Fuzzy logic and its applications in medicine

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Fuzzy set theory and fuzzy logic are a highly suitable and applicable basis for developing knowledge-based systems in medicine for tasks such as the interpretation of sets of medical findings, syndrome differentiation in eastern medicine, diagnosis of diseases in Western medicine, mixed diagnosis of integrated western and eastern medicine, the optimal selection of medical treatments integrating western and eastern medicine, and for real-time monitoring of patient data. This was verified by trials with the following systems which were developed by our group in Vietnam: a fuzzy expert system for syndromes differentiation in oriental traditional medicine, an expert system for lung diseases using fuzzy logic, case based reasoning for medical diagnosis using fuzzy set theory, a diagnostic system combining disease diagnosis of western medicine with syndrome differentiation of oriental traditional medicine, a fuzzy system for classification of western and eastern medications and finally, a fuzzy system for diagnosis and treatment of integrated western and eastern medicine. All the above mentioned systems were developed and tested at the hospitals.

1. Introduction

In recent years, computational intelligence has been used to solve many complex problems by developing intelligent systems. And fuzzy logic has proved to be a powerful tool for decision-making systems, such as expert systems and pattern classification systems. Fuzzy set theory has already been used in some medical expert systems.

In traditional rule-based approach, knowledge is encoded in the form of antecedent-consequent structure. When new data is encountered, it is matched to the antecedents clauses of each rule, and those rules where antecedent match a data exactly are fired, establishing the consequent clauses. This process continues until desired conclusion is reached, of no new rule can be fired. In the past decade, fuzzy logic has proved to be wonderful tool for intelligent systems in medicine. Some examples of using fuzzy logic to develop fuzzy intelligent systems are fuzzy systems in their microprocessors, fuzzy control of the subway system in the Japanese city of Sendai, fuzzy washing machines, fuzzy cameras and camcorders that map image data to lens settings, and fuzzy voice commands: “up”, “land”, “hover” to control an unmanned helicopters[8].

In this paper, we would like to discuss how fuzzy set theory and fuzzy logic can be used for developing knowledge-based systems in medicine. Some notions of fuzzy logic in the narrow and broad sense are introduced in section 2. Section 3 describes the formalism of a fuzzy rule based system in medicine. An example of applying fuzzy logic in knowledge based systems in medicine is made in section 4. Some conclusions are given in section 5.

2. Some notions of fuzzy logic in narrow and broad senses

In order to show how fuzzy sets theory and fuzzy logic are a suitable tool for representing and handling medical concepts, three questions should be answered. What is logic? What is fuzziness and what meaning has the term “fuzzy logic” [1]? We will then discuss the motivation of the use of fuzzy logic in medicine.

Logic studies the notions(s) of consequence: It deals with propositions, set of propositions and the relation of consequence among them. The task of formal logic is to represent all this by means of well-defined logical calculi admitting exact investigation. Various calculi differ in their definitions of sentences and notion(s) of consequence (propositional logic, predicate logic, modal propositional/predicate logic, and many-valued propositional/predicate logic). Often a logical calculus has two notions of consequence: syntactical (based on a notion of proof) and semantical (based on a notion of truth); then the natural questions of soundness (does provability imply truth?) and completeness (does truth imply provability?).

Medical fuzziness is impreciseness: a fuzzy proposition may be true in some degree. The word “crisp” is used as meaning “non-fuzzy”. Standard examples of fuzzy propositions use linguistic variables such as age with possible values young, medium, old or similar. The sentence “the patient is young” is true in some degree, the lower the age the more the truth. Truth of a fuzzy proposition is a matter of degree. “Fuzzy logic” in medicine has two different meanings – wide and narrow.

Let recall the preface made by Zadeh[2]. ”In narrow sense, fuzzy logic, FLn, is a logical system which aims at a formalization of approximate reasoning. in this sense, FLn is an extension of multivalued logic. However, the agenda of FLn is quite different from that of traditional multivalued logics. In particular, such key concepts in FLn as a concept of a linguistic variable, canonical form, fuzzy if-then rule, fuzzy quantification, the extension principle, the compositional rule of inference and interpolative reasoning, is not addressed in traditional systems. This is the reason why FLn has a much wider range of applications than traditional systems. In its wide sense, fuzzy logic, FLw, is fuzzily synonymous with fuzzy set theory, FST, which is the theory of classes with unsharp boundaries. FST is much broader than FLn and includes the latter as one of its branches”.

