Improving questionnaire screening of sleep apnea cases using fuzzy knowledge representation and aggregation techniques

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IMPROVING QUESTIONNAIRE SCREENING OF SLEEP APNEA CASES USING FUZZY KNOWLEDGE REPRESENTATION AND AGGREGATION TECHNIQUES

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Summary

In this article, joint medical and data analysis expertise is brought to bear using contrasting knowledge representation and aggregation techniques to solve a difficult medical diagnosis problem, that of sleep apnea syndrome screening.
Key Words: fuzzy representation, sleep apnea diagnosis, questionnaire, aggregation

1. INTRODUCTION

Screening of Apnea cases is a difficult diagnosis problem, at present not satisfactorily resolved by standard statistical modelling techniques. We propose that part of the problem is due to the inherent fuzzy nature of a significant part of the data: questionnaire responses. We use fuzzy representation for the replies to the questions in the questionnaire to capture information which is otherwise lost, and we evaluate this method in comparison to existing methods of crisp data capture.

The article is structured as follows: in section 2, a clinical description of the sleep apnea syndrome is given; in section 3, the theoretical aspects of building membership functions is presented; in section 4, aggregation techniques are detailed; in section 5, the test data is described; in section 6, fuzzy and crisp rule based diagnosis is described; in section 7 results for aggregation based diagnosis are detailed; finally, section 8 discusses some conclusions on the present work, results and future areas to be focussed on.

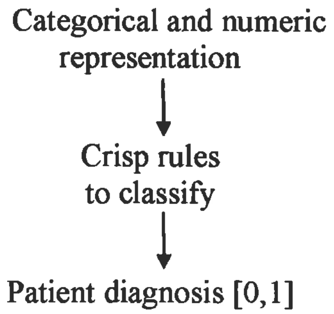

Figure 1a: Standard (crisp) questionnaire screening

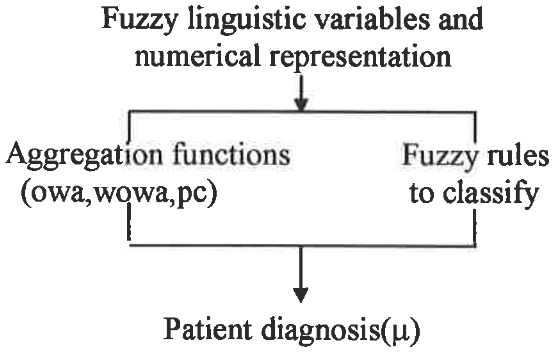

Figure 1b: Summary of methods under evaluation

2. THE SLEEP APNEA SYNDROME

The Obstructive Sleep Apnea Syndrome (OSAS) is a set of secondary clinical manifestations relating to the ceasing (apnea) or reduction (hypopnea) of air flow during sleep, caused by a partial or total collapse of the upper air way at the faringe level. The severity of the OSAS is defined by the *apnea hypopnea index* (AHI) or the number of apneas plus the number of hypopneas per hour during sleep. Generally an AHI $\exists$10-15 is considered pathological.

2.1 CLINICAL PRESENTATION

There are diverse symptoms associated with OSAS. They often become introduced insidiously during a certain period of time and are often overlooked in clinics and even by the patients themselves, due to their lack of specificity. The snore is one of the principal symptoms. The long snoring history which refer to patients with OSAS reflects the increase of resistance of the upper air tract during sleep. The presence of respiratory pauses witnessed by the room partner is another important data referenced in the literature, and tends to be a good symptom predictor.

2.2 PREVALENCE

The prevalence of OSAS oscillates between 1-9% according to studies. This difference in the percentages obtained reflects the diversity of methods and criteria used to diagnose OSAS and the possible differences in the populations that have been studied. The study of reference is that realised in the population of Wisconsin by Young et al[13], where the prevalence obtained reached 2% for females and 4% for males, showing minimum symptoms. When we extrapolate these results to the general population, 9% of women and 24% of men would present sleep related respiratory alterations. This elevated prevalence in adults is considered to be a significant problem for public health.

