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Medical Knowledge and Fuzzy Expert System

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ABSTRACT

The term medical knowledge is a superimposed concept for the relationships between symptoms and diagnoses a physician may find in books, journals, monographs, but also in practical experience. In the second half of the 20th century medical knowledge was also stored in computer systems. To assist physicians in medical decision- making and attendance medical expert systems have been constructed that use the theory of fuzzy sets, which was founded in 1965 by Zadeh. The present article delineates two specific pathways resulting from a bifurcation in the history of applied fuzzy expert systems in medicine. This bifurcation occurred in the 1970's in the history of the theory of fuzzy systems, when Zadeh published the "rule of max-mim composition" and other researchers applied this rule in different areas. This was the origin of two research areas : fuzzy relations, introduced by Elie Sanchez in Marseille. Later on both concepts were used to construct medical knowledge-based systems in medicine. We present two Viennese systems representing these concepts: the "fuzzy version" of the Computer-Assisted DIAGnostic System (CADIAG) which was developed at the end of the 1970s, and a fuzzy knowledge-based control system, FuzzyKBWean, which was established as a real-time application based on the use of a Patient Data Management System (PDMS) in the intensive care unit (ICU) in 1996.

***Keywords*:** Phelonephritis, chills, hematology, diagnosis, Pathology, antecedent, consequent, susceptible, robust, ventilation, respiratory.

1. Introduction

The history of computerized medical diagnosis is a history of intensive collaboration between Physicians and Mathematicians respectively Electrical Engineers and Computer Scientists. In the late 1950s Ledley and Lusted published Reasoning Foundations for Medical Diagnosis [1], Lipkin and Hardy [2], and Ledley [3], wrote on the methods for the use of card and needle systems for storage and classification of medical data and systematic medical decision- making. In the 1960s and 1970s various approaches to computerized diagnosis arose using Bayes rule [4, 5], factor analysis [6], and decision analysis [3]. On the other side artificial intelligence approaches came into use, e.g., DIALOG (Diagnostic Logic) [7] and PIP (Present Illness Program) [8], which were programs to simulate gathering and diagnosis using databases in form of networks of symptoms and diagnoses.

2.1. Medical knowledge

We use the term “symptom” for any information about the patient’s state of health, anamnesis, signs, laboratory test results, ultrasonic results, and X- ray findings. Based on this information a physician has to find a list of diagnostic possibilities for the patient. To master this process he had to study many relationships of obligatory or facultative proving or excluding symtoms for diagnosis in books and journals and in his practical experience. These certain information about relationships that exist between symptoms and symptoms, symptoms and diagnoses, diagnoses and diagnoses and more complex relationships of combinations of symptoms and diagnoses to a symptom or diagnosis are formalizations of what is called medical knowledge.

In 1976 in Toronto, Canada, Alongo Perez-ojeda called this network linked by logical relations “medical knowledge”. The basic conception of his master thesis Medical Knowledge Network. A Database for computer Aided Diagnosis was the representation of “Medical knowledge” using an associative model of the human memory.

Perez-Ojeda designed a prototype system to be used in the search for an adequate strategy to simulate an approximate reasoning model in medical decision- making and he gave examples of typical elements of medical knowledge ([9], P.32):

- “A runny nose is almost always present in a common cold”.
- “Acute phelonephritis and infection”.
- “Acute pyelonephritis presents occasionally fever, or chills, and malaise”.

The diseases common cold and acute pyelonephristis are presented by the abbreviations D_1 and D_2 and runny nose, fever, bladder irritation, infection, chills, and malaise by S_1 to S_6. Therefore the network of medical knowledge could be graphically constructed by elementary knots and arcs.

However, Perez- ojedamodeled the relations (usually, occasionally, and almost always) by mathematical probability modifiers :

$$D_1 \xrightarrow{\text{almost always}} S_1$$

$$D_2 \xrightarrow{\text{usually}} S_3 \text{ AND } S_4$$

$$D_2 \xrightarrow{\text{occasionally}} (S_2 \text{ OR } S_5) \text{ AND } S_6$$

Figure 1. Examples of elements of the network of medical knowledge.

2.2. Computer- assisted diagnostic (CADIAG- 1)

In the nineteen- sixties and- seventies, the Department of Medical Computer Sciences of the University of Vienna Medical School at the Vienna General Hospital envisaged the development of a computer assisted diagnostic system that did not use stochastic methods. “It was intended to develop a system which is not based on statistical assumptions like normal distribution, mutual independency of symptoms, constant probabilities of symptoms in different populations and at different observation times. There is no need for information about the frequency or lack of certain symptoms with the sick or the healthy. Therefore rare complaints are considered as well as frequent diseases" ([10], P.141).