Based on Zadeh’s opinions on “fuzzy logic”, we may conclude two things: First, in the broad sense, every thing dealing with fuzziness may be called “fuzzy logic”. Second, in the narrow sense, formal calculi of many-valued logic to be the base of fuzzy logic.

Now, let us deal with “fuzzy logic” in medicine in broad sense. In the medicine, especially, in oriental medicine, most medical concepts are fuzzy. The imprecise nature of medical concepts and their relationships requires the use of “fuzzy logic". It defines inexact medical entities as fuzzy sets and provides a linguistic approach with an excellent approximation to texts. "Fuzzy logic" offer reasoning methods capable of drawing approximate inferences. For example, in Oriental medicine, for a back pain that is not caused by a disease, acupuncture is often very efficient. Rules of oriental medicine include words like "severe pain" that are difficult to formalize and to measure. On the other hand, traditionally, mathematics uses crisp (well-defined) property P (x), i.e. properties that are either true or false. Each property defines a set: {x | x has a property P}. In 1965, L. Zadeh [9] proposed a theory that explains how to formalize "fuzzy" (non-crisp) properties: A crisp property P can be described by a characteristic function $\mu: X \to \{0,1\}$. A fuzzy property can be described as a function $\mu: X \to [0,1]$. The value $\mu(x)$ indicates the degree to which x has the property (e.g. to which x has pain). An example of representing a medical concept "high fever" as a fuzzy set is illustrated in Figure 1.

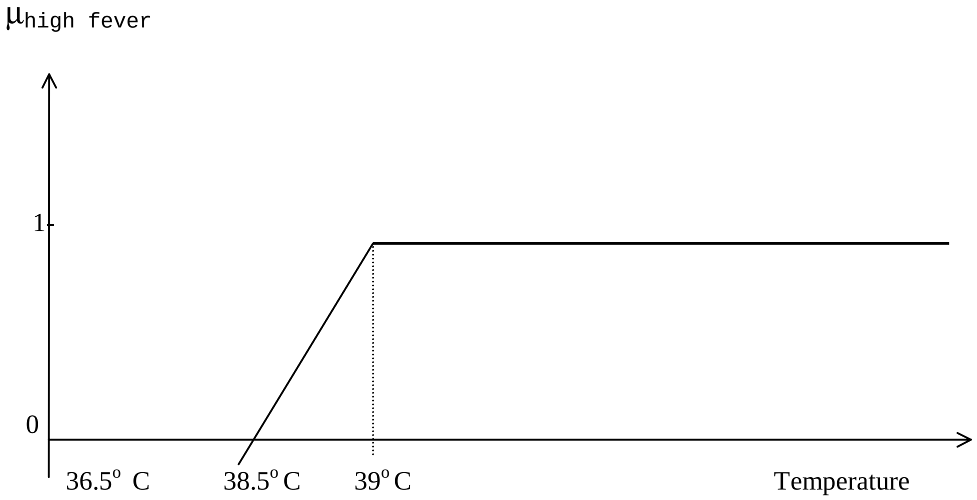


Figure 1: Representing a medical concept "High Fever"

In figure 1, a) if x is grater than 39° C, then membership function $\mu(x)$ of medical concept "High Fever" is 1 i.e. means that x has surely "high fever", b) if x is less than 38.5° C, then membership function $\mu(x)$ of medical concept "High Fever" is 0 i.e. means that x has surely not "high fever", c) if x is in the interval [38.5° C, 39° C], then x has a property "high fever" with some degree in [0,1].

In the rules of knowledge base of rule based systems, fuzzy properties are often connected by logical words like "and", "or", "not". In traditional set theory, these operations correspond to $\wedge$, $\vee$, $'$. So, we need to extend these operations to fuzzy sets.