2.3 MORBIDITY AND MORTALITY

Daytime hypersomnolence has been related to a reduction of physical and mental effectiveness, in the daily activity of the individual, including the work environment, and the ability to drive automobiles (drive worse and have greater risk of suffering traffic accidents). As well as daytime hypersomnolence, a certain relation has been identified between OSAS and systemic arterial hypertension. The patient with OSAS tends to present an elevated sympatic activity, which can cause an increase in the daytime blood pressure.

2.4 DIAGNOSIS

The predictive value of the clinical data in OSAS diagnosis is low. Hoffstein [6] published results that indicated that clinical data explains 36% of the variability of the IAH (apnea hypopnea) and Katz [7] reported a figure of 39%, other authors report lower figures (table1). The subjective clinical evaluation of the interviewer has also been evaluated and tends to have a low sensibility and specificity, in the order of 55%-65% respectively, for correctly classifying the sick. On the other hand, The predictive models for IAH based in clinical data have a higher sensibility of up to 90%. Their specificity, in the best of cases, does not reach 70% (table 2).

RDI
respiratory
disturbance
index
[illegible]

The reference method for OSAS diagnosis is the polysomnogram. It consists of the simultaneous recording of a number of sleep parameters, which allow us to identify its different phases and the correlation of these with cardiorespiratory events such as apneas, desaturation of oxyhemoglobine and changes in cardiac rhythm. For sleep measurement, including body position changes, respiratory effort and efficiency in ventilation, there exist multiple methods and each clinic tends to use its own variables which are obtained with the resources available in each centre.

At present, it is not appropriate to define rigid diagnostic criteria in this rapidly developing area. Neither is it possible to identify the ideal equipment for sleep studies.

3. QUESTIONNAIRE RESPONSE REPRESENTATION

3.1 THEORETICAL BACKGROUND

Parmenidean Pairs

In general, the representation which we adopt is based on the use, already habitual, of fuzzy partitions with trapezoidal membership function. In [2] a method is presented which automatically constructs a system of 5 linguistic labels which represent the ordered values of a variable derived from what we call a *'parmenidean pair'*, which responds to the basic antagonistic values that the variable may assume. This method is very appropriate for variables which represent responses to questions like 'Do you snore while you sleep or have you been told that you do?' for which we cane define the fuzzy values NEVER, RARELY, SOMETIMES, FREQUENTLY, ALWAYS derived from the basic antagonism of NEVER, ALWAYS.

Table 1. Multiple linear regression models

Study	n	Diagnostic criterion	Predictive variables	r^2
Stradling (1991)	1001	ID4%>5	Neck circumference, alcohol consumption, age, obesity	0.14
Davies (1992)	150	ID4%	Sleep when inactive Neck circumference	0.13 0.35
Hoffstein (1993)	594	AHI>10	BMI,age, sex, snoring, exploration of ORL	0.36
Flemons (1994)	180	AHI>10	Neck circumference, HTA, snoring, observed apneas	0.34
Deegan (1994)	250	AHI≥15	BMI, age, alcohol consumption	0.19

ID4%: index de desaturation with fall of 4%. AHI: apnea-hypopnea index. r^2: regression coefficient. BMI: body mass index. ORL: otorrinolaringologic exploration. HTA: arterial hypertension.

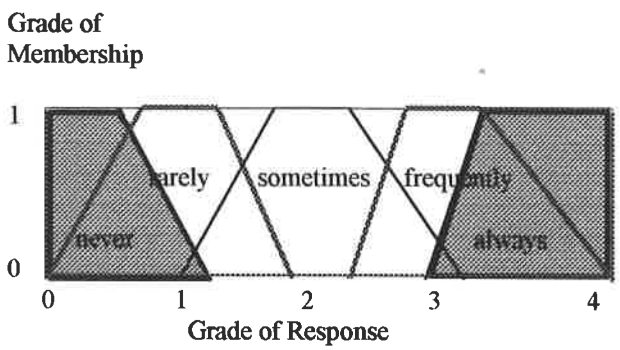

Figure 2. Representation of Ordinal Variables

Figure (2) shows a simple fuzzy representation for a typical questionnaire 'response' variable.