In 1976, the second generation of the system was developed on the basis of three-valued logic. Here, in addition to symptoms and diagnoses being considered to be diagnoses are also included. For this system known as CADIAG- I. (Computer Assisted DIAGnostis, version- I), the following relationships between symptom (S_i) and disease (D_j) have been defined:

- Op: S_i is obligatory occurring and proving for D_j.
- E: S_i forces obligatory exclusion of D_j.
- FP: S_i is facultative occurring and proving for D_j.
- ON: S_i is obligatory occurring and not proving for D_j.
- FN: S_i is facultative occurring and not proving for D_j.
- NK: A specific relationship between the symptom and the disease is not known.

With three- valued logic these relationships could be expressed in the form of three-valued logic operators : the symptam's values could be present (1), absent (0), or not investigated $(\frac{1}{2})$, whereas the possible diagnoses' values could be present (1), absent (0), or possible $(\frac{1}{2})$.

As an example we show here the three-valued logic truth table of the relationship OP (S_i is obligatory occurring and proving. S_i must be present for D_j and S_i proves D_j; $S_i \Leftrightarrow D_j$.)

D_j / S_i	0	$\frac{1}{2}$	1
0	1	$\frac{1}{2}$	0
$\frac{1}{2}$	$\frac{1}{2}$	$\frac{1}{2}$	$\frac{1}{2}$
1	0	$\frac{1}{2}$	1

Figure 2. Three- valued logic truth table of OP: $S_i \Leftrightarrow D_j$

Here only a brief review may show their logical analysis of this diagnosis process :

- x, y, ... are used to represent 'attributes'. A patient may have an attribute such as, for instance, a sign 'fever' or a discase 'pneumonia'.

- Corresponding capital letters X, Y, ... are used to represent statements about these attributes.
- For example : Y represents the statement "The patient has attribute y".
- Negation $\neg$ Y : "The patient does not have attribute y".
- The combination X.Y represents the combined statement "The patient has the attribute x and the attribute y".
- The combination X+Y represents the combined statement "The patient has attribute x or attribute y or both".
- The statement "If the patient has attribute x then he has attribute y" is symbolized by $X \Rightarrow Y$.

With only two attributes, symptoms (S) and diseases (D), they defined
S (i) means "The patient has symptom i". i=1,2,......., n.
D (j) means "The patient has disease j", j=1,2, ..., m.
From a diagnostic textbook they took abstract example statements :
If a patient has disease 1 and not disease 2,
then he cannot have symptom 2

$$D(1).\neg D(2) \Rightarrow \neg S(2)$$

If a patient has either or both of the symptoms,
then he must have one or both of the diseases

$$S(1) + S(2) \Rightarrow D(1) + D(2)$$

To consider in general, more than two attributes, and more complicated expressions Ledley and Lusted used 'Boolean functions' f (X, Y, ...).

2.3. Medical knowledge as a fuzzy relation

A more far-reaching concept of modeling relationships between symptoms and diseases was introduced in 1974 by Elie Sanchez from Marseille, France, in his human biological doctoral thesis Equations de Relations Floues [11]. Sanchez planned "to investigate medical aspects of fuzzy relations at some future time" ([12], p.47).

In 1979 he introduced the relationship between symptoms and diagnoses by the concept of 'medical knowledge' : "In a given pathology, we denote by S a set of symptoms, D a set of diagnoses and P a set of patients. What we call "medical knowledge" is a fuzzy relation, generally denoted by R, from S to D expressing associations between symptoms or syndromes, and diagnoses, or groups of diagnoses" ([13], P.438). Sanchez adopted Zadeh's max-min-compositional rule as an inference mechanism. It accepts fuzzy descriptions of the patient's symptoms and infers fuzzy descriptions of the patient's diseases by means of the fuzzy relationships described earlier. If a patient's symptom is S_i then the patient's state in terms of diagnoses is a fuzzy set D_j with the following membership function:

$$\mu_{D_j}(d) = \max \ \min\{\mu_{S_i}(s); \mu_R(s,d)\}, s \in S, d \in D.$$

$\mu_R(s,d)$ is the membership function of the fuzzy relation "medical knowledge".
With P, a set of patients, and a fuzzy relation Q from P to S, and by 'max-min composition' we get the fuzzy relation T = Q $\circ$ R with the membership function.

