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Using soft computing to define standards of care in glaucoma monitoring

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Abstract A fuzzy knowledge base encapsulating core expert rules for glaucoma follow up is developed and subsequently refined into a standard of care by reconciling several expert opinions. The Learning from Examples (LFE) [1] technique is used in addition to expert interviews to generate fuzzy rules from numerical data, and soft competition defines a fuzzy consensus metrics for the expert opinions. Web-based extension of this system into a comprehensive set of e-Health services for the glaucoma community enables, besides wide accessibility of the expert knowledge, continuous improvement of the core rule set (standard of care) with the perspectives of several experts.

Keywords Fuzzy knowledge base, Soft competition, Consensus analysis, Standards of care, Glaucoma, e-Health

1 Introduction

Glaucoma is a progressive eye disease that damages the optic nerve, *usually* associated with increased intraocular pressure (IOP). If left untreated, it can lead to blindness. It is a chronic eye disease that demands a lifetime treatment. There have been recent prevalence assessments that conclude that glaucoma is one of the leading causes of blindness worldwide [2]. Five to seven million people around the world are blind from all types of glaucoma; this disease is responsible for 15% of world blindness, after cataract and trachoma [3].

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Elevated intraocular pressure is an important risk factor for glaucoma; yet, it is quite weak as a factor to predict the disease. A recent study[2] showed that 10% of subjects with high intraocular pressure convert into glaucoma over a five year period, and 5% of treated subjects eventually convert into glaucoma. Glaucoma is essentially a multifactorial disease where vascular, hereditary, lifestyle and dietary factors each play a role. Several factors can significantly impact a patient, making it difficult to determine in some cases the risk factor and the need or not for medication or closer follow-up. High intraocular pressure (IOP), geometrical eye dimensions, high blood pressure, high cholesterol, ethnic background, moderate to high myopia, among other factor can influence the progression of glaucoma [4–7].

There are various diagnostic methods used to determine the presence or absence of glaucoma, but none can effectively identify the disease in its early stages unless routine screening is conducted. Current treatment of glaucoma is aimed at lowering intraocular pressure, which usually, but not always, stops the disease progression [3].

Although usually glaucoma is easy detectable in its advanced stages (when there is a high damage in the optic nerve already), the presence or absence and severity of conditions vary in the early stages of the disease and for each person. Such circumstances make diagnosis quite difficult in the early stages, when frequent assessments are necessary [3].

In about 80% of the cases the diagnosis of glaucoma is fairly evident for expert ophthalmologists. There are many cases however where a specialist is not able to determine if the patient has glaucoma or not. For that reason assessing risk and disease progression is essential in determining treatment as well as the right time for a follow-up assessmend [8].

One of the major problems facing glaucoma specialists in North-America (and not only) is the lack of a standard of care clearly pointing towards follow-up timelines and treatment procedures. Each specialist has its own 'standards' based on their experience and first-hand knowledge acquired from long-term monitoring a particular patient. Extending experience acquired with a patient to another with similar conditions doesn't always work – as such each case needs as much as possible individual consideration – and this is what makes the task of the specialist so difficult. Even with decades of years of experience glaucoma spe-

[1] www.Transfertech.de
[2] the treatment during this study wasn't very aggressive, it only brought the intraocular pressure down 20%.

cialists meet 'new' and 'unknown' cases in which they are confronted with the difficulty (or even impossibility) to make a decision.

In Canada there are absolutely no official standards regarding glaucoma follow-up [9]. The US *target pressure guidelines* are extremely weak regarding follow-up, as the physician's flexibility ranges from 3 to 24 months, as such not pointing towards any specific responsible decision (given the fact that a patient who needs follow-up in 3 months, would go blind if requested for follow-up in 24 months!) [10].

This strongly points to an immediate need to improve the target pressure guidelines to help glaucoma specialists decide when they should treat and how aggressive they should treat. Besides the main beneficiaries – the glaucoma experts – these improved standards would help all general ophthalmologists (although this is to date an extremely difficult endeavour given the wide range of disagreement in the ophthalmic and glaucoma communities.)

The purpose of our work is to develop a core rule base for glaucoma follow-up, by encoding reconciled expert opinions into a fuzzy expert system. This core rule set will point towards a standard of care for glaucoma monitoring and follow-up.

2
Soft computing in glaucoma diagnosis and monitoring

A major disadvantage of the current health care practices is that they do not use the available patient data acquired with time to learn from past experience not to repeat procedures that have been proven not effective. The capability of fuzzy systems to encode relevant information in form of fuzzy If-Then rules and process a vast amount of data, becomes very useful [11]. The already available hospital or practice patient charts can be used to learn and refine the knowledge base of fuzzy rule-based systems [12–15]

Given that the transcripts of several knowledge acquisition sessions with the glaucoma specialists are characterized by a terminology of vague expressions like "*high* IOP", "*Severe kind of* Glaucoma", "I want (to give the patient) *some but not too much* (sedation drops)" and so on, fuzzy reasoning appears as an appropriate tool for emulating the expert thinking.

Artificial Neural Networks (ANN) have proven useful especially in monitoring visual field tests where the patient is required to respond to a machine; these test results are quite prone to have a lot of noise produced by the patient while taking the test. Some of those attempts were made to reduce that noise, thus helping ophthalmologists detect damage progression. [16–18]

There have been many successful approaches using ANN and Fuzzy logic to aid ophthalmologists determine whether there is presence or absence of glaucoma damage and how severe patients' condition is,; all of them classify patients into different categories: "normal", "glaucoma suspect", and/or "glaucomatous" [19–24]. Decision trees have proven useful in the classification of the disease into "stable" and "progressive glaucoma" [25].

Computational intelligence techniques were successful in the detection of glaucoma, e.g. by implementing a 'watch dog' [26]; in this case the monitoring systems react by displaying an alarm together with a visualization of related parameters and an on-line query directed to the ophthalmic knowledge-based information system [27–30].