From a semantic point of view, a FLV (Fuzzy Linguistic Variable) can be identified by 3 parameters: its relative *position* with respect to the other ones, its degree of *imprecision*, and its degree of *uncertainty*, these last can be merged into a single concept of *softness*, as opposed to *crispness*.

Characteristics

Separability / cluster separation: the overlap between two trapezoids is proportional to the degree of separability of the two corresponding fuzzy sets. If fuzzy sets A and B have a 40% overlap (by average overlap of their respective trapezoid areas) we could assign a 'goodness' of distinguishability of 40%. We could assign a threshold within which it is desirable to maintain (for example 50%). Only one cluster can have 100% membership at a time. The sum of the memberships must be 100%. Only 2 memberships are allowed at a time.

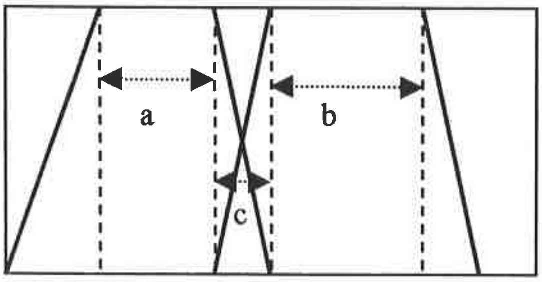

Figure 3. Cluster Overlap = Separability

Degree of fuzziness: in terms of the trapezoids, the more gradient the sides have, the fuzzier is the corresponding fuzzy set. If the sides are vertical the set becomes crisp.

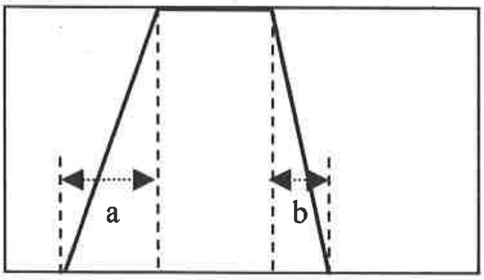

Figure 4. Degree of Fuzziness Df ≅ a+b. Df=0⇒crisp.The wider a and b, the more fuzzy is the corresponding fuzzy set.

Interpolation

We consider fitting a membership function to a finite number of known membership values. Assuming continuity, we can determine the remaining membership values using an interpolation scheme. Traditional interpolation schemes fail to satisfy restrictions of membership functions such as the [0,1] boundedness condition and the fuzzy-convex property. Chen and Otto[1] presented a constrained interpolation scheme as a solution. Chen and Otto used McAllister and Rouliers idea of a second order Bernstein polynomial to perform a constrained interpolation.

Why would we use interpolation? In the Parmenidean Pairs method described previously, we have discussed some aspects involved in trapezoidal membership function definition. The assumption for trapezoids is that they are a simplification of what is really a non-linear function. To best fit the true function we should apply a technique which is able to construct a curve from a limited number of initial points, or from the original data characteristics.

Converting linear membership function into non-linear

We now consider the ascendant and descendent gradient lines on each side of the trapezium. In practise we can try different forms of trapezium with differing gradients, and determine which gives bests results.

Also we can try a curve instead of a straight line for the ascending and descending gradients. To achieve this, we can use an interpolation technique such as that described in the previous section to construct the curve. Or we can simply define a sine/cosine/'S',/sigmoid curve. We can try different curves and establish that which gives best results and is therefore a best "fit" to the data. This method, along with defuzzification techniques, is considered by Gerstorfer in [4]

In some cases we may wish to strengthen a transition with hedges like "very" or "extremely" or weaken it with, for example, "slightly". We can perform strengthening by, for example, a sigmoid-like function.

