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A fuzzy model for medical diagnosis

Carlos A. Holzmann[1], Claudio A. Perez[1] & Eduardo Rosselot[2]
[1] Ingenieria Biomédica, Departamento de Ingenieria Electrica, Universidad de Chile; [2] Departamento de Medicina, Hospital Clinico, Universidad de Chile.

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Summary

A medical diagnosis support system based on a fuzzy model for illnesses is proposed. The model for each disease is a lattice structure composed by unidirectional fuzzy relations among intermediate diagnostic units (IDU). Its evaluation is sequential: it starts at the bottom units, the observable medical evidence (symptoms), and progresses through the IDUs to the cusp unit, representing the disease. Three types of IDUs are defined: for associated, non-associated and excluding evidence. These units represent medical concepts gathering knowledge under a common characteristic or criterion of diagnostic interest. Fuzzy unidirectional relations are used to quantify the medically known dependence between IDUs.

The model is specified for six cardiopathies, identifying and calibrating its parameters using data from patient's records. The model performance is evaluated comparing results with the diagnosis provided by three medical observers on new patient's records. Concordance histograms are shown as an objective measure for the model performance. A discussion about application of the diagnosis sensitivity respect to symptoms and respect to IDUs relations is performed.

Introduction

Computerized systems for decision making in medicine are relatively new. Formerly, emphasis was placed on the uses of a variety of numeric technics such as statistical formulas, decision trees, etc. [6, 8, 13], and later some associated problems to diagnosis have been approached, as: patient information acquisition; codification and control of variables which define patients and populations; representation of knowledge associated to appreciations or common sense; among others [5, 7, 10].

The theory of fuzzy sets, presented by L. Zadeh [15] has been applied to a variety of fields including medical diagnosis [1, 2, 9, 12, 14]. This theory seems to be specially suitable to model the medical diagnostic process, since it depends upon appreciations which are not precisely quantifiable, such as patient's subjective sensations, and interpretation of signs and results of instrumental procedures.

In this work, a model for medical diagnosis aid, based on fuzzy theory is developed, pursuing the general idea of emulating the physician's procedure to determine patients' diseases. Former applications of fuzzy theory on diagnosis have used an oversimplified model which assumes that all symptoms are independent, thus the most significant determines the disease [12, 14]. In most cases this conception is insufficient since it disagrees with medical knowledge. This work is based on the empirical evidence that, to arrive to a diagnosis, the physician's reasoning includes a computing step through a mental model for diseases, using the patient symptoms as input information. The referred mental model, seldom sufficiently explicit in the physician's mind, is the synthesis of knowledge acquired through theory and experience. This knowledge relates symptoms through hierarchically ordered superior units (clinical manifestations, syndromes, etc.) representing concepts commonly used in the description of an illness. The relations among these units form the structure of the model.

In this work, unless otherwise specified, under the denomination of symptom will be included also those manifestations called signs and instrumental findings, which all together constitute the observable evidence.

The medical support system

Let $D = \{_1, \ldots, D_m\}$ be the universe of diseases and $S = D_1 \{S_1, \ldots, S_n\}$ be the universe of symptoms. Each patient induces a fuzzy set in S as a grade of membership, s, to each of his symptoms is assigned. The model for one disease consists in a lattice structure composed of *Intermediate Diagnostic Units* (IDU) ordered hierarchically from the symptoms (atomic diagnostic units) up to the disease (cusp of the lattice). These IDUs are based on concepts and knowledge from medicine. The first level IDUs gather symptoms under a common characteristic or criteria of diagnostic interest, and IDUs of higher levels gather symptoms and other IDUs from inferior levels. Three types of IDUs, each of them with a formula to compute its grade of membership,are defined. The associative IDU gathers, in an additive manner, those symptoms which must be present to arrive at a conclusion; the non-associative IDU gathers symptoms among which only one of them, the most significant, is sufficient; and the excluding IDU permits to consider symptoms which reduce the diagnosis feasibility when their intensity increases (useful for differential diagnosis).

Through this mode the diagnosis is obtained calculating the grade of membership of each IDU to the patient, along the lattice structure, from the symptoms to the diseases. Each relation among IDUs is specified through a parameter, r, whose value, initially set by experts, considers the symptom upper threshold characteristic. These parameters are adjusted by hand on a trial and error basis, to meet the overall diagnostic criterion of the specialists. All grades of membership and relation values are in the interval (0,1).