$$\mu_T(p,d) = \max \ \min\{\mu_Q(p,s); \mu_R(s,d)\}, p \in P, s \in S, d \in D.$$

This new fuzzy version of the computer assisted diagnostic system, CADIAG- 2, appeared in 1980. In Adlassnig's fuzzy logical model of computer- assisted medical diagnosis, all symptoms $s_i \in S$ are considered to be fuzzy sets of different universes of discourse X with membership functions $\mu_{s_i}(x)$, for all $x \in X$, indicating the strength of x's affiliation in S_i, while all diagnoses $D_j \in D$ are considered to be fuzzy sets in the set P of all patients under consideration, with μ_{D_j} (p) assigning the patient p's membership to be subject to D_j.

To describe medical knowledge as the relationship between symptom S_i and disease D_jAdlassnig found two fuzzy relationships, namely occurrence – how often does S_i occur with D_j? And confirmability how strongly does S_i confirm D_j? – ([14], p.225). These functions could be determined by

- linguistic documentation by medical experts and
- medical database evaluation by statistical means or a combination of both.

In both ways to determine these fuzzy relationships between symptoms and diagnoses, occurrence and confirmation, they have been defined as fuzzy sets. When physicians had to specify these relationships by only giving answers like always, almost always, very often, often unspecific, seldom, very seldom, almost never, and never, they chose fuzzy sets which have been defined by Adlassnig's determination of their membership functions. In the case of medical databases, the membership functions' values of occurrence and confirmability could be defined as relative frequencies.

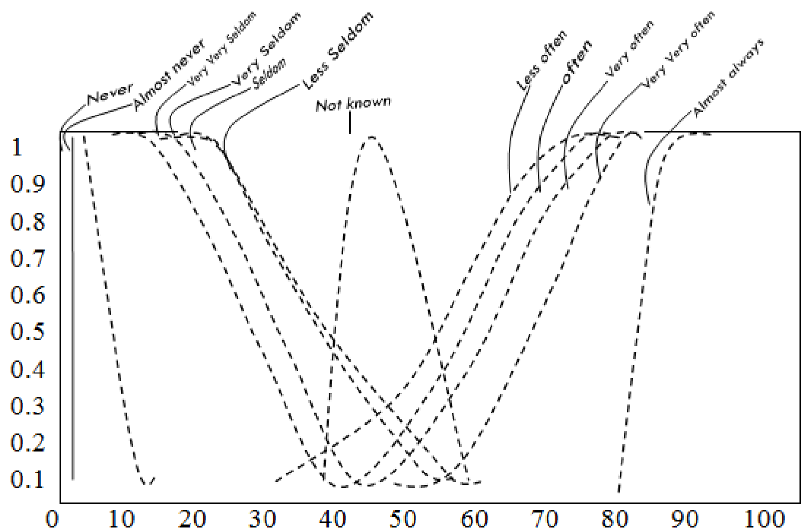

Figure 3. Membership functions of the fuzzy sets occurrence o (former presence P) and confirmability c (former conclusiveness c)

Thus, in CADIAG- 2, the fuzzy relationships between symptoms (or symptom combinations) and diseases are given in the form of rules with associated fuzzy relationship tupels (frequency of occurrence o, strength of confirmation c); their general formulation is ([15], p.262):

* IF antecedent THEN consequent WITH (o, c)

In particular, the following fuzzy relationships exist ([15], p.262;K=set of symptom combinations SC_i) :

S_i, D_j (occurrence relationship) $R^o{}_{SD} \subset \Sigma \times \Delta$

S_i, D_j (confirmation relationship) $R^c{}_{SD} \subset \Sigma \times \Delta$

SC_i, D_j (occurrence relationship) $R^\circ{}_{SCD} \subset K \times \Delta$

SC_i, D_j (confirmation relationship) $R^c{}_{SCD} \subset K \times \Delta$

S_i, S_j (occurrence relationship) $R^\circ{}_{SS} \subset \Sigma \times \Sigma$

S_i, S_j (confirmation relationship) $R^c{}_{SS} \subset \Sigma \times \Sigma$

D_i, D_j (occurrence relationship) $R^\circ{}_{DD} \subset \Delta \times \Delta$

D_i, D_j (confirmation relationship) $R^c{}_{DD} \subset \Delta \times \Delta$

To deduce diseases $D_j \in D$ suffered by patient $P_k \in P$ from observed symptoms $S_j \in S$ in CADIAG- II we use three max-min- compositions as inference rules :