We can use Zadeh's S-Function:

$$S(x;\alpha,\beta,\gamma) = \begin{cases} 0 & x \leq \alpha \\ \left(\dfrac{x-\alpha}{\beta-\alpha}\right)^2 & \alpha < x \leq \beta \\ \left(\dfrac{x-\beta}{\gamma-\beta}\right)^2 & \beta < x \leq \gamma \\ 1 & \gamma < x \end{cases}$$

Now

$$f(x) = \begin{cases} \dfrac{1}{2} + \dfrac{\sqrt[3]{(x-1/2)}}{2\times\sqrt[2]{(1/2)}} & x > 1/2 \\ \dfrac{1}{2} - \dfrac{\sqrt[3]{(1/2-x)}}{2\times\sqrt[2]{(1/2)}} & x \leq 1/2 \end{cases}$$

The use of $f(S(x;\alpha,\beta,\gamma))$ increases all the membership values above 0.5, and decreases all the others. This is the definition for "very"; for "extremely" we can replace in formula 2 the 3rd root by the nth root (for a suitable $n > 3$, n odd).

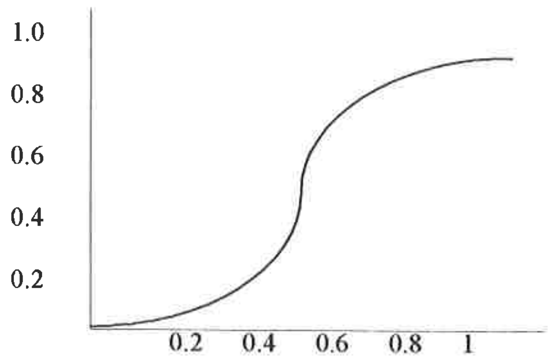

Figure 5. Zadeh's s-function used to customise membership transition

For linear and non-linear membership gradients, we assume a symmetrical relation between the descending membership value for the preceding fuzzy set and the ascending membership grade for the following fuzzy set (which sum to 1).

3.2 SLEEP STUDIES QUESTIONNAIRE

For each question we designed a membership function which can be overlaid on each scale to calculate grade of membership to each linguistic label.

The patient draws a cross on the continuous scale (see next page, S5) to indicate his/her response to the question.

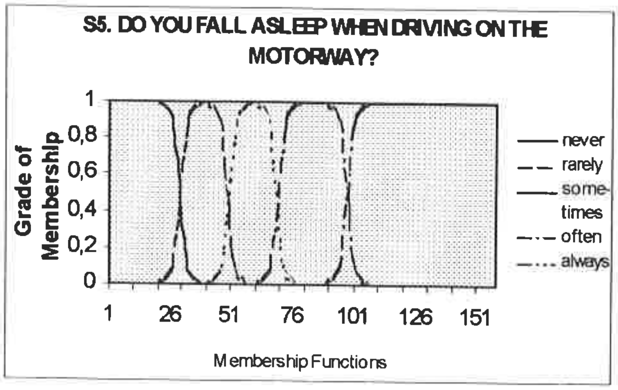

Figure 6. Example of representation for a critical question

In the questionnaire, this question would appear as:

S5. Do you fall asleep while you are driving on the motorway?

never rarely sometimes frequently always

Note that we can convert to categorical if we so desire, and that way we have both crisp and fuzzy data capture.

The membership functions can be generated by various methods. We have chosen and applied the following methods to the same questionnaire and have contrasted the results:

(i) Direct drawing of membership functions - the simplest solution for triangular and trapezoidal forms.

(ii) Use of parmenidean pair algorithm to calculate the form, size, overlap, geometric characteristics of the functions, still being triangular and trapezoidal forms.

(iii) Use of automatic generation method using interpolation technique from the input data values (Chen and Otto).

4 AGGREGATION TECHNIQUES

4.1 FUNCTION DESCRIPTIONS

In this section we consider methods of grouping input variables. The objective is to improve the quality of the inputs, rank their 'usefulness', and achieve a representation which is closer to the underlying nature of the data. Another effect of grouping variables is to reduce the dimensionality of the model, which leads to a simpler interpretation of the results.

4.1.1 WM – WEIGHTED MEAN

Weighted mean has as input a data vector and a weight vector. The weight vector contains one degree of reliability value between 0 and 1, for each corresponding data value.

4.1.2 OWA - ORDERED WEIGHTED AVERAGE

Ordered weighted average has as input a data vector and a weight vector. The weight vector contains one degree of relevance value between 0 and 1, for each corresponding data value.