According to the theory of fuzzy systems [4] the equations of a fuzzy mapping of $R \times R \rightarrow R$, are arbitrary; thus this freedom is used here to obtain the required performance of the associative, non-associative and exclusive IDU.

The degree of membership in an associative IDU is computed by

$$d = (1/n) \sum_{i=1}^{n} [1 - (|r_i - s_i|{*}k_i)^{1/2}] \tag{1}$$

where r_i is the i-relation grade of membership between the IDU and its i-symptom; s_i is the symptom grade of membership to the patient (symptom intensity). The constant $k_i = 0$ if $s_i \geqslant r_i$ and $k_i = 1$ otherwise.

The value of r_i is determined by the i-th symptom intensity upper threshold, so that for stronger intensities than this threshold the i-th contribution to the diagnosis remains constant at a maximum. For instance, the intensity of Emotional Lability, a symptom for the diagnosis of Chorea, has maximum consequence once it is found to overcome a critical significative value, previously determined by experts. In this case the relation value has been set in accordance as r = s (critical evidence of emotional lability) = 0.7. Clearly the relation value r = 1 must be used when the diagnosis monotonically increases with the symptom intensity, both reaching together their corresponding maximum values. In the above example, this happens with Purposeless Movements.

Fig. 1 shows an example of associative IDU in the case of the diagnosis of Chorea, a clinical manifestation* of the Rheumatic Fever.

The degree of membership for the non-associative IDU is computed by

* In this work any finding with diagnostic significance, directly evaluated or deduced, is referred to as clinical manifestation (e.g. symptoms, syndromes, etc).

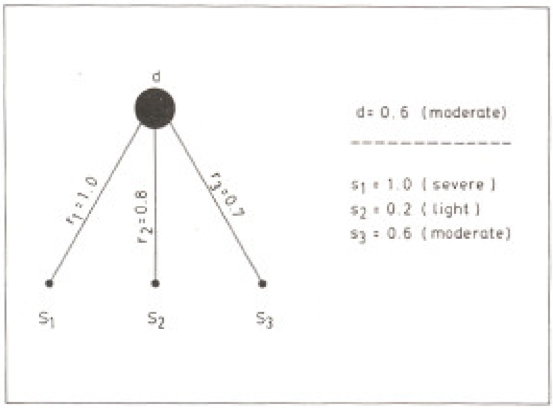

Fig. 1. Associative IDU for Chorea. The degrees of membership are specified for relations and symptoms. The diagnostic result is computed by eq. (1). Three symptoms related to this IDU are shown: purposeless movements, S_1, muscular weakness, S_2, and emotional lability, S_3.

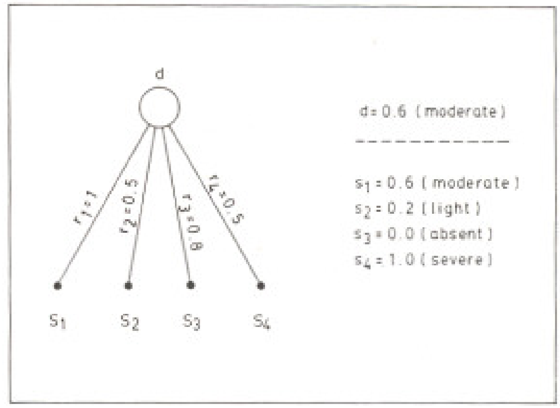

Fig. 2. Non-Associative IDU for evidence of streptococcal infection. The degrees of membership are specified for relations and symptoms. The diagnostic result is computed by eq. (2). Four symptoms related to this IDU are shown; increased ASO titer, S_1, positive throat culture for group A streptococci, S_2, history of recent scarlet fever, S_3, history of recent pharyngotonsillitis, S_4.

$$d = \max_i \min (s_i, r_i) \qquad (2)$$

In contrast to the equation for associative symptoms, where all symptoms actively participate in the IDU diagnosis, this expression yields only to the symptom which determines the most significative contribution. Each possible contribution is given by the minimum value among the relation, r_i (fixed), and the corresponding symptom intensity, s_i. Thus the relation r_i, is an upper threshold value for the corresponding intensity, passed which the possible contribution cannot increase further. Moreover, the values of r_i rank the symptoms by their possible maximum contribution, thus they must be set considering the symptoms relative importance for the intermediate diagnosis.

