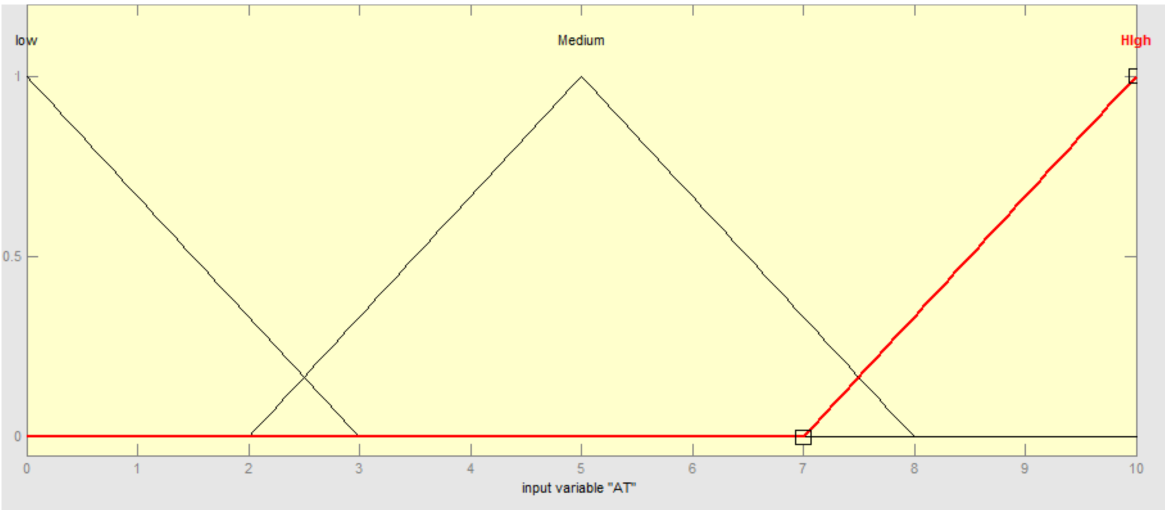

Figure 4- Membership function of the AT

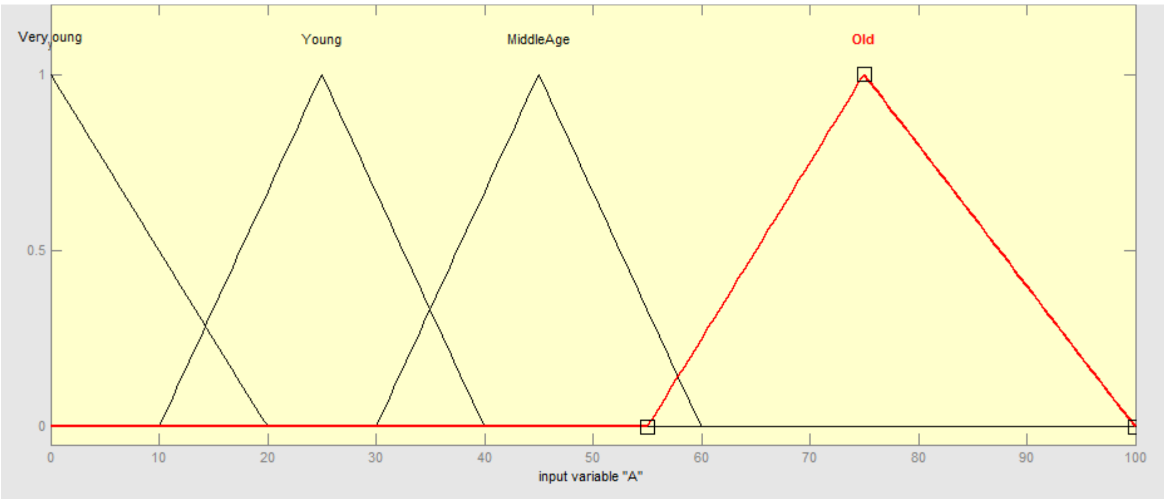

Figure 5- Membership function of the Age

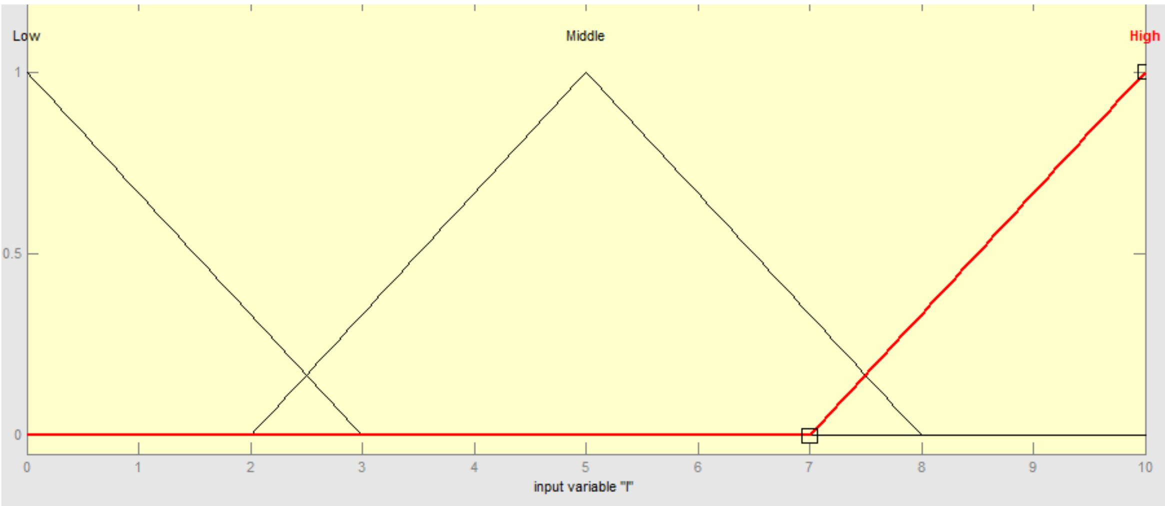

Figure 6- Membership function of the I

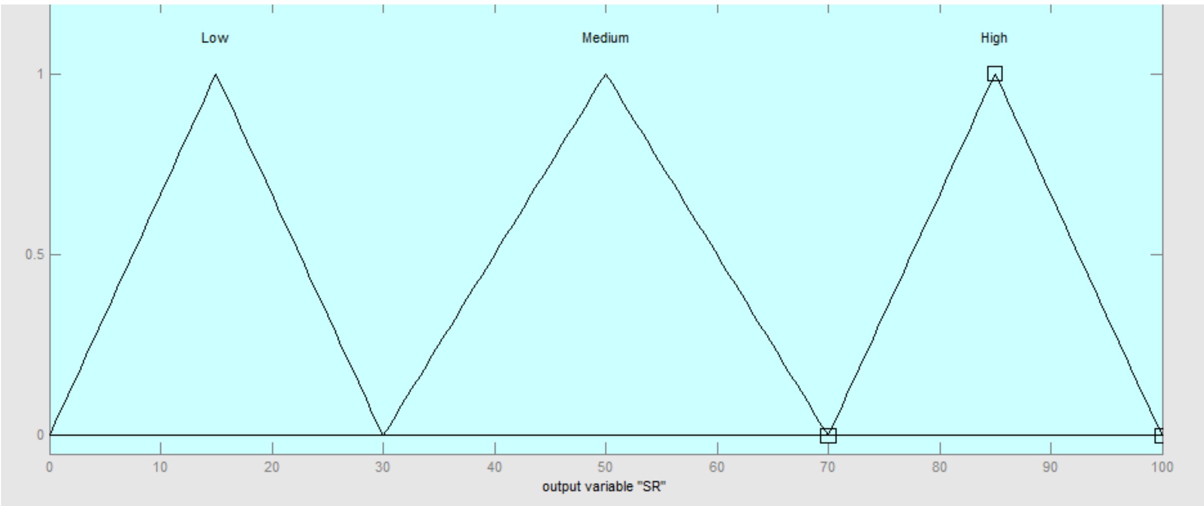

Figure 7- Membership function of the SR

After the inputs are fuzzified, you know the degree to which each part of the antecedent is satisfied for each rule. If the antecedent of a given rule has more than one part, the fuzzy operator is applied to obtain one number that represents the result of the antecedent for that rule. This number is then applied to the output function. The input to the fuzzy operator is two or more membership values from fuzzified input variables. The output is a single truth value [6].

Total of 36 rules are formed. For example, Rule 1, Rule 15 and Rule 18 can be interpreted as follows:

Rule 1: If AT is low and A is Very Young and I is Low then SR is low, i.e., if the patient's AT is low and patient is very young and patient's I is Low, then schizophrenia risc is low.