The approach of Yager [12] is to consider the problem of aggregating criteria functions to form overall decision functions. One of the main factors in the determination of the structure of aggregation functions is the relationship between the criteria involved. At one extreme we have the case where all the criteria have to be satisfied. At the other extreme we have the case where the satisfaction of any of the criteria is sufficient.

The former can be interpreted as an 'AND' situation and the latter as an 'OR' situation. Dubois defined in [3] a class of operators called t-norms which provide a way of quantitatively implementing the 'AND' aggregation. A related class of operators called co-t-norms, provide a way of implementing the 'OR' operator.

Often, when we wish to formulate a multiple criteria decision function, the type of aggregation really needed is neither 'AND' nor 'OR', but somewhere inbetween these. It is in this situation where the ordered weight averaging (OWA) operator can be deployed. OWA permits an adjustment of the degree of 'anding' and 'oring' implicit in the aggregation.

Definition: A mapping F from

$$I^n \rightarrow I \text{ (where } I = [0, 1])$$

is called an OWA operator of dimension n if associated with F, is a weighting vector W,

$$W = \begin{bmatrix} W_1 \\ W_2 \\ \cdots\cdots \\ W_n \end{bmatrix}$$

such that

1) $W_i \in (0,1)$
2) $\Sigma_i W_i = 1$

and where

$$F(a_1, a_2, ..., a_n) = W_1 b_1 + W_2 b_2 + ... + W_n b_n,$$

where b_i is the ith largest element in the collection $a_1, a_2, ..., a_n$. **B** is called an ordered argument vector if each element $b_i \in [0,1]$ and $b_i \geq b_j$ if $j > i$. Given an OWA operator F with weight vector **W** and an argument tuple $(a_1, a_2, ..., a_n)$ we can associate with this tuple an ordered input vector **B** such that **B** is the vector consisting of the arguments of F put in descending order. It is important to note that weights are associated with a particular ordered position rather than a particular element.

Linguistic Quantifiers and OWA Operators

In binary logic we have linguistic quantifiers such as 'there exists' and 'for all'. In natural language we have linguistic quantifiers such as 'almost all', 'few', 'many', 'most'. The weights associated with the OWA function determine the kind of quantifier it is effecting. By varying the assignment of the weights in

W we can move from a Min type "for all", quantifier, to a Max type "there exists" quantifier. Also we can capture aggregations which emulate concepts like "most", etc. For these reasons, the OWA operators provide an interesting class of operators.

4.1.3 THE WOWA OPERATOR

Torra in [9] described the Weighted OWA operator (WOWA), which combines advantages of the weighted mean and the OWA operator, thus solving some of the shortcomings of the latter two operators. It considers two weight vectors: ρ corresponding to the relevance of the sources (as in weighted mean), and ω corresponding to the relevance of the values (as in OWA).

One of the difficulties in using aggregation operators is the initial fixing of the associated parameters, for example the weights of each information source. In [10], Torra explains a machine learning method for determining the weights of the aggregation function.

4.2 APPLICATION DETAILS

4.2.1 USE OF THE WEIGHTING VECTORS FOR APNEA DATA

For weighted mean the weights tell us the reliability of each information source. For OWA the weights tell us the ordering of the values, so that extreme values can be diminished and central values made more significant. For WOWA operators, we have two weighting vectors, as explained in the previous section.

4.2.2 DATA PROCESSING

We typically use aggregation techniques to fuse values into a smaller number of factors. We do this for at least two reasons: **(i)** Increase the information content per data; **(ii)** Simplify the inputs and the resulting data model; **(iii)** Make the data more manageable; **(iv)** In aggregating we discover relations between the linguistic labels and between the variables.

There are two levels of aggregation which we consider: **(a)** Aggregate all the crisp responses of the patient to the subjective questions (a total of 41); **(b)** Aggregate a preselected subset of variables with high discriminant value, which include clinical data (age, neck circumference, etc. ..) and some question responses.

In aggregating we have considered all data as numeric. The crisp question responses have orderable numeric values from 1 to 5, where 1 represents the linguistic label *never* and 5 represents the linguistic label *always*.

