

# Fuzzy Conditional Inference for Medical Diagnosis

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# Fuzzy conditional inference for medical diagnosis

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*Abstract*— The uncertainty in medical diagnosis is Fuzzy rather than Probable (likelihood). In This paper, we discuss the Fuzzy inference in medical diagnosis. The method of fuzzy conditional inference is proposed to deal with uncertainty in Medical diagnosis which do not fall under Zadeh [4] fuzzy inference.

Keywords—fuzzy logic, fuzzy conditional inference, medical diagnosis)

#### I. INTRODUCTION

Medical Diagnosis involves processes that are suitable to approximate rather than precise analysis. Until recently Probability theory was the only existing theory to approximate medical diagnosis. There are many theories to deal approximate medical diagnosis including the Probability theory with Baye's approach, Certainty factor model and Dempster-Shafer theory [1]. There are other models Possibility theory and Fuzzy theory also available to deal uncertainty in Medical diagnosis.

The fuzzy theory allows us to represent set membership as a possibility distribution [6]. Fuzzy theory is the most effective than the other theories because Fuzzy theory depends on degree of belief rather than likelihood.

Zadeh[6] proposed different methods of fuzzy conditional inference to deal uncertain information. Sanchez[3] discussed these methods of inference for medical diagnosis. The medical diagnosis with these methods of inference needs prior information. The method of fuzzy conditional inference is needed when the total information is not available. In the following, we discuss briefly description of medical knowledge interms of fuzziness.

## II. FUZZY LOGIC

Fuzziness occurs when the body of information is not clearly known. In medical knowledge, symptoms and diagnosis are Fuzzy rather than likelihood. For example "John has headache (0.9)", "John has chest pain (0.6)" where 0.9 and 0.6 are Fuzzy values. Fuzziness is usually represented in the unit interval [0, 1].

Given some universe of discourse X, a fuzzy subset A of X is defined by its membership function  $\mu_A$  taking values on the unit interval [0, 1], i.e.,

$$\mu_A$$
 : X --> [0, 1]

Suppose X is finite set. The fuzzy subset A of X may be represented as

 $A = \mu_A (x_1) / x_1 + \mu_A (x_2) / x_2 + \mu_A (x_3) / x_3 + \mu_A (x_4) / x_4 + \mu_A (x_5) / x_5$ 

where  $x_1, x_2, x_3, x_4, x_5$  are individuals and "+" is union.

The fuzzy subset "headache" may be represented as headache =  $0.4/x_1 + 0.6/x_2 + 0.8/x_3 + 0.7/x_4 + 0.5/x_5$ 

The fuzzy set type -2 is given by

Headache = { 0.4/mild, 0.6/moderate, 0.9/severe, 0.45/normal }

John has "mild headache" with fuzziness 0.4 etc.,

The propositions may contain quantifiers like "very", "more or less", etc. These propositions can be reduced to simple propositions by using power operators. The square operator is used for "very", "most" (concentration), etc. The square root operator is used for "more or less" (diffusion), etc.

For instance,

Very headache = (Headache)<sup>2</sup>

$$= 0.16/x_1 + 0.36/x_2 + 0.64/x_3 + 0.49/x_4 + 0.25/x_5$$

The fuzziness in medical knowledge may be divided into two kinds, one is fuzzy number set and the other is discrete fuzzy set. The fuzzy number set contains usually integers or real numbers. The discrete fuzzy set contains usually linguistic variables.

For example, fuzzy number set in medical knowledge is given by

fever (in F) = { 0.4/98.5, 0.5/99, 0.6/101, 0.7/103 }

Blood pressure (in mm. Hg)= { 0.3/(110/70), 0.5/(120/80), 0.6/(125/100), 0.7/(130/120)}

where 110, 120, 125, 130 are diastolic pressure and 70, 80, 100, 120 are systolic pressure

Discrete fuzzy set in medical knowledge is given by

Rash = { 0.4 / mild , 0.6 / moderate , 0.8 / serious }

Conjectivities = { 0.3 / serious , 0.7 / purulent , 0.8 / chronic purulent }

A brief description of medical knowledge in terms of fuzziness is given herein.

In a given hypothesis, a set of symptoms is denoted by S, a set of diagnosis is denoted by D and a set of patients is denoted by P.

Let A, B, and C be the fuzzy subsets related to symptoms, diagnosis and patients on S, D and P which are characterized by membership functions

 $\mu_A(s)$ ,  $\mu_B(d)$  and  $\mu_C(p)$ , where  $s \in S$ ,  $d \in D$ ,  $p \in P$ .

The inference for composition of two Fuzzy subsets can be expressed as follows [6].