Rule 15: If AT is Medium and A is Very Young and I is High then SR is Medium, i.e., if the patient's AT is Medium and patient is very young and patient's I is High, then schizophrenia risc is medium.

Rule 18: If AT is Medium and A is Young and I is High, then SR is High, i.e., if the patient's AT is medium and patient is young and patient's I is high, then patient's SR is high.

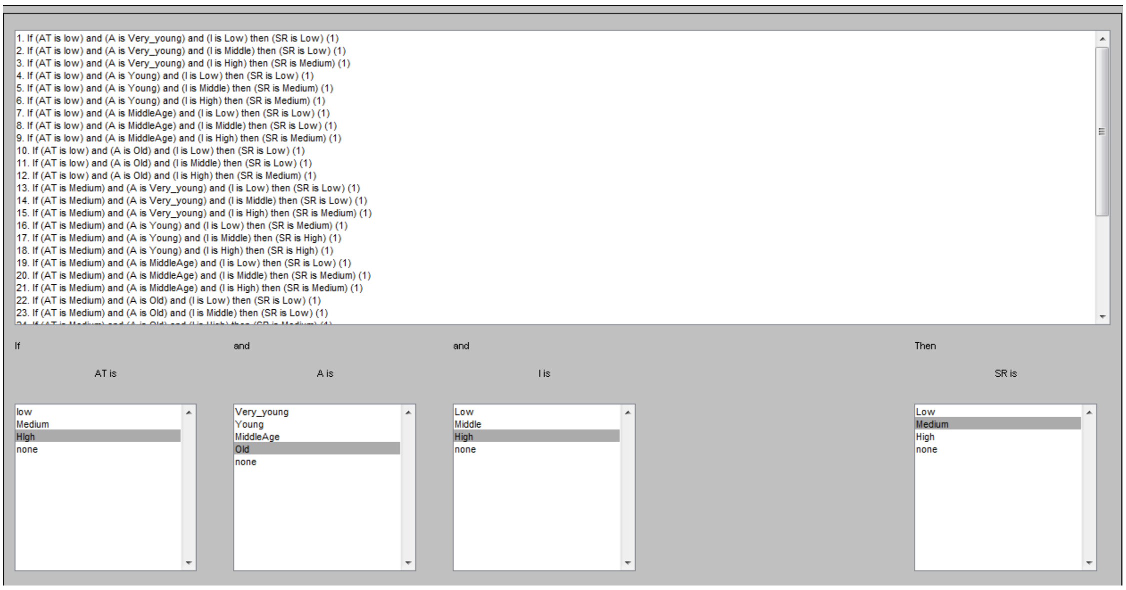

Figure 8- Fuzzy rules

For the inference mechanism the Mamdani max-min inference was used.

Because decisions are based on the testing of all of the rules in a FIS, the rules must be combined in some manner in order to make a decision. Aggregation is the process by which the fuzzy sets that represent the outputs of each rule are combined into a single fuzzy set. Aggregation only occurs once for each output variable, just prior to the fifth and final step, defuzzification.

The input for the defuzzification process is a fuzzy set (the aggregate output fuzzy set) and the output is a single number. As much as fuzziness helps the rule evaluation during the intermediate steps, the final desired output for each variable is generally a single number. However, the aggregate of a fuzzy set encompasses a range of output values, and so must be defuzzified in order to resolve a single output value from the set. Perhaps the most popular defuzzification method is the centroid calculation, which returns the center of area under the curve.

For the inputs AT=8, A=25, I=9, the output SR=85, i.e for the patient with AT equals 8, 25 years old and I equals 9, the SR is 85%.