* hypothesis and confirmation $R^1{}_{PD} = R_{PS} \circ R^c{}_{SD}$ defined by

$$\mu_{R^1{}_{PD}}(P_k, D_j) = \max \ \min\{\mu_{R_{PS}}(P_k, S_i); \mu_{R^c{}_{SD}}(S_i, D_j)\}$$

* exclusion (by present symptoms) $R^2{}_{PD} = R_{PS} \circ (1 - R^c{}_{SD})$ defined by

$$\mu_{R^2{}_{PD}}(P_k, D_j) = \max \ \min\{\mu_{R_{PS}}(P_k, S_i); 1 - \mu_{R^c{}_{SD}}(S_i, D_j)\}$$

* exclusion (by absent symptoms) $R^3{}_{PD} = (1 - R_{PS}) \circ R^o{}_{SD}$ defined by

$$\mu_{R^3{}_{PD}}(P_k, D_j) = \max \min\{1 - \mu_{R_{PS}}(P_k, S_i); \mu_{R^o{}_{SD}}(S_i, D_j)\}$$

CADIAG - 2 was very successful in partial tests, e, g, in a study of 100 patients with rheumatic diseases; CADIAG- 2 elicited the correct diagnosis in 94% ([15], p, 264). More results can be found in [14, 15].

2.4. Fuzzy control in medicine

Fuzzy control techniques have recently been applied in various medical processes such as pain control [16] and blood pressure control [17]. Fuzzy control compared to classical control theory (PID control), which is a Fuzzy logic approach to control, offers the following advantages [18, 19].

* It can be used in systems, which cannot be easily modeled mathematically. In particular, systems with non linear responses that are difficult to analysis may respond to a Fuzzy control approach.

* As a rule based approach to Fuzzy control can be used to efficiently represent an expert's knowledge about a problem.
* Continuous variables may be represented by linguistic constructs that are easier to understand, making the controller easier to understand, making the controller easier to implement and modify. For instance, instead of using numeric values temperature may be characterized as "cold, cool, warm, or hot".
* Fuzzy controller may be less susceptible to system noise and parameter changes; in other words, they will be more robust.
* Complex processes can be controlled by relatively few logical rules, permitting an easily comprehensible controller design an faster computation for real- time applications.

In other words, fuzzy control can be best applied to production tasks that heavily rely on human experience and intuition, and which therefore rule out the application conventional control methods. The use of Patient Data Management Systems (PDMS) in Intensive Care Units (ICU) since 1992 has made it possible to apply fuzzy control applications in real-time in this medical field.

Mechanical ventilation is such an example. One purpose of mechanical ventilation is to achieve optimal values of arterial O_2-partial pressure (PO_2) and arterial CO_2- partial pressure (PCO_2) while ensuring careful handling of the lung:

* F_iO_2<60(else oxygen toxicity)

* Low inspiratory pressures p_1<35 (else barotraumas)

* Small shear forces equivalent to small tidal volumes (else volume trauma)

* Prevent atelectasis formation (else shear forces at reopening).

In addition the patient has to be carefully handled in order to avoid cardiac failure and respiratory muscle fatigue. Both of these conditions have to be observed if the heart rate or the respiratory rate increases. The value pO_2 states whether the nation sufficient pO_2 is not continuously available because it would entail taking a blood sample. O_2- saturation (SpO_2) provided by pulsoximetry is more convenient because SpO_2 is permanently available. pCO_2, states whether alveolar ventilation is sufficient. Similarly, the end-tidal CO_2 ($EtCO_2$) is permanently available, but at the disadvantage of being an indirect measure of pO_2. Thus of the weaning system are SpO_2 and $EtCO_2$. For instance, the Biphasic Positive Airway Pressure (BIPAP) controlled mode is an integrated mode of ventilation of Evita ventilators (Evita, Drager, Lubeck, Germany).

This mode allows spontaneous inspiration during the whole respiratory cycle and thus permits a very smooth and gradual transition from controlled to spontaneous breathing. Ventilatory adjustments are based on two pressure levels: inspiratory pressure (p_i or P_{high}) and expiratory pressure (P_E or P_{low}); on two durations, inspiration time (t_i) and expiration time (t_E), as well as on the fraction of inspired O_2 (F_iO_2). Within this mode, five parameters can be adjusted.