<u>WOWA aggregation applied to questionnaire responses</u>

For WOWA operators, weighting vector ω contains the relative weight of each data source and weighting vector ρ contains the reliability of each data source.

To each question we assign these two weights: ω in this context indicates the significance of each question to the global outcome; ρ indicates the reliability of the response to each question. We can use ω to eliminate outliers, for example, giving more weight to the values closest to the mean. Consider the following:

	Q_1	Q_2	Q_3	
ρ	0.25	0.50	0.25	, $\Sigma\rho = 1$
ω	0.10	0.80	0.10	, $\Sigma\omega = 1$

In this case, via the ω vector, we have said to give more consideration to Q_2, while Q_1 and Q_3 do not influence so much in the outcome. This may occur, for example, in the situation that the patient only has to respond affirmatively to one of the questions (Q_2) in order to give a positive global outcome. If, on the other hand, we had assigned 0.33 to Q_1, Q_2 and Q_3, the patient would have to respond affirmatively to all three questions in order for the global outcome to be positive.

5. TEST DATA

We have available the data of the standard crisp questionnaire, for 154 patients, captured over a 1 year period. The test set consists of 68,2% positive outcome and 31.8% are negative outcome.

The questionnaire consists of two main sections: the first records clinical data; the second section consists of 41 questions to which the patient responds. The questions are divided in 3 subsections: 15 general sleep questions, 16 respiratory related questions and 9 somnolence related questions. Based on this information, the doctor then gives a clinical evaluation: healthy; simple snorer; doubtful; typical apnea; other illness. We simplify this to: typical apnea; no apnea.

We have chosen a subset of variables from the questionnaire which in the literature (see tables 2 and 3) have been identified as the most discriminatory variables with respect to apnea diagnosis. These are: age, sex, weight, body mass index, neck circumference, alcohol intake, blood pressure, snoring and daytime sleepiness. The first 7 variables are clinical data and are crisp. For snoring information, we have used the responses to 4 respiratory related questions: R1, R2, R11 and R13 (see table 2).

For daytime sleepiness information, we have used the responses to 4 somnolence related questions: S3, S4, S5, S6 (see table 2). They were chosen as the key discriminatory questions with the highest statistical correlations with the output flag (apnea, yes or no).We have test data to demonstrate the techniques used in a simplified manner, as

Table 2. Discriminant variables: example minimum set with weighting factors for aggregation

variable	description	relia-bility*	rele-vance*
age	age in years	1	0.5
sex	sex 1 or 2	1	0.7
weight	weight in Kg	1	0.7
IMC	body mass index in Kg/m^2	1	0.7
Neck circum-ference	Neck circumference in cm.	1	1
alcohol	Alcohol intake	0.7	0.5
HTA	Arterial hypertension mmHg	1	0.7
R1	Do you snore when sleeping or have you been told that you do?	0.7	0.9
R2	Does your snoring wake your partner or can it be heard from another room?	0.7	0.9
R11	Do you have head-ache when you wake up in the morning?	0.7	0.9
R13	Do you feel as if you haven't rested when you get up in the mornings?	0.7	0.9
S3	Do you fall asleep when at the cinema, theatre, or other spectacle?	0.4	1
S4	Do you sleep in meetings or in public places?	0.5	1
S5	Do you fall asleep while driving on the motorway?	0.4	1
S6	Do you fall asleep against your will during the daytime?	0.6	1

*the values of these columns are then converted proportionately to normalised values so that $\Sigma\rho = 1$ and $\Sigma\omega = 1$, as in Table 4.

summarised in tables 3 and 4, and in the following section 6.

6. RULE BASED DIAGNOSIS

We consider as example a reduced questionnaire consisting of a selection of the variables in table 2 (above). This results in 3 rules and 1 meta-rule, which provide an overall diagnosis with respect to the inputs.