Let A and B be the two Fuzzy subsets on S and D.

$$\mu_{A \vee B}(s, d) = \max (\mu_A(s), \mu_B(d))/(s, d)$$
(disjunction)

$$\mu_{A^{A^{B}}}(s, d) = \min (\mu_{A}(s), \mu_{B}(d))/(s, d)$$
(Conjunction)

 $\mu_{A'}(s) = (1 - \mu_{A}(s))/s$ 

(negation)

 $\mu_{A \to B}(s, d) = \min(1, (\mu_A(s) + \mu_B(d)))/(s, d)$  (implication)

## **III. FUZZY CONDITIONAL INFERENCE**

Let A be the Fuzzy subset of S related to symptoms and B be the Fuzzy subset of D related to diagnosis.

Let R = A --> B be the fuzzy implication from symptoms S to diagnosis D. The fuzzy inference for diagnosis is given by  $u_{R}(d) = \min(\max_{x \in S} |u_{R}(x) |u_{R}(x) |d_{R})/d_{R}$ 

$$\mu_{B}(d) = \min(\max_{s \in S} [\mu_{A}(s), \mu_{R}(s, d)])$$

(1)

Consider the two fuzzy implications Q from the patients P to symptoms S and T from the patients P to diagnosis D. The fuzzy implication T using the fuzzy implications Q and R is given by

 $\mu_{T}(p, d) = \min(\max_{s \in S}[\mu_{Q}(p, s), \mu_{R}(s, d)])/(p, d)$ (2)

The method of fuzzy conditional inference (1) needs prior medical information. Usually diagnosis will be made from symptoms. The fuzzy conditional inference can be define suitably to estimate diagnosis using the symptoms in the following.

Let  $A_1, A_2, \ldots, A_n$  be the fuzzy subsets of symptoms and B be the fuzzy subset of diagnosis. The fuzzy nested condition is given by

if  $(A_1 AND A_2 AND \dots A_n)$  then B or

if A then B where  $A = A_1 AND A_2 AND \dots A_n$ 

and is equivalent to

if  $A_1$  then ( if  $A_2$  then ( ... ( if  $A_n$  then B )))

For instance,

if more or less fever and very cough

and conjuctivities and very runny\_nose and more or less rash

then patient has measles

The fuzzy conditional inference may be define using the symptoms and is given by

 $\mu_{R}(s\ ,\ d)=\mu_{Ai}\ \_\ {}_{B}(s\ ,\ d)=min\ \{\ \mu_{Ai}\ (s)\ \}$  where  $i{=}1{\dots}n$ 

 $= \mu_{\rm B}(d)/d$ 

(3)

By substituting fuzzy conditional inference (3) in the fuzzy inference (2), we get

 $\mu_{B}(d) = \min \left( \max_{s \in S} \left[ \mu_{A}(s) , \mu_{B}(d) \right] \right) / d$ 

(4)

We can easy verify that the fuzzy conditional inference (3) and (4) will give the same fuzziness. **EXAMPLE 1** 

Consider the typical rule with symptoms with fuzziness.

| if very fever              |       | (.36) |
|----------------------------|-------|-------|
| and more or less rash      |       | (.87) |
| and body_ache              | (0.8) |       |
| and chills                 |       | (0.5) |
| than diagnosis is shielden |       |       |

then diagnosis is chicken\_pox

Using the fuzzy inference (3), the diagnosis is given by chicken\_pox with fuzziness 0.36.

#### **EXAMPLE 2**

Consider the two typical rules

if hemoglobin is very low

and hematocrit is very low

then anemic.

if anemic

and mean corpuscular volume is low

and mean corpuscular hemoglobin concentration

then the anemia can be classified hypocromic anemia.

The linguistic terms are describing the various parameters as follows.