Fig. 2 presents an example of a non-associative IDU in the case of the diagnosis of Evidence of Streptococcal Infection, a clinical manifestation of the Rheumatic Fever.

The degree of membership for the excluding IDU is computed by

$$d = \begin{cases} s_0 & \text{if } \quad s_0 \geq \beta \\ [s_0 - \alpha s_r] \,/\, [1 - (\alpha/\beta) s_k] & \text{if } \alpha\ s_r < s_0 < \beta \\ 0 & \text{if } \quad s_0 \leq \alpha s_r \end{cases} \qquad (3)$$

where s_k, s_0 and d are the excluding symptom, the clinical mainifestation and the diagnosis respective degree of membership to the patient. Many excluding symptoms can be related by one exclusive IDU; in such a case the most restrictive one prevails, i.e. $\min (d_k)$ for all s_k.

In differential diagnosis the excluding symptom is considered to be proper of another illness so that, if the relation to that disease is r_k, the relation to the one under consideration is its complement, $\overline{r_k} = (1 - r_k)$. The parameter β is the upper critical value above which the diagnosis is equal to the clinical manifestation intensity, regardless of the excluding symptom value. For instance, age is an excluding symptom for Rheumatic Fever but if the clinical manifestations are strong enough, i.e. greater than β, the diagnosis is Rheumatic Fever, regardless of the patient's age. On the contrary, if the clinical findings are not that strong, the excluding symptom becomes significant in reducing their contribution to the diagnosis. The rate of reduction is controlled by the parameter α which is a lower threshold for the clinical manifestations, below which the diagnosis is null; it is proportional to the relation $(1 - \overline{r_k})$ and ranges between zero and $m\beta$ ($m<1$).

Fig. 3 presents an example for an excluding IDU in the differential diagnosis between Rheumatic Fever and Infective Endocarditis.

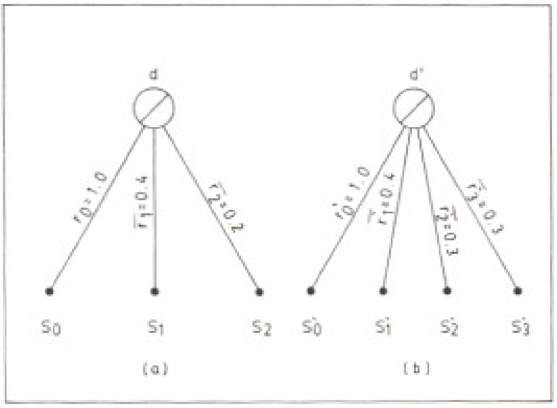

Fig. 3. Excluding IDU for differential diagnosis between rheumatic fever RF (a) and infective endocarditis IE (b). Degrees of membership are specified for relations and symptoms. The diagnostic result is computed by eq. (3). The symbol (·) is used to differentiate between FR and IE. S_0 represents the clinical manifestation degree of membership to the patient. The excluding symptoms for RF are: positive blood cultures, S_1, and old age, S_2; for the IE are: negative blood cultures, S_1', young age, S_2', increased ASO titer, S_3', [3, 11].

In Table 1 the degree of membership to the patient for excluding symptoms, s_1, s_2, s_3 and the clinical manifestation, s_0, are specified for each disease. The upper threshold used in both IDUs is $\beta = 0.6$ and the parameter $\alpha = 0.3\ (1 - \overline{r}_k)$. Comparing the values resulting from the clinical manifestation and the diagnosis in both diseases, i.e., s_0 and d or s_0' and d', the discrimination improvement becomes evident.

Application to six cardiopathies

The model has been specified for six cardiopathies: Rheumatic Fever, Infective Endocarditis, Mitral Incompetence, Mitral Stenosis, Aortic Incompetence, and Cardiac Failure; this is the universe of diseases, D. The corresponding universe of symptoms, S, is constituted by 142 manifestations. The lattice structure of all six diseases is composed of 86 IDUs and 295 relations among them. An initial value to these relations was assigned by a specialist and hence forth calibrated by hand on a trial and error basis to meet the expert criteria. This adjustment was performed using data from 64 patient records with known diagnosis. For the sake of space, Fig. 4 shows the lattice structure modelling Rheumatic Fever only.

The model performance is evaluated comparing its diagnostic results with those stated in the patients records and those carried out by three medical observers, using data taken from another group of 39 patients. All the 103 patients records were selected to include at least one of the six cardiopathies.