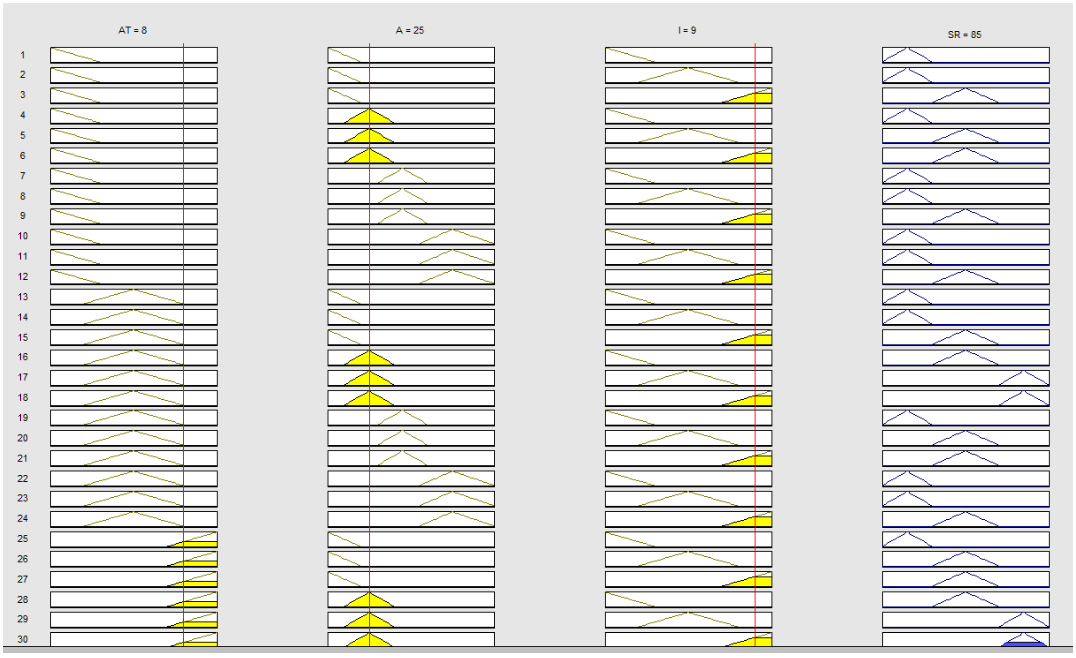

Figure 9- Calculation of the value SR for the values AT=8, A=25 and I=9

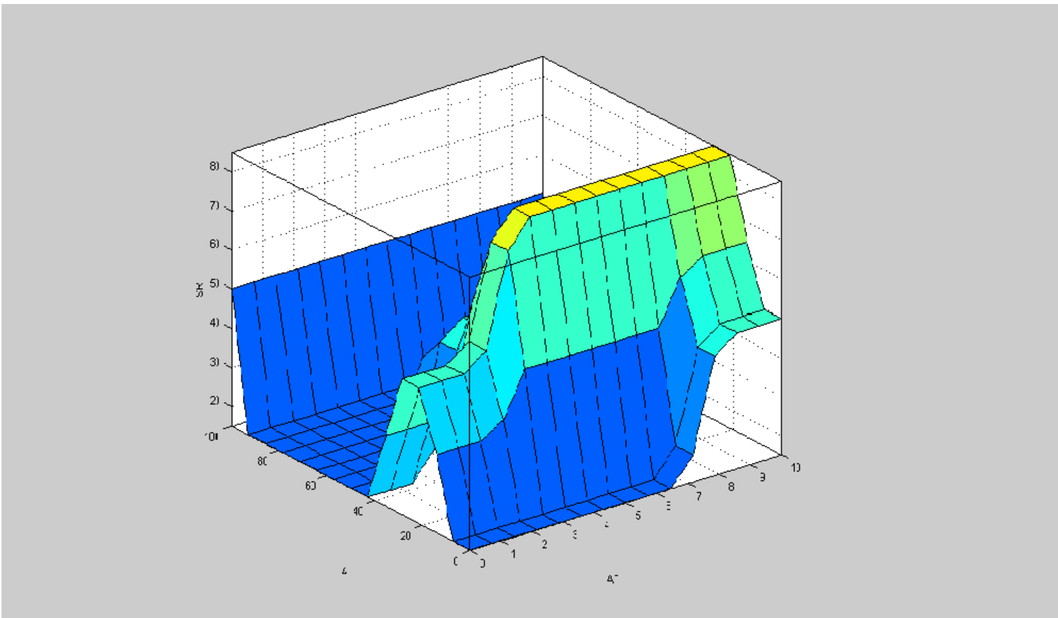

Figure 10- Surface Viewer

4 Conclusions

This paper presents a Fuzzy Expert System for Medical Diagnosys. We study the possibilities of using fuzzy logic in building agent software assuming the role of an experienced medical person, which benefits of a vast medical knowledge regarding symptoms and diseases and has the role to orientate the young resident doctors in the process of diagnosis establishment.

The last section describes a design of a Fuzzy Expert System for determination of the possibility of the diagnosis of schizophrenia, which can be used by the specialist doctors for treatment and by the resident doctors for learning the scope.

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Man Diana-Ofelia
Babes-Bolyai University
Department of Computer Science
400084 Cluj-Napoca
ROMANIA
E-mail: mandiana77@yahoo.com