| paramet   | ers as fol |           |                   |           |            |            |
|-----------|------------|-----------|-------------------|-----------|------------|------------|
|           | hemogle    | obin gran | ns /100 L         |           |            |            |
|           | 4          | 8         | 12                | 14        | 16         | 20         |
|           | high       |           | 0                 | 0.1       | 0.2        | 0.4        |
|           | 0.6        | 1.0       |                   |           |            |            |
|           | normal     |           | 0                 | 0.3       | 0.6        | 1.0        |
|           | 0.6        | 0.3       |                   |           |            |            |
|           | low        |           | 1.0               | 0.8       | 0.7        | 0.6        |
|           | 0.4        | 0         |                   |           |            |            |
|           | very low   | w = (low) | $(r)^2 = \{ 0 \}$ | 1, 0.64,  | 0.49, 0.3  | 6, 0.16,   |
| 0.3 }     | 2          |           | /                 |           |            |            |
|           | hematod    | crit % of | blood sar         | nple      |            |            |
|           | 20         | 25        | 30                | 35        | 40         | 45         |
|           | high       |           | 0                 | 0         | 0.1        | 0.2        |
|           | 0.4        | 1.0       |                   |           |            |            |
|           | normal     |           | 0                 | 0.2       | 0.6        | 1.0        |
|           | 1.0        | 0.6       |                   |           |            |            |
|           | low        |           | 1.0               | 1.0       | 0.4        | 0.3        |
|           | 0.2        | 0         |                   |           |            |            |
|           | very lov   | v = (low) | $^{2} = \{ 1.0, $ | 1.0, 0.16 | , 0.09, 0. | $04, 0 \}$ |
|           |            |           |                   |           | icrons(re  |            |
| cell volu |            | 1         |                   |           | × ×        |            |
|           | 50         | 65        | 80                | 95        | 110        | 125        |
|           | high       |           | 0                 | 0         | 0.1        | 0.2        |
|           | 0.4        | 1.0       |                   |           |            |            |
|           | normal     |           | 0                 | 0.3       | 0.8        | 1.0        |
|           | 0.7        | 0.3       |                   |           |            |            |
|           | low        |           | 1.0               | 0.9       | 0.4        | 0.2        |
|           | 0.1        | 0         |                   |           |            |            |
|           |            | corpuscul | ar hemo           | oglobin   | concentra  | ation g    |
| hb/dl     |            | r         |                   | . 0       |            |            |
|           | 20         | 25        | 30                | 35        | 40         | 45         |
|           | high       |           | 0                 | 0.1       | 0.2        | 0.4        |
|           | 0.8        | 1.0       | -                 |           |            |            |

| 20      | 25  | 50  | 55  | 40  | 45  |
|---------|-----|-----|-----|-----|-----|
| high    |     | 0   | 0.1 | 0.2 | 0.4 |
| 0.8     | 1.0 |     |     |     |     |
| normal  |     | 0   | 0.3 | 0.8 | 1.0 |
| 0.7     | 0.2 |     |     |     |     |
| low     |     | 1.0 | 0.9 | 0.4 | 0.2 |
| 0.1     | 0   |     |     |     |     |
| Suppose | •   |     |     |     |     |

the patient has hemoglobin is low (0.8), hematocrit is low (1.0), mean corpuscular volume is low (0.4) and mean corpuscular hemoglobin concentration is low (1.0).

The diagnosis from the two above rules will be given anemia with 0.64 fuzziness and classified hypocromic anemia with fuzziness 0.16.

## IV. FUZZY MEDICAL EXPERT SYSTEM

The fuzzy inference (3) can be directly interpreted in the Fuzzy expert system shells or EMYCIN.

The fuzzy medical knowledge base contains the rules and facts about the domain. Such rule-based representation is allowed in an expert system. The knowledge acquisition in fuzzy system gathers symptoms, fuzzy value and quantifier and stores as facts in fuzzy knowledge base.

Consider the medical knowledge base which contains three fuzzy rules.

if very fever and more or less rash and body\_ache and chills then chicken\_pox. If more or less cough

and more or less

then mumps.

If there is more or less cough and more or less sneezing and very runny\_nose then wooping\_cough.

Inference engine asks the questions during the consultation to compromise the symptoms where the symptoms are defined with fuzziness. When all the symptoms compromise for rule then the diagnosis will be given with fuzziness.

Consider the rule "if symptom is fever and symptom is rash and symptom is body\_ache and symptom is chills then the diagnosis is chicken\_pox".

If the goal is to diagnose chicken\_pox then system triggers the rule and states examine its antecedent propositions.

The system examines one of its antecedent objects i.e., fever. After the value of the object at the sub goal fever has been obtained, fuzzy value can be calculated using square operator, then the system changes to another sub goal rash and so on. Finally, this rule is fired if the antecedent part is satisfied completely. Thus, the goal diagnosis chicken\_pox can be found by the evaluation of the rule with the matched facts with minimum fuzziness of the symptoms. Similarly the system will continue for the other fuzzy rules.

## V. CONCLUSIONS

The uncertainty in medical diagnosis is discussed using fuzzy logic. Sanchez[3] interpretation of Zadeh's fuzzy logic[6] for medical diagnosis is discussed. Zadeh's fuzzy conditional inference is needed prior information about symptoms and diagnosis. Usually the diagnosis will be made from the symptoms. Thus, the fuzzy conditional inference is proposed suitably to diagnose with the symptoms which do not fall under the Zadeh[6] fuzzy conditional inference. This fuzzy conditional inference is discussed for Medical Expert Systems..

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