As mentioned in the introduction, there is a need for standard follow-up guidelines of care in glaucoma (such guidelines would indicate when it is best for a patient to be checked again for disease progression.) A first step towards defining standards of care in glaucoma follow up is to investigate as much and as widely as possible expert patterns in follow up decisions. For this purpose we have developed an expert system encoding follow up rules acquired with the expertise of Dr. A. C. S. Crichton (Former President of the Canadian Glaucoma Society) [31]. To encode complex linguistic knowledge we have chosen fuzzy technology [32]. To date we have reached a core rule base consisting of about 30 core rules. It may contribute to the creation of the Canadian follow-up guidelines [9].

To enable accessibility of our expert system we have developed a comprehensive web-based access[3] which facilitates as well patient access (e.g. to follow their progress from home).

3
Problem description

Follow-up time decision is critical in the prevention of the effects glaucoma can have on the patient's vision. If the monitoring is not sampled appropriately the disease progression can easily get out of hand and lead to the patient's blindness, without hope left even for surgical intervention. As per Fig. 1, the procedure followed by ophthalmologists involves the following steps:

- During the first visit the patient is diagnosed, a treatment is established and the date for the next visit is determined.
- In subsequent visits, the patient is assessed again and the follow-up time (as well as the treatment adjustment) is determined based on the assessment and on the disease progression.

In the following section the Input/Output variables are described in detail.

4
Linguistic variables description

4.1
Intraocular pressure

Acronyms used: IOP_OD, IOP_OS

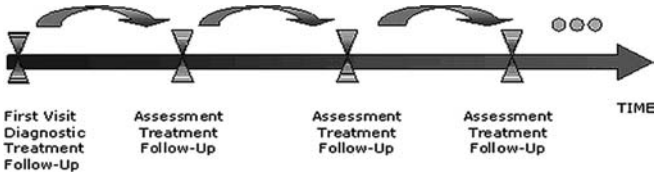

Fig. 1. Usual assessment-treatment-follow-up procedure

[3] www.GlaucoMax.com

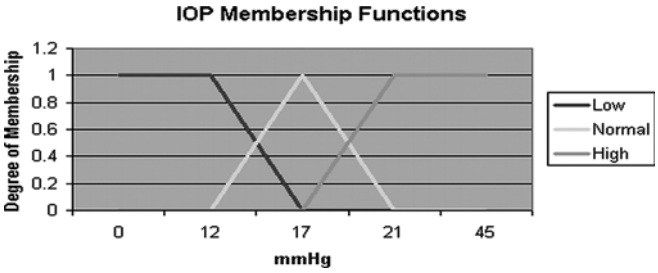

Fig. 2. Membership functions for intraocular pressure

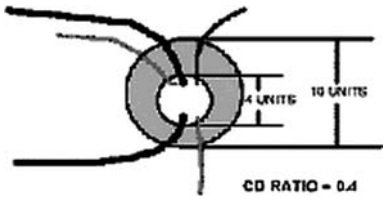

Fig. 3. Front view of optic nerve head

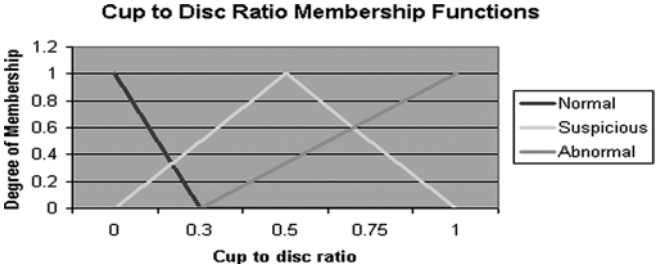

Fig. 4. Membership functions for cup-to-disc ratio

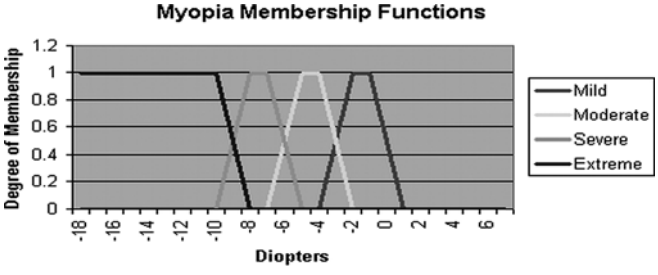

Fig. 5. Membership functions for myopia

Type: INPUT variable

Description: The inner pressure of the eye. Normal intraocular pressure is usually in the range of 12–21 mmHg, although people with relatively low pressures can have glaucoma and people with high pressure can have healthy eyes.

Universe of discourse: [0, 45]

Measurement unit: Millimetres of mercury mmHg.

Source: A device (usually a tonometer) is used to measure the pressure in the eye [35].

Terms: LOW/NORMAL/HIGH

Membership functions:

4.2 Cup to Disc Ratio

Acronyms used: CD_Ratio_OD, CD_Ratio_OS

Type: INPUT variable

Description: The optic nerve's appearance is often described in terms of cup to disc ratio. The ratio is an image that an eye care professional can view by looking through a dilated pupil to the optic nerve (ophthalmoscopy). Cup/disc ratios greater than 0.5 or asymmetric (uneven) ratios are considered suspicious for glaucoma. The diameter of the cup can be expressed as a fraction of the diameter of the disc both in the vertical and horizontal meridians. The cup-to-disc ratio is genetically determined. Most eyes have a horizontal cup-disc ratio of 0.3 or less and only 2% have a ratio greater that 0.7. A ratio greater than 0.3 should be regarded with suspicion; but it may not necessarily be a pathological case. Any difference should therefore be regarded with suspicion until the possibility of glaucoma has been excluded.

Universe of discourse: [0;1]

Measurement unit: % (it is a ratio).

Source: The ophthalmologist estimates the ratio by examining the back of the eye. Figure 3 shows the geometrical relationship used by the ophthalmologist to determine the CD Ratio [35].

Terms: NORMAL/SUSPICIOUS/ABNORMAL

Membership functions:

4.3 Myopia

Acronyms used: Myopia _OD, Myopia _OS

Type: INPUT variable

Description: The ability to see close objects more clearly than those at a distance. A condition where the eyeball is too long and steep, so that light rays focus before they reach the retina. The result is difficulty in seeing distant objects clearly.

Universe of discourse: [−20, 20]

Measurement unit: Diopters

Source: Optometer

Terms: MILD/MODERATE/SEVERE/EXTREME

Membership functions:

4.4 Age

Acronyms used: Age

Type: INPUT variable

Description: Patient's Age at the moment of the first visit.