The model was simulated in a PC microcomputer

Table 1. Differential diagnosis between Rheumatic Fever and Infective Endocarditis, for 8 patients. The excluding symptoms for RF are: positive blood cultures, s_1, and old age, s_2. For the IE are: negative blood cultures s_1', young age, s_2', increased ASO titer, s_3', [3, 11]. s_0, s_0' and d, d' represents the clinical manifestations and the differential diagnosis for RF and IE, respectively. The diagnostic result is computed by eq. (3).

Patient no.	Excluding symptoms					Clinical manifestations and differential diagnosis			
	RF		IE			RF		IE	
	s_1	s_2	s_1'	s_2'	s_3'	s_0	d	s_0'	d'
1	0	0	1	1	1	0.76	0.76	0.31	0.15
2	0	0	1	1	0	1.00	1.00	0.14	0.00
3	0	0	1	1	0	0.68	0.68	0.37	0.25
4	0	0	1	1	1	0.88	0.88	0.38	0.26
5	1	1	0	0	0	0.35	0.18	1.00	1.00
6	1	1	0	0	0	0.36	0.20	0.66	0.66
7	0	1	1	0	1	0.46	0.37	1.00	1.00
8	0.6	1	0.4	0	0	0.40	0.27	0.76	0.76

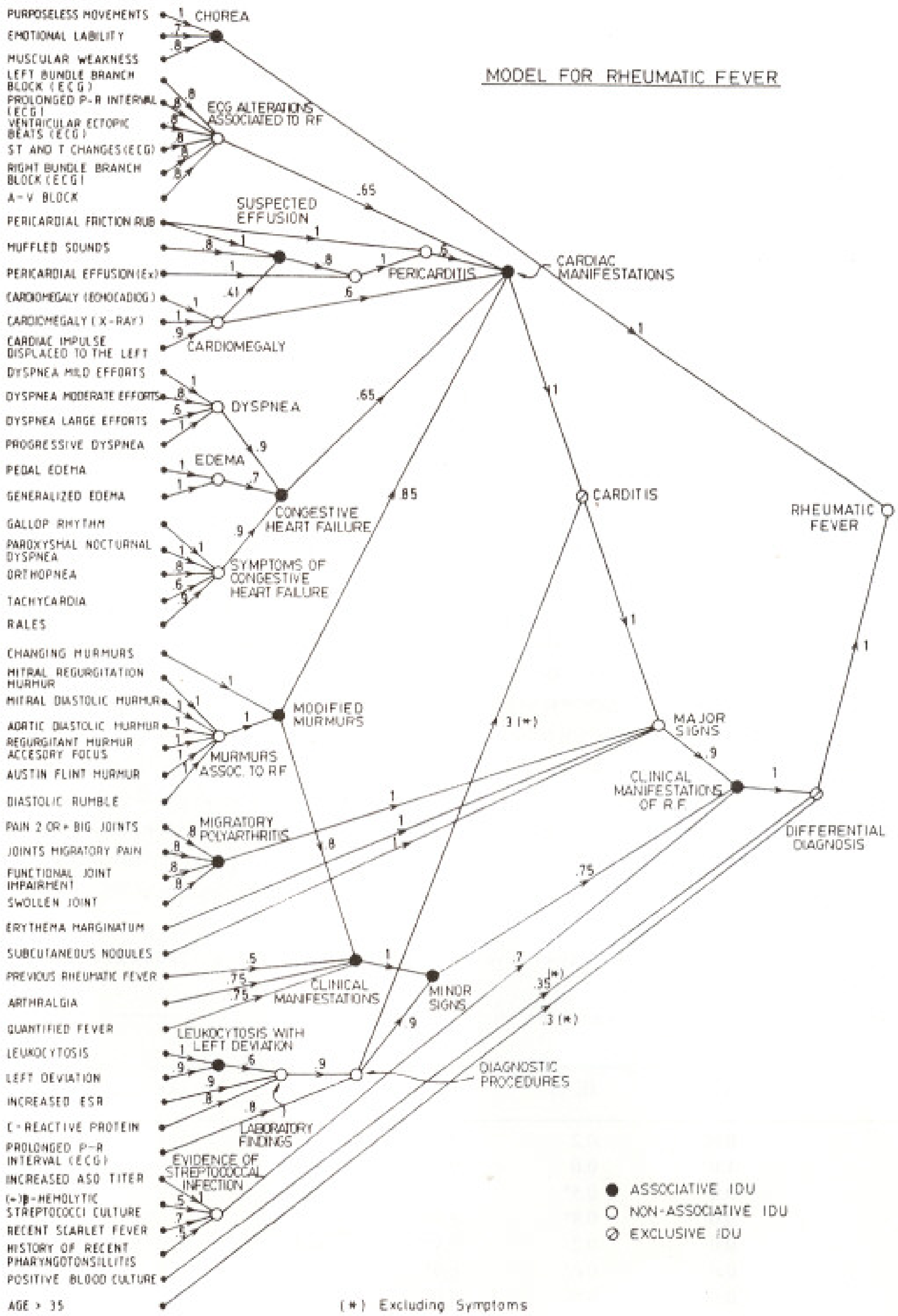

Fig. 4. A model for Rheumatic Fever. The symptoms, on the left, are connected to the disease, on the right, through a hierarchically ordered structure composed by associative, non-associative and excluding intermediate diagnostic units.

using BASIC. The main program evaluates each IDU through the corresponding equation (1), (2) or (3), following the hierarchical lattice structure of the disease, and beginning with the data obtained from each patient record. In this procedure, zero values were assigned to the non-examined symptoms, except for the excluding symptoms where the value one was chosen so they would not revoke the diagnosis. The preceding criteria assures the weaker diagnosis in view of the available information (excepting excluding symptoms).

Results

For the sake of space, Table 2 presents the diagnosis of the six cardiopathies for only twelve selected patients among those thirty-nine which were not used in identifying the model. This selection includes those cases showing the best and worse concordance with the known records. The * with the figures in the table, mark the patients known record diagnosis thus indicating concordance with the model whenever the marked degree of membership is