Intersection: For modeling "and" we use t-norm:

Definition: A binary operation $\wedge$: $[0,1]\mathrm{x}[0,1] \to [0,1]$ is called a t-norm if it satisfies the following properties:

1. $1 \wedge x = x$ (1 acts as an identity)
2. $x \wedge y = y \wedge x$ (commutativity)
3. $x \wedge (y \wedge z) = (x \wedge y) \wedge z$ (associativity)
4. if $w \le x$ and $y \le z$ then $w \wedge y \le x \wedge z$ (monotonicity)

Note that $0 \wedge x \le 0 \wedge 1 = 0$, so, $\wedge$ is idempotent.

Disjunction: For modeling "or" we use t-conorm:

Definition: A binary operation $\vee$: $[0,1]x[0,1] \to [0,1]$ is called a t-conorm if it satisfies the following properties:

5. $0 \vee x = x$ (0 acts as a zero element)
6. $x \vee y = y \vee x$ (commutativity)
7. $x \vee (y \vee z) = (x \vee y) \vee z$ (associativity)
8. if $w \leq x$ and $y \leq z$ then $w \vee y \leq x \vee z$ (monotonicity)

Negation: Negation is an involution

$n: [0,1] \to [0,1]$ (i.e., $n^2 (x) = x$).

The simplest and most widely used negation operation is

$n(x) = 1-x$.

If we have negation, then due to the de Morgan laws [3] :

$$A \cap B = (A' \cup B')$$

$$A \cup B = (A' \cap B')$$

It is sufficient to define either $\cap \, or \cup$.

Here are three basic examples of t-norms which are often used for reasoning in fuzzy medical systems.

a) $a \wedge b = \min (a, b)$. The corresponding t-conorm (union) can be obtained by using de Morgan laws:
   $a \vee b = (a' \wedge b')' = 1-(1-a) \wedge (1-b) = \max (a,b)$.
b) $a \wedge b = a . b$. The corresponding t-conorm is
   $a \vee b = 1-(1-a) . (1-b) = a + b – a . b$.
c) $a \wedge b = \max (a + b – 1, 0)$. The corresponding t-conorm is
   $a \vee b = \min (a + b, 1)$.

In a similar way, three basic examples of t-conorms are:

d) $a \vee b = \max (a, b)$. The corresponding t-norm is
   $a \wedge b = 1-(1-a) \vee (1-b) = \min (a, b)$.
e) $a \vee b = a + b – a . b$. The corresponding t-norm is
   $a \wedge b = 1-(1-a) . (1-b) = a . b$.
f) $a \vee b = \min (a + b, 1)$. The corresponding t-norm is
   $a \wedge b = \max (a + b – 1, 0)$.

Comments: All these operations are a generalization of the classical Boolean logic. What is a t-norm or a t-conorm used depending on concrete applications and experiences of medical doctors?

3. Rule Based fuzzy systems in medicine

In rule-Based fuzzy systems in medicine, experts often formulate their statement in terms of rules of the type:

If x is A and y is B then z is C

For example,

If back pain is severe and patient is old then apply acupuncture to a certain point for a long time.

Here:

x is patient's pain, A is "severe";

y is patient's age, B is "old"

z describe treatment's time, C is "long time"

Now, we describe the formalization of such if-then rules in the rule base of expert systems. For each rule:

If x_1 is $A_{1,}$ ..., x_n is A_n then z is C

We can compute the degree to which the conditions are applicable as

$$\mu_{cond} = \mu\, A_1(x_1) \wedge ... \wedge \mu\, A_n(x_n)$$

Them, for each possible z, we can compute the degree to which the rule holds:

$$\mu_{rule} = \mu_{cond} . \wedge \mu_{\,C}(z).$$

If we have several rules $r_{1,...,}\, r_n$, then the degree μ (z) to which one of them is applicable for a given effect z is:

$$\mu\,(z) = \mu_{\,r1}(z) \vee .... \vee \mu_{\,rn}(z).$$

Finally, we find the "most probable" value z and use it, e.g., we take $\bar{z}$ for which

$$\int \mu\,(z).(z - \bar{z})^2\, dz \rightarrow \min_{\bar{z}} \quad \text{i..e.,}\ \bar{z} = \frac{\int z\mu(z)dz}{\int \mu(z)dz}$$