6.1 CRISP RULES

In the crisp form the patient has the following clinical descriptive data: Sex=male; age=upper-middle; weight=middle; neck-circumference= middle. The patient has responded in the questionnaire with the following: Q_{R1} = frequently, Q_{R2} = frequently, Q_{R11} = sometimes, Q_{R13} = sometimes; Q_{S3} = frequently, Q_{S4} = frequently, Q_{S5} = rarely, Q_{S6} = sometimes. The crisp rules will be:

IF sex is male **Rule 1**
AND age is (middle or upper-middle or upper)
AND weight is (middle or upper-middle or upper)
AND neck-circumference is (middle or upper-middle or upper)
THEN outcome is positive

IF R_1 is frequently **Rule 2**
AND R_2 is frequently
AND R_{11} is (sometimes or frequently)
AND R_{13} is frequently
THEN outcome is positive

IF S_3 is frequently **Rule 3**
AND S_4 is frequently
AND S_5 is (rarely or sometimes)
AND S_6 is (rarely or sometimes)
THEN outcome is positive

and the crisp version of the meta rule:

IF Rule 1 is positive **Meta Rule 1**
AND Rule 2 is (positive or negative)
AND Rule 3 is positive
THEN Diagnosis = positive

If we pass the example data given previously through the rules, rule 1 gives *positive*, Rule 2 gives *negative*, rule 3 gives *positive*, and meta rule 1 gives *positive*.

6.2 FUZZY RULES

In the fuzzy form we consider the patient has the same clinical descriptive data and has given the same responses to the questionnaire. But this time, the responses have been indicated on a continuous scale which has been used to read off as the membership grade for each linguistic label. The fuzzy rules will be:

{Rule 1 stays the same as its variables are not considered as fuzzy}

IF R_1 is frequently{0.7} **Rule 2**
AND R_2 is frequently {0.6}
AND R_{11} is (sometimes{0.8} or frequently{0.2})
AND R_{13} is frequently{0.0}
THEN outcome is positive
{t-norm(0.7,0.6, tconorm(0.8,0.2),0.0)}

IF S_3 is frequently {0.8} **Rule 3**
AND S_4 is frequently {0.75}
AND S_5 is (rarely {0.8} or sometimes{0.35})
AND S_6 is (rarely{0.4} or sometimes{0.7})
THEN outcome is positive
{t-norm(0.8,0.75,t-conorm(0.8,0.35), t-conorm(0.4,0.7)}

gives positive {0.0} for rule 2 (assuming that t-norm takes the *Min* and t-conorm takes the *Max*. Rule 3, using the same processing, gives positive {0.4}. These values correspond to row 1 of table 3.

The fuzzy version of the meta rule is:

IF Rule 1 is positive **Meta Rule 1**
AND Rule 2 is (positive{0.0} or negative{1.0})
AND Rule 3 is positive **{0.4}**
THEN Diagnosis = admit
{t-norm(tconorm(0.0,1.0),0.4)}

Input					Outcome	
Rule and meta rule outcomes					Fuzzy rules	Crisp rules
	$Rule_1$	$Rule_2$	$Rule_3$	Meta-$Rule_1$		
Grade of m.	1	0.00	0.40	0.40 admit	admit	admit
Grade of m.	1	0.20	0.40	0.20 do not admit	do not admit	admit
Grade of m.	1	0.70	0.80	0.70 admit	admit	admit
Grade of m.	0	0.80	0.00	0.00 do not admit	do not admit	do not admit

Table 3. Membership grades for 3 rules and 1 meta rule with corresponding outcomes for crisp and fuzzy rules.

	Input								Outcomes		
	Projection of crisp responses (0=never to 4=always) on normalised scale										
	R_1	R_2	R_{11}	R_{13}	S_3	S_4	S_5	S_6	Wowa	Owa	Principal Components
Data vector ω vector* ρ vector**	0.60 0.12 0.15	0.60 0.12 0.15	0.60 0.12 0.15	0.60 0.12 0.15	0.60 0.13 0.09	0.60 0.13 0.11	0.20 0.13 0.09	0.20 0.13 0.11	0.52 admit	0.84 admit	1.15291 admit
Data vector ω vector ρ vector	0.60 0.12 0.15	0.60 0.12 0.15	0.40 0.12 0.15	0.60 0.12 0.15	0.60 0.13 0.09	0.60 0.13 0.11	0.20 0.13 0.09	0.20 0.13 0.11	0.49 do not admit	0.84 admit	1.15324 admit
Data vector ω vector ρ vector	0.60 0.12 0.15	0.60 0.12 0.15	0.60 0.12 0.15	0.60 0.12 0.15	0.60 0.13 0.09	0.60 0.13 0.11	0.40 0.13 0.09	0.40 0.13 0.11	0.56 admit	0.89 admit	1.15466 admit
Data vector ω vector ρ vector	0.40 0.12 0.15	0.40 0.12 0.15	0.60 0.12 0.15	0.60 0.12 0.15	0.60 0.13 0.09	0.60 0.13 0.11	0.20 0.13 0.09	0.20 0.13 0.11	0.46 do not admit	0.84 admit	1.15353 admit