BIPAP was first described in a study published in 1989 by a group led by M. Baum and H. Benzer and it was incorporated in the Evita ventilator in the same year [20]. Earlier studies conducted by Stock et al. used the term APRV (Airway Pressure Release

Ventilation) [21] to describe a method of ventilation, which used the same mechanical principle as BIPAP, but started from a different premise. BIPAP as pressure- controlled ventilation with freedom of respiration and spontaneous breathing on two levels (see figure 4).

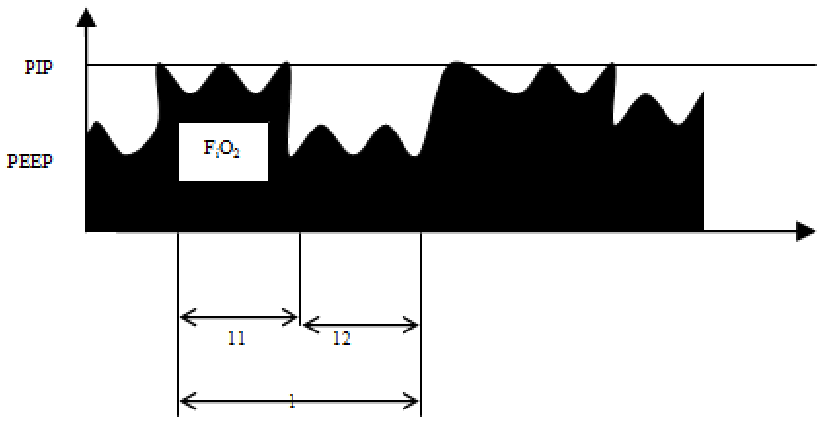

Figure 4. BIPAP ventilation mode

The procedure for weaning a patient with respiratory insufficiency from mechanical ventilation is a complex control task and requires expertise based on long-standing clinical practice. Fuzzy knowledge- based weaning (FuzzyKBWean) is a fuzzy knowledge-based control system that proposes stepwise changes in ventilator settings during the entire period of artificial ventilation at the bedside in real time.

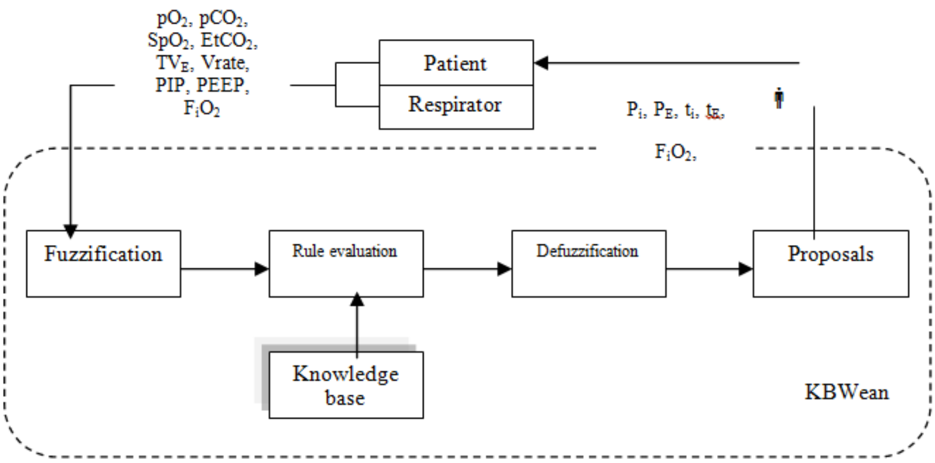

Figure 5. The FuzzyKBWean control process.

Information is obtained from a PDMS operating at the ICU with a time resolution of one minute. The system is used for postoperative cardiac patients at the Vienna

General Hospital. A large part of the explicitly given and implicitly available medical knowledge of an experienced intensive care specialist could be transferred to the fuzzy control system. Periods of deviation from the target are shorter using FuzzyKBWean . [22, 23].

3. Conclusion

In medicine, two fields of fuzzy applications were developed in the 1970's: computer assisted diagnostic systems and intelligent patient monitoring systems. Both developments of Zadeh's "rule of max-min composition" namely fuzzy relations and fuzzy control have been applied in these areas.

For obvious reasons, the available body of medical data (on patients, laboratory test results, symptoms, and diagnoses) will expand in the future. As mentioned earlier, computer-assisted systems using fuzzy methods will be better able to manage the complex control tasks of physicians than common tools.

Most control applications in the hospital selling have to be performed within critical deadlines; Decisions have to be made locally and promptly. This is a setting that requires a local hospital intranet rather than the possibilities of the world- wide internet.

Using current web technology, integrated systems of both types of fuzzy systems described above can be easily implemented as internet and intranet applications.

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