4. Application of fuzzy logic in developing rule based systems in medicine

In this section, we will illustrate the application of the above formalism for incorporating negative knowledge into fuzzy knowledge – based systems by using ordered Abilian group[7]. We used this formalism to design expert systems for lung disease diagnosis[4], for syndrome differentiation in Eastern medicine[5] and for diagnosis of combing western and eastern medicine in diagnosis[6]. An example of the performance of the diagnostic system for Lung Diseases diagnosis using fuzzy logic is shown below.

4.1 Application of fuzzy logic in developing rule based system for diagnosis of lung diseases: DoctorMoon[6].

DoctorMoon has been programmed in Borland Delphi 4.0 and run on Microsoft Windows 9x. It's easy to install and has a friendly interface.

System's interface

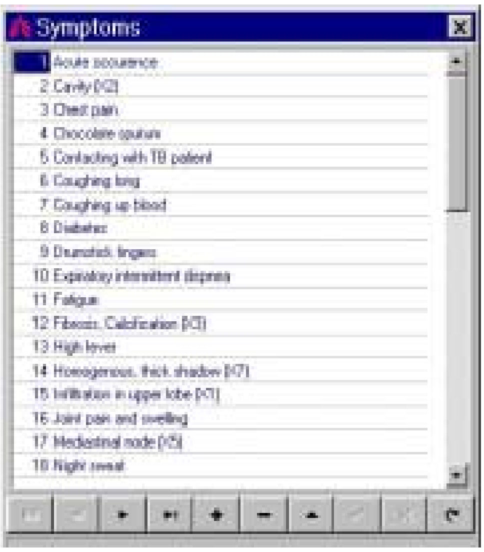
4.1.1 Knowledge base

The knowledge base of DoctorMoon is managed by a Borland Paradox Database consisting of 700 records, each represents a rule.

Knowledge acquisition.

The goal at this stage is to provide DoctorMoon with the brain of an experienced doctor. We used two methods of acquisition:

- Most of the rules in DoctorMoon were provided by doctors in the Vietnam National Institute of Tuberculosis and Lung Diseases (VNITLD). We listed all the popular lung disease symptoms (about 30 symptoms) and sorted them by their importance. This importance was determined by the doctors, and relate to how often the symptom are observed from a patient suffering from a certain lung disease. After sorting, the most important combinations of the most important symptoms were formed. This means most of popular clinical status criteria would be considered. These combinations would be used as <Condition> in the rules. For each combination, the doctors then based on their knowledge and experiences drew a conclusion about a patient's illness. This conclusion includes <*Conclusion*> and <*Grade*> of a rule.
- Rules are automatically formed. A program will browse the patient database to summarize the common syndromes that affirm or exclude a certain lung disease and then create new rules. This is done by applying suitable statistical theories as shown in [3]. A large number of rules can be created very quickly in this way, but rules' accuracy is not high.



List of symptoms

List of diseases

a. Verifying the Knowledge base

The more correct the rules are, the better the diagnosis will be. After acquisition, DoctorMoon had undergone much testing and the knowledge base had been corrected several times. Diagnostic tests were conducted to determine which rules were incorrect by comparing the conclusion of DoctorMoon to the conclusion of doctors. A group of lung disease experts will keep making changes until the conclusions from the diagnostic system were acceptable. Those changes can be made at every part of a rule: the <*Condition*>, the <*Conclusion*> or the <*Grade*>.

On the other hand, as the correctness of the knowledge base depends upon doctors' judgment, it's necessary to test doctors' diagnostic ability. So far, DoctorMoon has not been able to carry out that task.

b. Validating the Rule base.

A very important aspect of the knowledge base is the issue of truth maintenance and conflict resolution. This means that conflicts and coincidence between any pair of rules must be eliminated and besides, rules must be related logically: e.g., a rule with the <*Condition*> consisting of 3 symptoms must affirm the infection with higher grade than a rule with the <*Condition*> consisting of 2 diagnostic symptoms.