Universe of discourse: [0, 120]

Measurement unit: years

Source: Patient's charts

Terms: YOUNG/MIDDLE-AGED/OLD

4

Membership functions:

4.5 Follow-Up

Acronym used: Follow-Up

Type: OUTPUT variable

Description: This variable is the output of the system. It determines in months, when the patient has to come back to see the ophthalmologist for a control or follow-up.

Universe of discourse: [0, 24]

Measurement unit: Months

Terms: IN A FEW WEEKS/IN A FEW MONTHS/IN SOME MONTHS/IN MANY MONTHS/IN A LONG TIME

Membership Functions:
The membership function shapes for all the input/output variables were elicited from the knowledge acquisition sessions with the expert, Dr. Andrew Crichton.

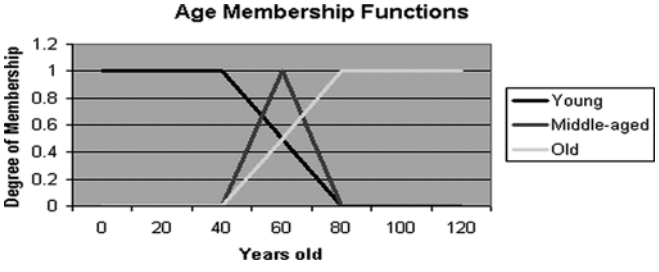

Fig. 6. Membership functions for age

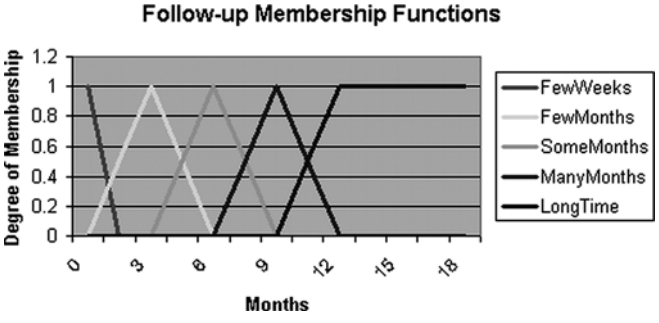

Fig. 7. Membership functions for follow-up

5 Fuzzy knowledge base design

Two sources of knowledge were used to determine the fuzzy rule base of our expert system (Fig. 8): expert knowledge and numerical data from patients' charts, from which rules were extracted using the Learning from Examples (LFE) [33] automated generation method.

The process is carried out in five steps:

1. Initial knowledge acquisition sessions by means of opened and structured interviews with the expert.
2. Conceptualization of the knowledge acquired in the first step by: establishing the strategic procedure followed by the expert, determination of the linguistic variables, etc.
3. Preparation of data from patients' charts, aiming to obtain two sets of I/O variables: One for training and the other one for testing the fuzzy system.
4. Fuzzy model generation using the LFE method.
5. Evaluation of the quality of the solution provided by this method. The output obtained by the system using this method is compared against the real follow-up estimated by the expert in order to evaluate if further tuning is necessary. If this is the case, the corresponding corrections or modifications are made, and steps 1–5 are followed again.

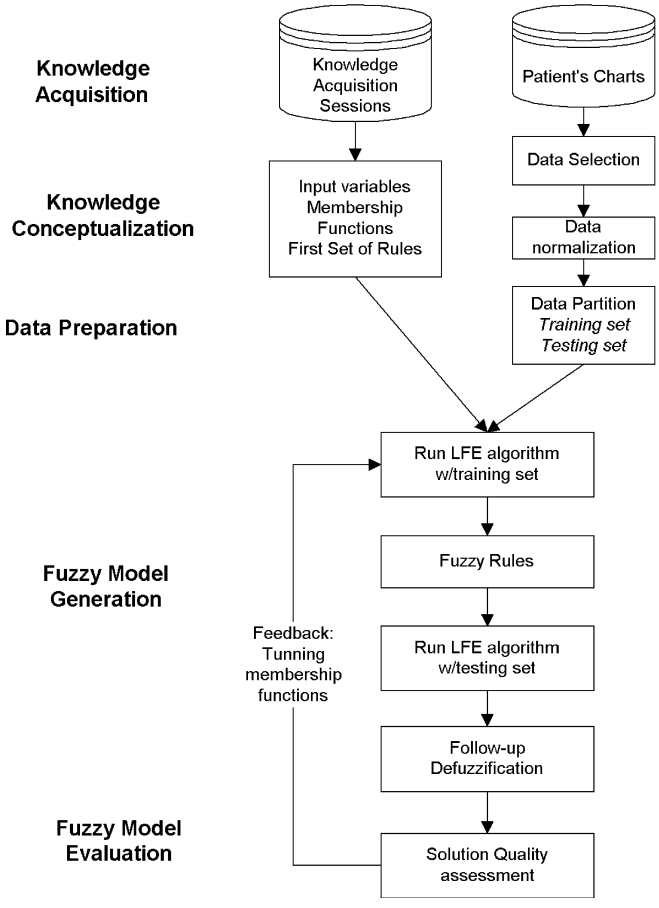

Fig. 8. Design of the fuzzy knowledge base

As inputs for the LFE algorithm we used the input and output variables, the membership function's shapes and the limit values for each of those membership functions.

5.1 Data preparation

After a broad research on one hundred patient's charts, 49 were selected as most relevant to our model (The input variables used to model the present fuzzy system were the most important ones in the follow-up estimation of these cases.)

According to Passino et al. [1], the training data set is critical to succeed at modelling the fuzzy system. Intuitively we should cover the whole input space uniformly. In our case the data was gathered from patient's charts, as we were trying to cover the input space as widely as possible.

Before continuing with the data partition in two sets, training and testing, a simple normalization was done to fit the data in the same hyper-space, especially for the cases of myopia which ranges from −20 to 20, and cup-to-disc ratio, which have values below one.

Once these modifications were done to the original data set, we divided it into a training data set and a testing data set. Tables 1 and 2 show these two sets.

5.2 Learning from Examples (LFE)

To illustrate how LFE works, let's first consider a simple example with only two input variables: IOP and CD _Ratio; and one output variable: Follow _up.