Table 4. Input responses for 8 questions with corresponding outcomes from aggregation methods. (the 8 question responses correspond to the inputs to rules 2 and 3 defined previously in Table 2). *w vector=relevance; **p vector=reliability.

If we pass the example data given previously through the fuzzy rules, rule 1 gives *positive*, Rule 2 gives *negative{1.0}*, rule 3 gives *positive{0.4}*, and meta rule 1 gives *positive{0.4}*.

Comparing the fuzzy and crisp rules in this example, although the outcomes for individual rules and meta rule are the same, the membership grade gives a weaker support for the fuzzy case. This information of course, is not apparent for the crisp decision based rules. In Table 3 we see a summary of fuzzy and crisp rule diagnosis which agrees in 3 out of 4 cases.

7. AGGREGATION TEST RESULTS

In interpreting the aggregations results for all aggregation techniques, we need to define a threshold which indicates where 'do not admit' ends and 'admit' starts. We establish this by running known cases through and noting the values generated as output. We need a spectrum of cases, from a strongly positive case, to a strongly negative case, and a spectrum of intermediate cases ordered by degree of evidence of the apnea syndrome. This is measured clinically in terms of < 10 apneas / hour and >= 10 apneas / hour, so it is possible to assign a numeric quotient to the grade of incidence of apnea.

In Table 4 (previous page), we benchmark 3 aggregation methods. Rows 1 to 3 are positive cases (admit), case 2 being *borderline*: from which we derive the % success rate of correct diagnosis of patients who <u>have</u> apnea syndrome; and row 4 is a strongly negative case (do not admit): from which we derive the % success rate of correct diagnosis of patients who <u>do not</u> <u>have</u> apnea syndrome.

We see that WOWA agrees with OWA and principal components for cases 1 and 3, and does not agree for the borderline case (2) and the strongly negative case (4). Principal components and OWA give positive outcomes for all four cases, thus having a high precision for positive diagnosis and low precision for negative diagnosis (high sensibility and low specificity as commented in section 2.4) which is a typical result for standard statistical techniques used in the literature [11].

8. CONCLUSIONS

This work has been jointly developed with medical and data analysis expertise. We have chosen an area in which there is real room for improvement, due to the lack of precision of existing screening methods (especially for negative case prediction), and the high cost and resource requirements for sleep centre testing. We have considered two fundamental aspects from a data analysis point of view: representation of the data and aggregation.

We have evaluated a selection of techniques for generating membership functions, and aggregating data values. We can compare these different techniques to choose the most effective for different question variables and data types.

In comparing our methods with previous studies (table 1) we have used an approach untried in the literature of apnea diagnosis, which has tended to focus on multiple linear regression and logistic regression models.

As future developments, we think that the questionnaires themselves should be improved by using repeat questions at different points to detect unreliable responses, and better subgroups of questions to detect diseases other than apnea, simple snoring, and other conditions. Also, we propose a detailed evaluation of different membership function construction techniques, and search for a minimal discriminant set, using datamining techniques such as rule induction, neural network and RBF algorithms. Other future areas will be to tune and calibrate the individual membership functions for each question, and find the best weights for the ρ and ω vectors, thus defining the correct reliability and relevance for each variable.

This work opens a promising area for questionnaire data capture and processing where linguistic labels and subjective / uncertain inputs play an important role.

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