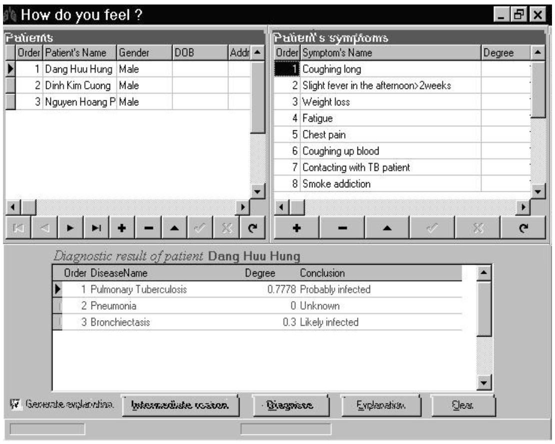
Conflict resolution was performed by a software module in the program. The module identifies all conflicts and illogical relationships between rules so that necessary changes can be made. Normally, this module is activated whenever a new rule is created.

4.1.2 A patient database

A patient database was created and has been updated. This database plays a crucial role in the automatic knowledge acquisition. Besides, it can ease the administrative work and management in VNITLD (Vietnam Institute of Tuberculosis and Lung Diseases). As it stores all information about patients as well as their medical records (clinical status, doctor's diagnosis, treatment and other information) it can effectively help to refine and improve DoctorMoon by giving comparison between diagnoses of the system and doctor.

4.1.3 Developing reasoning engine

DoctorMoon has a friendly interface which allows users to enter input data: the symptoms observed from the patient and their severity of illness. Once the diagnostic process takes place, all rules that match the patient i.e., rules of which the <*Condition*> are included in the input data and will contribute to the reasoning process and then to final conclusion.



Diagnosing

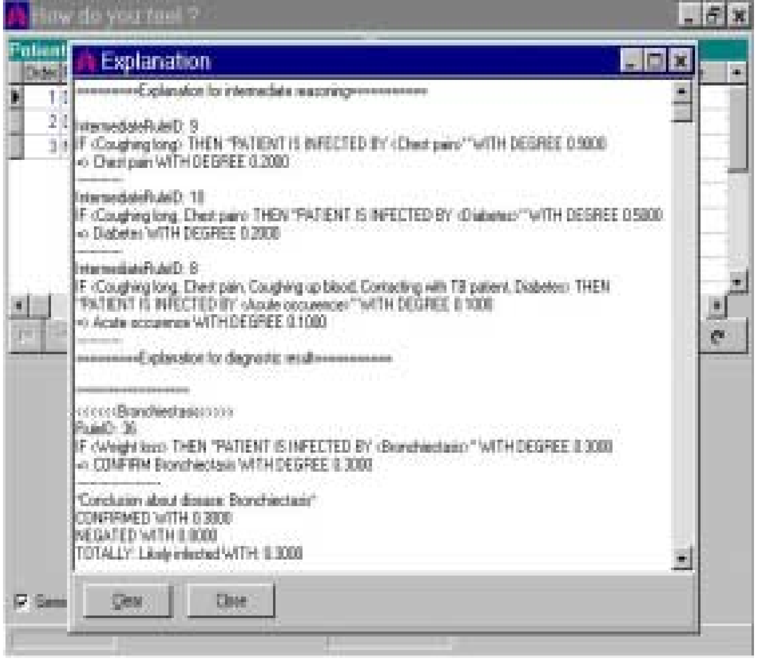
The upper left panel lists patients in the database. We can browse through this list and simultaneously see the list of all symptoms corresponding to each patient in the upper right panel. The bottom panel shows the diagnosis given to the patient by Doctor Moon

4.1.4 Diagnosing more than one disease

Theoretically, DoctorMoon is able to diagnose an unlimited number of diseases. The number of diseases that the system can diagnose absolutely depends on the knowledge base. To enable DoctorMoon to diagnose a new disease, all we have to do is to make a new entry in the disease list and acquire the necessary rules to upgrade the knowledge base. So far, the system is familiar with Pulmonary Tuberculosis, Lung Abcsess, Lung Cancer, Asthma, Pneumonia, Bronchiectasis.