5.2.1 LFE with Two Input – One Output

The membership functions are chosen a priori for each input universe of discourse (as detailed in Sect. 3.) It is important to recognize that the number of membership functions on each universe of discourse affects the accuracy of the system approximation.

The rules are constructed by using the training data set. The input portions of the training data pairs are used to form the premises of the rules, while the output portions of the data pairs are used to form the conclusions.

Each rule is assigned a degree value that quantifies how certain we are that the rule represents an input-output data pair. The degree is calculated by multiplying the membership values of the IOP, CD _Ratio and Follow-Up variables for the rule generated for the current data pair, as follows:

- If the degree of a new rule is greater than the corresponding degree of an existing rule and the premises for both rules are the same, then the new rule will replace the existing one.
- If the degree of the new rule is lower than the degree of an existing rule with the same premises, then the new rule is not added.
- If the premises of the new rule are different from those of all other rules, then the new rule is added.

The process continues until all data pairs are considered.

Once the rules are created, we are ready to start a simulation with the testing data set. The input data from each data pair is loaded, their membership functions are calculated, and according to the results obtained the corresponding rules are fired, and the fuzzy result is obtained.

Table 1. Training data set

IOP_OD	IOP_OS	CD_Ratio _OD	CD_Ratio _OS	Myopia _OD	Myopia _OS	Age	Follow-up
12	10	9	9.5	11.25	13.75	86	4
12	12	6	6	12.25	13.25	56	3.5
13	14	6	5	12.5	13.75	59	8
14	12	3	4	11	10.75	43	3
16	16	4	4	16.75	18.5	67	6
17	16	9	4	15	15	70	0.5
17	17	4	5	15	15	39	0.5
18	16	4	0.1	14.75	14.5	75	1.75
18	18	2	2	13.25	13.5	43	12
18	18	5	5	16.5	17	64	4
19	13	6	4	11.5	12	63	6
19	16	5	4	7.75	8	49	12
19	19	3	3	15	15	64	8
19	20	9	5	16	15.25	61	0.5
19	21	7	9	6	6.75	50	1.5
20	20	7	7	12.5	12.5	62	1
20	24	3	3	17.75	17.75	60	4
21	21	6	4	16.25	16.75	51	0.5
21	22	2	2	11.5	11.75	45	2
21	23	7	7	12	15	50	1
22	22	7	6	16	16.75	67	1
23	14	8	7	6.5	7.25	42	0.5
23	24	4	4	13.75	13.75	33	1
24	20	4	3	10	11.25	69	0.75
34	34	4	4	10.25	10.5	45	0.25

Table 2. Testing data set

IOP_OD	IOP_OS	CD_Ratio_OD	CD_Ratio_OS	Myopia_OD	Myopia_OS	Age	Follow-up
11	16	6	4	14	16	66	0.5
12	13	8	7	16.5	15.75	87	0.75
13	13	9.5	9	13.75	12	80	0.5
14	13	3	2	12.5	14.25	58	6
14	14	7	0	10.75	11.25	54	0.5
15	19	8	9	9.25	9	40	4
16	16	5	6	16.25	15.5	65	1
17	16	8	7	13.5	15.25	81	1
17	18	5	7	15.75	15.75	62	6
18	19	6	5	15	15	55	4
20	11	5	3	17.25	12	32	6
20	21	8	9	11.75	11	83	0.75
21	17	3	3	14.75	15.75	67	1
22	24	5	5	14.25	14.25	73	2
23	14	8	7	6.5	7.25	42	0.5
23	24	6	4	15	15.5	57	1
23	24	6	9.5	15	15	57	0.75
23	30	5	6	8.75	9.25	51	0.75
23	33.5	6	9.5	8.25	10.25	78	0.5
24	20	8	4	29	28.75	85	0.25
26	21	6	4	15.25	15.25	58	3
28	26	7	5	14.25	15	61	0.25
29	26	8	6	13.75	14.5	60	0.5
34	29	7	7	12	12.25	55	0.75
11	16	6	4	14	16	66	0.5
34	29	7	7	12	12.25	55	0.75

In order to get a crisp value from this result, two defuzzification methods were implemented and compared: Centroid and Weighted Average.

The formula used for the centroid method is as follows [35]:

$$z^* = \frac{\int \mu_{\underline{A}}(z) \cdot z \, dz}{\int \mu_{\underline{A}}(z) \, dz} \quad (1)$$

The formula used for the Weighted Average method is as follows [34]:

$$z^* = \frac{\sum \mu_{\underline{C}}(\overline{z}) \cdot \overline{z}}{\sum \mu_{\underline{C}}(\overline{z})} \quad (2)$$

The output membership functions initially were set to 5 as obtained from the interviews with the glaucoma expert. However as a result of a solution quality assessment they were tuned from 5 to 25, achieving better results.

The new Membership Functions for the follow-up are presented in Fig. 9.

As it was necessary to name each membership function with a different term, we decided to use the original 5 terms used by the expert as foundation, and subdivide each of them into 5 regions as shown in the membership graph.

Figure 10 illustrates the performance of the LFE algorithm in this case.

The relative error generated by both defuzzyfication methods compared to the real cases (the output in the testing data set) is illustrated in Fig. 11. By "error" we indicate the difference in follow-up in months between the result obtained with the LFE method and the actual follow up determined by the expert at the time of the visit for the same case.

The dispersion observed comes from the lack of information used to create the rules, that is, the use of only two variables is not enough to achieve reasonable results.

Once the LFE method was adjusted and tuned, we were able to add the rest of the variables in order to achieve more accurate results.

5.2.2 LFE with all 7 input variables

The Follow-up obtained using our chosen seven variables, IOP_OD, IOP_OS, CD_Ratio_OD, CD_Ratio_OS, Myopia_OD, Myopia_OS and Age is presented in Fig. 12.