high. In almost every case this value is greater than 0.5, except in patients # 3 and # 12. Nevertheless these singularities are easily explained because in the patients records the diagnosis of Cardiac Failure, in patient # 3, and Mitral Incompetence and Stenosis, in patient # 12, were not consigned by the physician, even though the determining symptoms had been stated, probably because they were considered secondary conclusions regarding the patient main disease.

The outcome, partially shown in the table, enables to set the model diagnostic threshold at a value of 0.5 for a satisfactory performance, at least for the 103 analyzed cases.

As an objective measure of the global model performance, concordance histograms comparing the model diagnostic results to those carried out by three medical observers, using the same input data as the model, are shown in Fig. 5a to 5c.

The histograms plot the difference between the degree of membership of pairs of diagnosis, over the thirty-nine patients. The second diagnosis in each pair is taken as reference. The differences are classified in subintervals of 0.1 within $[-1, +1]$. Negative and positive differences correspond to negative and positive false results, relative to the reference diagnosis, respectively. The ordinate shows the number of occurrences within each interval.

Each set, of curves, in Fig. 5, shows one histogram plotting one of the three observers relative to himself (using two diagnosis of each patient by the double-blind procedure) and one histogram plotting the model diagnosis relative to the mean

Table 2. Degree of membership of six cardiac siseases for twelve selected patients. The '*' indicates the diagnosis in the patient's record and the figures themselves, the model diagnosis.

Patient no.	Diagnosis					
	RF	IE	MI	MS	AI	CF
1	0.6*	0.2	0.7*	0.8*	0.1	0.2
2	1.0*	0.0	0.7*	0.0	0.0	0.2
3	0.0	0.5*	1.0*	0.0	0.0	1.0
4	0.0	0.8*	0.9*	0.3	1.0*	1.0*
5	0.0	0.2	0.9*	0.0	0.0	0.4
6	0.0	0.6*	0.9*	1.0*	1.0*	0.8*
7	0.0	0.0	0.0	0.0	0.7*	1.0*
8	0.0	0.0	0.0	1.0*	1.0*	0.7*
9	0.0	0.0	0.0	0.0	0.8*	1.0*
10	0.3	0.0	0.0	0.0	0.0	1.0*
11	0.0	0.6*	0.8*	0.0	1.0*	0.1
12	0.0	0.5*	0.8	1.0	0.0	0.4