4.1.5 Explaining the diagnostic results

In this medical expert system, a indispensable feature is the ability of explaining the diagnostic results: why and how the results are generated. During the diagnostic process, DoctorMoon records all the reasoning steps: getting patient’s symptoms, matching rules, diagnosing, etc., for generating a report when the diagnosis has been done.



Explanations

Each patient is diagnosed for all available diseases. The diagnostic process is recorded in details in the patient's record and stored in the patient-database. The recorded process includes as many sections as number of available diseases. In each section, we can keep track of which rules in the rule base were fired, and how the conclusion was made.

4.1.6 Testing and evaluation

DoctorMoon had undergone several tests in VNITLD. In these tests, the system was given a set of symptoms as clinical status of a patient, TUBEDIAG diagnosed that patient and returned the conclusion. The conclusion was judged by a group of experienced doctors in VNITLD to evaluate the diagnostic capability of the system.

First, DoctorMoon was given clinical status of real patients. In most cases, DoctorMoon drew the same conclusion as the last conclusion of the doctor in the records.

Next, experts gave DoctorMoon some special combinations of symptoms as some rare, special patients. After diagnosing, DoctorMoon sometimes returned too strong affirmative or exclusive conclusion as compared to the expected conclusion given by doctors. The reason was the knowledge base was not large enough to cover most possible cases and some rules had to be corrected.

The evaluation found DoctorMoon's diagnoses to be acceptable and in order to improve system's performance in special cases, the knowledge base needs to be strengthened. The reasoning engine is good.

5. Conclusion

We have to spend more time on this study to archive our objective, that is to formalize medical entities as fuzzy sets, and formalize reasoning in rule based systems in medicine. We have tried to distinguish the notion of "fuzzy logic" in the broad and narrow sense. In this paper, we use "fuzzy logic" in the broad sense to formalize approximate reasoning in medical diagnostic systems. We have applied this formalism to build a fuzzy Expert System for Syndromes Differentiation in oriental traditional medicine, an expert system for diagnosis of western medicine such as for the diagnosis of lung diseases using fuzzy logic, then a diagnostic system combining disease diagnosis of western medicine with syndrome differentiation of oriental traditional medicine. We have shown the performance of the diagnostic system for lung diseases as an example. Our further work is to apply the soft computing techniques such as fuzzy logic, neural network, genetic algorithms, learning and expert systems in order to developing intelligent systems in diagnosis and therapy of integrated western and eastern medicine[18-22].