In most of the cases the results were satisfactory except for some cases where the LFE predicted smaller values. Those cases were carefully analyzed; as a result we found

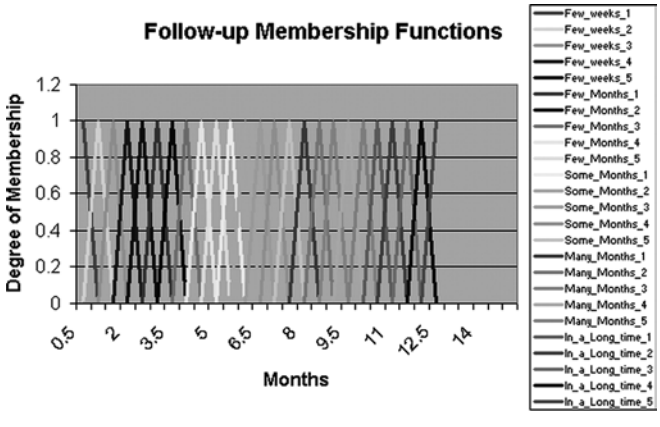

Fig. 9. New membership functions for follow-up

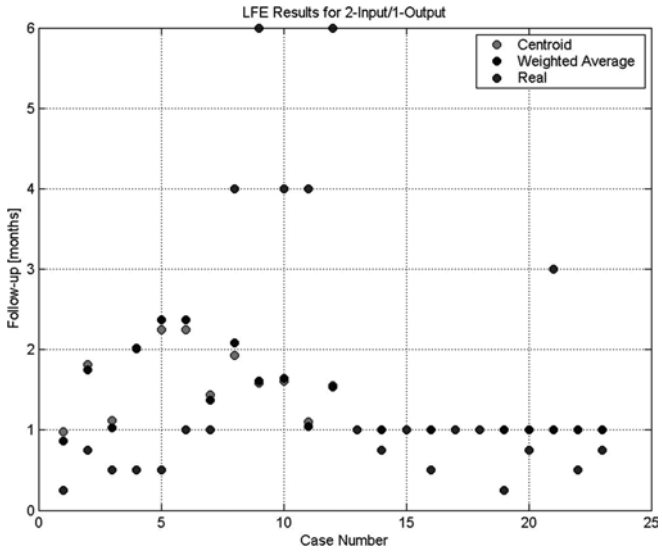

Fig. 10. LFE algorithm used for a 2 inputs-1 output system

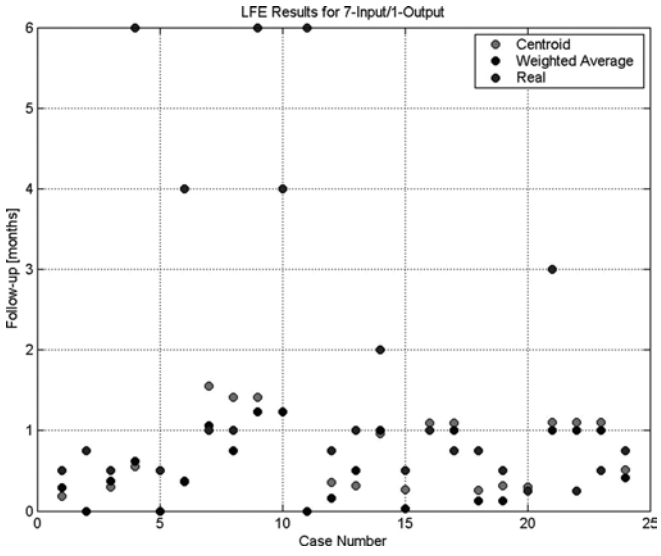

Fig. 12. LFE algorithm used for a 7 inputs-1 output system

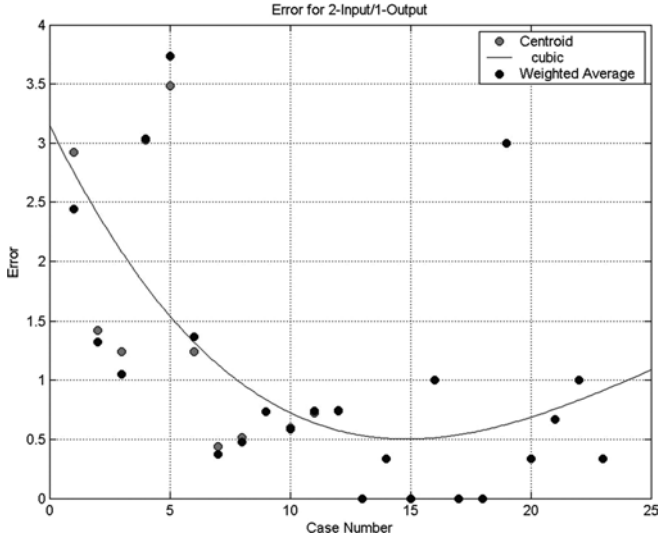

Fig. 11. Relative errors for the 2 inputs-1 output system

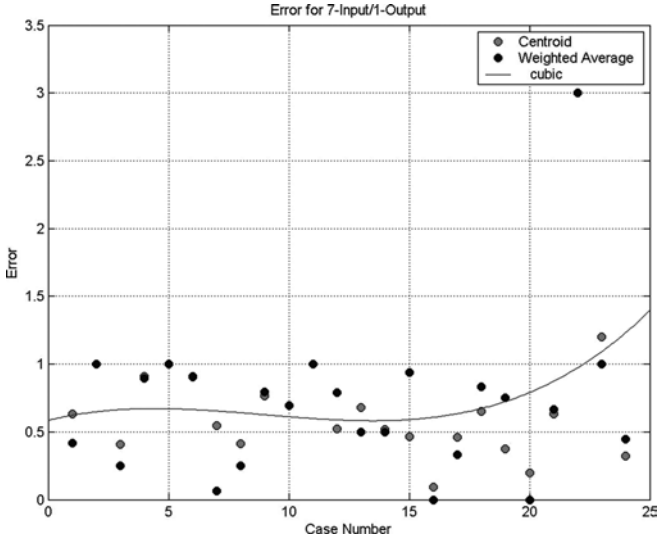

Fig. 13. Relative errors for the 7 inputs-1 output system

that the doctor considered other factors in determining the follow-up time, for example family history of Glaucoma, patients referred from other ophthalmologists, etc. Therefore new variables should be included in the rule set:

- Treatment: Whether the ophthalmologist gave the patient a new treatment, changed it or not.
- Family history: if the patient appears to have healthy eyes but has family history of glaucoma, the ophthalmologist would like to follow the patient a bit closer.

The corresponding error graph is shown in Fig. 13.