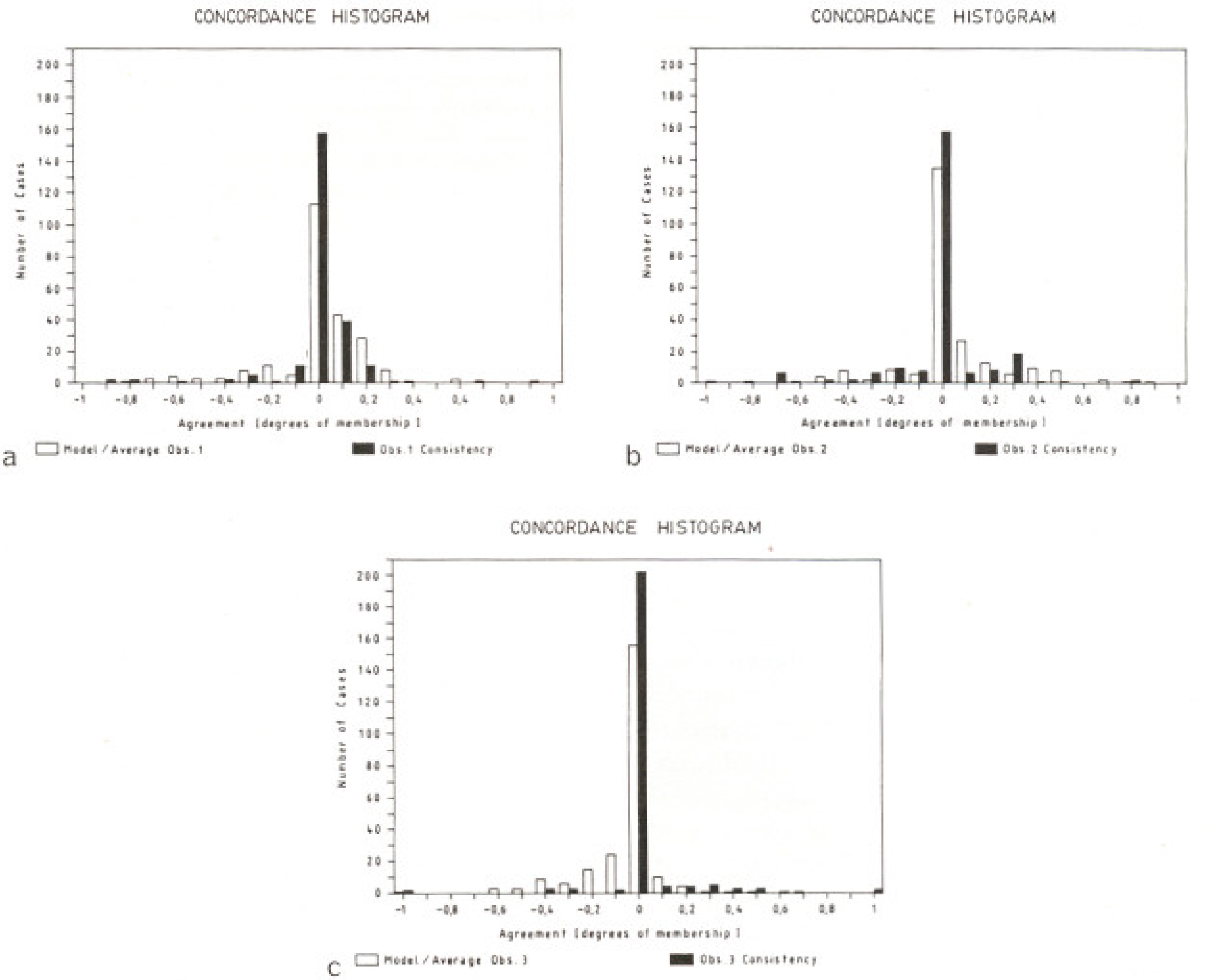

Fig. 5. Each figure, a, b, and c, shows two histograms presenting results obtained from one of the three medical observers. One is a concordance histogram (in white) obtained from the ratio between the diagnosis supplied by the model and the mean of the two diagnosis established by one medical observer for all patients. The other is an observer's consistency histogram (in black), obtained from the two diagnosis performed on each patient.

diagnosis of each patient (same data previously used). The first histogram represents the observer diagnosis consistency and the second permits to appreciate the model performance by itself, comparing it with the former.