6. References

1. Petr Hajek, Fuzzy logic from the logical point of view, Proc. SOFSEM'95: Theory and Practice of Informatics, Lecture Notes in Computer Science, Springer.31-49.
2. 2. Marks II, R., J.: Fuzzy logic Technology and Applications. IEEE Technical Activities Board, 1994.
3. Hung T. Nguyen, Elbert A. Walker, A First Course in Fuzzy Logic, Chapman & Hall/CRC, 1999 (Second Edition)
4. Nguyen Hoang Phuong, Hung H. Dang, Nadipuram R. Prasad, Development of a Supporting Expert System for Lung Diseases using Fuzzy Logic, J. Biomedical Soft Computing and Human Sciences, Vol. 5, No. 2, June 2000, 37-44 (Special Issue on MIF'99, Guest Eds.: T. Yanaru, A. Tamaki, S. Arita, Nguyen Hoang Phuong, E. Sanchez)
5. Nguyen Hoang Phuong, Approximate Reasoning for Oriental Traditional Medical Expert Systems. In Proc. the 1997 IEEE Inter. Conference on Systems, Man, and Cybernetics (SMC97), Orlando, Florida, USA, October 12-15, 1997, 3084-3089.
6. Nguyen Hoang Phuong, Torao Yanaru, Vu Quang Minh, Approach to Developing a diagnostic System combining Diseases diagnosis of Western medicine with syndrome differentiation of Traditional Medicine, J. Biomedical Soft Computing and Human Sciences, Vol. 5, No. 2, June 2000, 9-16 (Special Issue on MIF'99, Guest Eds.: T. Yanaru, A. Tamaki, S. Arita, Nguyen Hoang Phuong, E. Sanchez)
7. Nguyen Hoang Phuong, Towards Intelligent Systems for Integrated Western and Eastern Medicine, TheGioi Publishers, Hanoi, 1997. (book in English).
8. Bart Kosko, Fuzzy Engineering, Prentice Hall, 1997.
9. Zadeh, L.A. 1965. Fuzzy sets, Information and Control, Vol. 8, 338-353.
10. Kyung Sook Park, Yong Moon Chae, Mignon Park. Developing a Knowledge-Based System to Automate the Diagnosis of Allegric Rhinits. Biomedical Fuzzy and Human Sciences, vol. 2, no. 1, 9-18,1996.
11. Nguyen Hoang Phuong, Fuzzy Information Integration applied in Expert Systems, in Proc. of the 5th International Conference on Soft Computing and Information/Intelligent Systems (IIZUKA'98), Oct. 16-20, 1998, IIZUKA, Fukuoka, Japan, 414-417.
12. Nguyen Hoang Phuong, Ngo Hoang Anh, Bach Hung Khang, Construction of Bayesian Network for Diagnosis of Tuberculosis, in Proc. of 5th ASIAN Science and Technology Week (ASTW) MICROELECTRONCS and IT CONFERENCE, 12-14 Oct., 1998, Hanoi, Vietnam, 124-129.
13. Chae Y M, Park I Y, Jang T Y:A Clinical decision support system for diagnosis of hearing losss. Kor J of preventive Med 22 (1): 57-64,1989.
14. Chung S K, Park IY, Jang T Y,Chae Y M: Decision making support system in Otolaryngology part-2 (diagnosis of hearing loss) Kor J of Otolaryngology 32: 768-789,1989.
15. Chung S K, Park IY, Jang T Y,Chae Y M: Decision making support system in Otolaryngology part-3 (diagnosis of allergic rhinitis) Korea Journal of Otolaryngology 33: 104-110,1990.
16. Young Moon Chea, Mignon Park "The Development of a Decision support system for Diagnosing Nasal Allergy" Yonsei Medical Journal: Vol. 33, No. 1, 1992.
17. Davis, R.C. Rich "Expert systems Part 1 Fundamentals". Tutorial no. 4 The Third Nation conference on Artificial Intlligence. Menlo Park,CA: Ammerican Association for Artifical Intelligence.

18. Nguyen Hoang Phuong, Scott A. Starks, V. Kreinovivh, Interval-Based Expert Systems and their use for Traditional Oriental Medicine. In Proceedings of VJFUZZY'98: Vietnam-Japan Bilateral Symposium on Fuzzy Systems and Applications, (Eds. Nguyen Hoang Phuong, Ario Ohsato), Halong Bay, Vietnam, 30 Sept-2 Oct., 1998, p. 697-703.
19. Nguyen Hoang Phuong, Scott A. Starks, V. Kreinovivh, Towards foundations for Traditional Oriental Medicine. In Proceedings of VJFUZZY'98: Vietnam-Japan Bilateral Symposium on Fuzzy Systems and Applications, (Eds. Nguyen Hoang Phuong, Ario Ohsato), Halong Bay, Vietnam, 30 Sept- 2 Oct., 1998, p. 704-708.
20. Nguyen Hoang Phuong. Approach to Combining Negative and Positive Evidence in CADIAG-2. In Proceedings of Third European Congress on Intelligent Techniques and Soft Computing (EUFIT'95), Aachen, Germany, August 28-31, 1995, 1653-1658.
21. Nguyen Hoang Phuong. Fuzzy Set Theory and Medical Expert Systems. Survey and Model. Proc. SOFSEM'95: Theory and Practice in Informatics, Lecture Notes in Computer Science, No. 1012, Springer-Verlag 1995, 431-436.
22. M. Daniel, P. Hajek, Nguyen Hoang Phuong. CADIAG-2 and MYCIN-like systems. International J. Artificial Intelligence in Medicine**.** Vol. 9, 1997, 241-259.