Comparing with the previous errors, shown in Fig. 11, a more stabilized system was obtained, as a result of adding more significant linguistic variables. Also a lower mean was achieved. The rules obtained with the LFE method are presented in Table 3.

Once we got these rules we had a new interview with the expert [34] and we found out that we should make the following changes:

- Add one more membership function for IOP: "Extremely high" for measurements above 30.
- Add a new variable that defines whether the cup-to-disc abnormality is glaucomatous or not: "CD_Glaucomatous" (Values: yes/no).
- The initial fuzzy partition for the follow up was an analytical one, meaning that we divided the output in uniformly distributed intervals. A new fuzzy partition was found during the fuzzy-rule-set validation interviews:

In 1 week/within 1 week/within 2 weeks/in 2 to 3 weeks/in 3 weeks/within 3 weeks/in 1 month/within 1 month/in 1 to 2 months/in 2 months/within 2 months/in 2 to 3 months/in 2 to 4 months/in 3 to 6 months/in 4 to 6 months, Fig. 14.

- Eliminate the use of both eyes, considering only the measurements of the most damaged one.
- The rules obtained from the algorithm have been slightly changed, as per Table 4.

Table 3. Fuzzy rule set created with the LFE method

Rule #	IOP_OD	IOP_OS	CD_RATIO_OD	CD_RATIO_OS	MYOPIA _OD	MYOPIA _OS	AGE	FOLLOW UP
1	Low	Low	Abnormal	Normal	Moderate	Moderate	Middle Aged	Few_Weeks_1
2	Low	Low	Abnormal	Abnormal	Moderate	Moderate	Young	Few_-Months_1
3	Low	Low	Abnormal	Abnormal	Moderate	Mild	Old	Few_-Months_3
4	Low	Low	Abnormal	Abnormal	Mild	Mild	Middle Aged	Few_-Months_2
5	Low	Low	Abnormal	Abnormal	Mild	Mild	Old	Few_Weeks_1
6	Low	Normal	Abnormal	Abnormal	Mild	Mild	Middle Aged	Few_Weeks_1
7	Normal	Low	Abnormal	Abnormal	Moderate	Moderate	Middle Aged	Some_-Months_2
8	Normal	Normal	Abnormal	Abnormal	Severe	Severe	Young	In_A_Long_Time_4
9	Normal	Normal	Abnormal	Abnormal	Moderate	Severe	Young	Few_-Months_3
10	Normal	Normal	Abnormal	Abnormal	Mild	Mild	Young	In_A_Long_Time_4
11	Normal	Normal	Abnormal	Abnormal	Mild	Mild	Middle Aged	Some_-Months_2
12	Normal	Normal	Abnormal	Abnormal	Mild	Mild	Old	Few_Weeks_2
13	Normal	High	Abnormal	Abnormal	Extreme	Severe	Young	Few_Weeks_3
14	Normal	High	Abnormal	Abnormal	Mild	Mild	Middle Aged	Few_Weeks_1
15	High	Low	Abnormal	Abnormal	Severe	Severe	Young	Few_Weeks_1
16	High	Low	Abnormal	Abnormal	Mild	Moderate	Young	Some_-Months_2
17	High	Normal	Abnormal	Abnormal	Mild	Mild	Old	Few_Weeks_2
18	High	High	Abnormal	Abnormal	Severe	Moderate	Young	Few_Weeks_1
19	High	High	Abnormal	Abnormal	Severe	Moderate	Old	Few_Weeks_1
20	High	High	Abnormal	Abnormal	Moderate	Moderate	Young	Few_Weeks_1
21	High	High	Abnormal	Abnormal	Moderate	Moderate	Old	Few_ Weeks_1
22	High	High	Abnormal	Abnormal	Moderate	Mild	Young	Few_Weeks_2
23	High	High	Abnormal	Abnormal	Moderate	Mild	Middle Aged	Few_Weeks_1
24	High	High	Abnormal	Abnormal	Mild	Mild	Young	Few_Weeks_1
25	High	High	Abnormal	Abnormal	Mild	Mild	Middle Aged	Few_-Months_1
26	High	High	Abnormal	Abnormal	Mild	Mild	Old	Few_Weeks_4

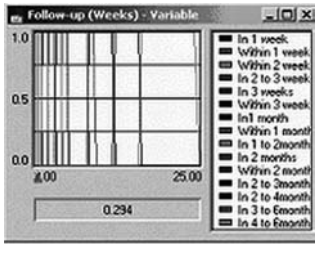

Fig. 14. Follow-up membership functions after validation

To expand the current knowledge base encoding Dr. Crichton's patterns of glaucoma follow-up, we plan to investigate the patterns of other Canadian glaucoma experts (selected from the most reputable internationally recognized ones) joined into what we call the Canadian Glaucoma Ring. In the next section we present the methodology by which we will reconcile the other expert opinions into a standard of care for glaucoma follow up.

6 Collaborative methodology for embedding various experts views into a knowledge base

The contribution of several experts to the development of a knowledge base brings enormous value, but at the same time it presents a big challenge to the knowledge engineers. To cope with this we have developed a methodology (Fig. 15) capable to deal with different expert opinions and consolidate the results in a rule set with each rule weighted by the degree of consensus reached among the experts. The methodology consists of the following steps:

Find the various patterns for each of the experts involved

Each expert analyzes the existing rules encoding Dr. Crichton's expertise and expresses either agreement or disagreement (arguing wherever possible why they disagree) as well as adding new rules in case the existing ones do not encompass their whole expertise. This will define the respective expert's *profile*.