Conclusions

In this work a fuzzy model structured in the form of a lattice is developed to represent the clinical manifestations associated to the medical diagnostic process. Three types of intermediate diagnostic units have been developed, to consider diagnostic concepts and criteria derived from medical knowledge. The model for one disease is a lattice structure composed of IDUs ordered hierarchically from the symptoms to the disease. In this manner illnesses can be represented in a relatively familiar way to the specialists.

The model was specified for the diagnosis of six cardiopathies, calibrated with recorded diagnosis of 64 patients and tested using another group of 39 patients records.

The test results are compared to those obtained from three medical observers using concordance histograms with each one of them. Nevertheless, to appreciate the model performance by itself, it was necessary to produce the observers autoconcordance histogram – using the double-blind procedure – to superimpose it to the previous ones. Comparing the three sets of curves shown in Fig. 5, the system performance proves to be quite satisfactory for the test group.

Other illnesses can be incorporated to the model by simple aggregation of the corresponding lattices structures; this aggregation can be simplified when common IDUs exist.

Two diagnostic sensitivity analysis are now possible; the first one refers to the change in diagnosis respect to a change in the relation values; and the second is the one regarding changes in the symptoms intensity. The sensitivity respect to the relations is of a technical consequence since it provides the basic information for automatizing the model parameter adjustment. The sensitivity respect to the symptoms, on the other hand, may be of valuable clinical use since it supplies the basic knowledge to rank the unknown symptoms by their importance for the diagnosis. This facility allows to properly select the next successive tests with a significant improvement in diagnostic strategies and efficiency. It is important to emphasize that due to the highly non-linear characteristic of the model, this ranking certainly depends on the symptomatic state of the patient.

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References

1. Adlassnig KP, Korlarz G, Scheithauer W, Effemberger H, Grabner G. Approaches to computer-assisted medical diagnosis. Comp Biol Med 1985; 15: 315–35.
2. Adlassnig KP, Kolarz G. Representation and semiautomatic acquisition of medical knowledge in CADIAG-1 and CADIAG-2. Comp Biomed Res 1986; 19: 63–79.
3. Alpert JS, Rippe JM. Manual of cardiovascular diagnosis and therapy. 1980; Little, Brown and Company, Boston.
4. Dubois D, Prade H. Fuzzy sets and systems, Academic Press, 1980; 68–93.
5. Kulikowski CA. Artificial intelligence methods and systems for medical consultation: IEEE Trans on Pattern Anal. Mach Intell Vol PAMI-2, No 5, 1980: 464–476.
6. Patric EA, Stelmack FP, Shen LYL. Review of pattern recognition in medical diagnosis and consulting relative to a new system model. IEEE Trans on System, Man and Cybernetics, Vol SMC4, no 1, 1974: 1–16.
7. Reggia JA. Computer-assisted medical decision making. In: Schwartz M, ed. Applications of computers in medicine. IEEE Press, 1982: 198–213.
8. Rogers W, Ryack B, Moeller G. Computer aided medical diagnosis: Literature review. Int J Biomed Comput 1979; 10: 267–289.
9. Sanchez E. Medical diagnosis and composite fuzzy relations. In: Gupta MM, Ragade RK, Yager RR. eds. Advances in fuzzy sets theory and applications. Amsterdam: North Holland Publishing Company, 1979: 437–444.
10. Shortliffe EH, Buchanan BG, Feigenbaun EA. Knowledge engineering for medical decision making: A review of computer-based clinical decision aids. Proc of the IEEE, Vol. 67, 1979; 1207–1224.
11. Skolow M, McIlroy MB. Clinical cardiology. Los Altos, California; Lange Medical Publications, 1978.
12. Soula G, Gouvernet J, Barre A, San Marco JL. Application of fuzzy relations to medical decision making. Medinfo 80, Proc of the Third World Conf on Medical Informatics, Tokyo, Japan, 29 Sept–4 Oct, 1980: 844–848.
13. Viglione SS. Applications of Pattern Recognition Technology. In: Mendel JM, Fu KS, eds. Adaptive learning and pattern recognition. New York: Academic Press, 1970: 115–161.
14. Welchsler H. A fuzzy approach to medical diagnosis. Int J Bio-Computing 1976; 7: 191–203.
15. Zadeh LA. Fuzzy sets. Information and control, Vol 8. 1965: 338–353.

Address for offprints:
C.A. Holzmann
Ingeniería Biomedica
Departamento de Ingeniería Electrica
Universidad de Chile
Casilla 412-3
Santiago
Chile