Investigate the differences and attempt to reconcile them

Once each expert has defined their profile (that is their own rule base) – we will investigate the differences and attempt to reconcile them as much as possible based on a deeper understanding of each expertise, argumentation, and trying to identify the particularity of each case

Table 4. Fuzzy rule set after validation

Rule #	IOP	CD_Ratio	CD_ Glaucomatous	Myopia	Age	Treatment	Follow -UP
1	Low	Abnormal	Yes				Within 2 months
2	Low	Abnormal	Yes	Severe			Within 1 month
3	Low	Suspicious	Yes				Within 2 months
4	Low	Suspicious	Yes	Severe			Within 1 month
5	Low					Change	3 to 4 weeks
6	Normal	Normal					3 to 6 months
7	Normal	Normal		Severe	Young	None	2 to 4 months
8	Normal	Abnormal	Yes				Within 2 months
9	Normal	Abnormal	Yes	Severe			Within 3 weeks
10	Normal	Abnormal	No				3 to 6 months
11	Normal	Abnormal	No	Severe			2 to 4 months
12	Normal	Suspicious	Yes				Within 2 months
13	Normal	Suspicious	Yes	Severe			Within 1 month
14	Normal	Suspicious					2 to 3 months
15	Normal	Suspicious		Severe			1 to 2 months
16	Normal					Change	3 to 4 weeks
17	High					None	Within 1 month
18	High	Abnormal	Yes				2 to 3 weeks
19	High	Abnormal	Yes	Severe			Within 2 weeks
20	High	Abnormal		Severe	Young	None	Within 3 weeks
21	High	Abnormal		Severe	Middle aged	Same	3 weeks
22	High	Suspicious	Not sure				In 1 month
23	High	Suspicious	Yes				In 2 months
24	High	Suspicious	Yes	Severe			Within 1 month
25	High	Suspicious		Moderate	Young	Same	Within 2 months
26	High	Suspicious		Severe	Young	Same	Within 1 month
27	High					Change	3 to 4 weeks
28	Extremely high						1 week
29		Abnormal	Yes				In 2 months
30		Suspicious	Yes				2 to 3 months
31		Suspicious	Yes	Severe			1 to 2 months

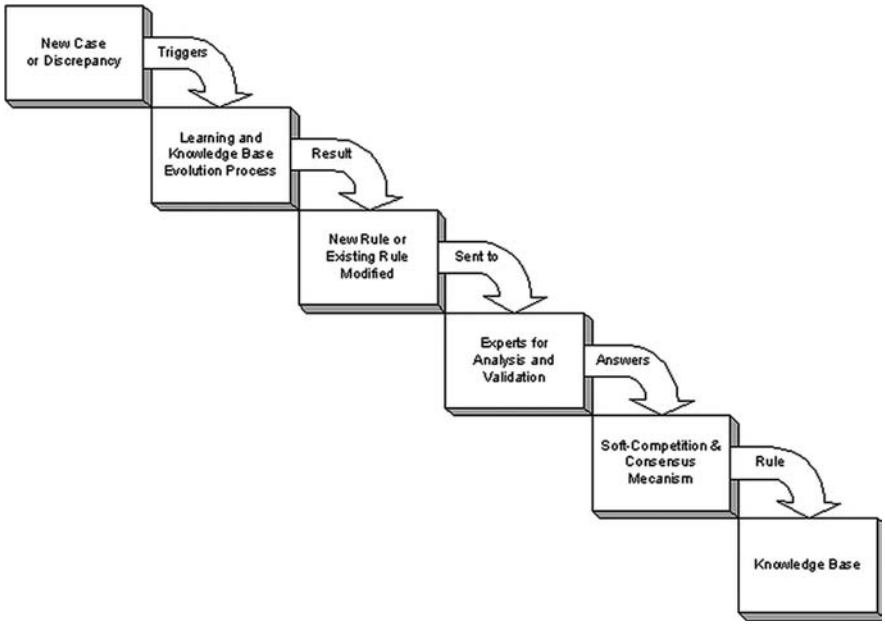

Fig. 15. Embedding various expert views into a knowledge base

that led to a different rule/experience/pattern for different experts. To enable this difficult task we have developed a methodology involving a 'consensus analyzer', Fig. 16, to be presented next.

Determination of the Core Rule Set (Canadian Standard of Care)

The result of this reconciliation process will be a *core rule set* shared by all the experts in the Canadian Glaucoma

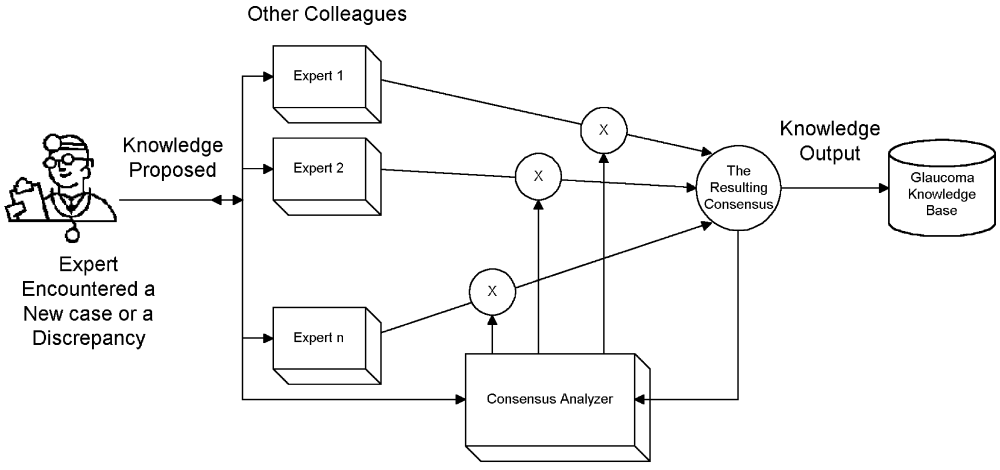

Fig. 16. Expert opinion reconciliation

Ring. However each expert will be able to keep their own variations of the rule set due the particularities of their patients and geographic area. This enables each expert to consult others about how they would treat specific cases and compare the results. This "simulation" characteristic gives to the system a tremendous power when dealing with complex cases.

7
Consensus metrics by soft competition

The goal of group decision making typically is to reach a consensus concerning a desired action or alternative from among those considered in the decision process. In this context, consensus is taken to mean *a unanimous agreement by all those in the group concerning their choice*.

Each time a new rule is proposed by an expert or an existing rule needs to be modified as a consequence of an expert's profile discrepancy to reconcile experts disagreement, the rule is presented to all the experts for evaluation. The expert opinions are analyzed by the Consensus Analyzer (Fig. 16) which evaluates the *distance* between each expert's opinion and the point of minimum consensus [35] (the point of maximum conflict to which the expert opinions are most distant from each other.) To evaluate this distance we use *soft competitive learning*, a very powerful methodology [36] which gives a fuzzy measure of the divergence in the expert opinions.

In contrast to the concept of *hard competition* that allows only one winner, *soft competition* not only gives a clear winner but more "neighbours" who are winners with a lower degree. The neighbour rules are used as inputs into a consensus procedure that performs fuzzy measures of the consensus obtained for each rule. Based on this information a decision about the rule being considered is made. The rule awarded the highest degree of consensus is selected and then incorporated into the knowledge base. The *not neighbours* opinions are discarded.

Our goal is to define a typical value of distance to consensus by asking the experts to indicate their preferences for each characteristic of the fuzzy rule, expressing each preference as a fuzzy value.

We will consider the individual preferences as fuzzy relations. Lets suppose we are developing consensus in a universe $X = \{x1, x2, \ldots, xn\}$; a fuzzy relation **R** of order n will have elements r_{ij} encoding the preferences given to x_I relative to $x_j r_{ij} = 1$ implies that alternative i is definitely preferred to alternative j. At the other extreme we have maximal fuzziness, where $rij = rji = 0.5$.

Two common measures of preference are defined here as average fuzziness in R and average certainty in **R:**

$$F(R) = \frac{tr(R^2)}{n(n-1)^{1/2}} \tag{3}$$

$$C(R) = \frac{tr(R \cdot R^{\mathrm{T}})}{n(n-1)^{1/2}} \tag{4}$$

where *tr* is the trace and T is the transposed of the matrix.

The measure F(R) averages the joint preferences in **R** over all distinct pairs in the cartesian space X × X. F(R) is proportional to the fuzziness or uncertainty about pairwise rankings. Conversely the measure C(R) averages the individual dominance of each distinct pair of rankings.

The two measures are dependent:

$$F(R) + c(R) = 1 \tag{5}$$

Measures of preference can be useful in determining consensus.

We define three type of consensus as follows:

Type I consensus: There is a clear choice, say alternative i (the ith column is all zeros) and the remaining (n−1) alternatives all have equal secondary preference (i.e. 1/2).

Type II consensus: There is one clear choice say alternative i but the remaining (n−1) alternatives all have definite secondary preference (of value 1).

Type Fuzzy consensus: Occurs when there is a unanimous decision for the most preferred choice, say alternative i but the remaining (n−1) alternatives have infinitely many fuzzy secondary preferences.

From the degree of preferences measures given in previous equations we can construct a distance to consensus metric defined as

$$m(R) = 1 - (2 \cdot C(R) - 1)^{1/2} \tag{6}$$

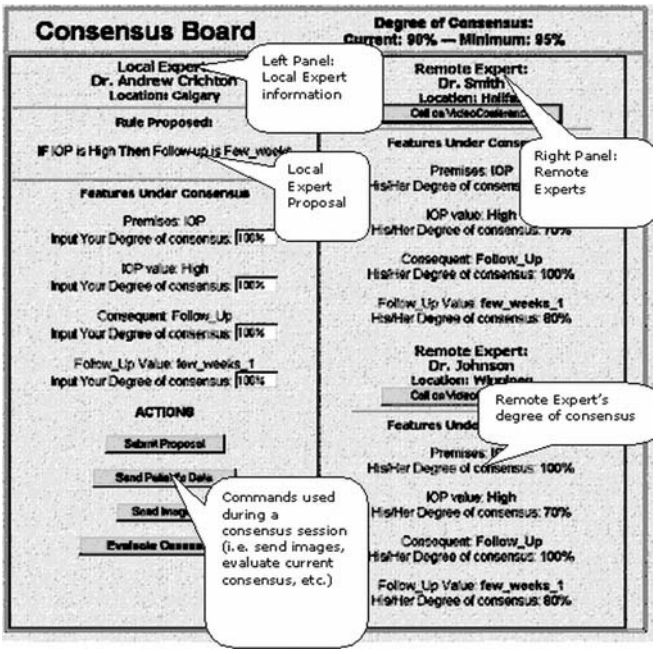

Fig. 17. User interface enabling expert interaction to reach consensus

where:

$m(R) = 1 - (2/n)^{1/2}$ for a Type I consensus relation
$m(R) = 0$ for a Type II consensus relation.
When $n > 2$, the distance between Type I and Type II consensus increases with n, as it becomes increasingly difficult to develop a consensus choice and simultaneously rank the remaining pairs of alternatives.

The value of distance to consensus quantifies the dynamic evolution of a group as the group refines its preferences and moves closer to a Type I or Type II or Type Fuzzy consensus. The vast majority of group preference situations eventually develop into Type Fuzzy consensus, Types I and II being typically only useful as boundary conditions.

Based on the consensus metrics, the rule base is tuned to embrace all opinions as much as possible (which means that the rules obtained will be positioned in the equidistant point to all expert opinions.) Once the predefined distance to consensus is reached, the rule is integrated in the knowledge base.

To enable expert interaction we are currently developing a web-centric extension of the glaucoma expert system [37, 38, 39](GlaucoMAX[4]) into which we will plug a dedicated user's interface for the Consensus Analyzer enabling expert opinions reconciliation (Fig. 17).

8
Conclusions and future work

A fuzzy prediction rule-set for follow-up in the glaucoma monitoring was developed using fuzzy modelling and learning from examples algorithm. This rule base is being refined using soft competitive learning to accommodate the perspectives of more experts. The perfected rule set, with each rule weighted by the *degree of consensus* reached among the experts, points towards a standard of care in glaucoma follow up and treatment.

The LFE technique proved that the number of membership functions for the output variable was too low. Therefore it was elevated from 5 to 25 following the symmetrically and uniformly distributed division. With the validation interviews, that number was modified to be 13 and neither symmetrically nor uniformly distributed. This revealed the fact that the mathematical algorithm was not enough to refine the membership functions; it only focused on the rule building. The resulting fuzzy rule set from the LFE algorithm was composed of 26 rules, which were refined and validated with the expert in the validation interviews, resulting in a final fuzzy rule set of 31 rules.

Each Membership Function of all linguistic variables obtained as a result of the present work will be optimized by using Fuzzy Clustering techniques in order to get more accurate membership function shapes. The initial Core Glaucoma Ring will be subsequently expanded to encompass other Canadian and International glaucoma experts that will join our GlaucoMAX system to benefit from the shared expertise.

[4] www.GlaucoMAX.com

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