How Expert is EXPERT for Fuzzy Logic-Based System!

Kalyani Bhole, Sudhir Agashe and Jagannath Wadgaonkar

Abstract Anesthesia, an utmost important activity in operation theater, solely depends upon anesthesiologist, an expert. In the case of absence of expertise, drug dosing may go under-dose or overdose. To overcome this problem, an expert-based system can be designed to guide newcomers in the field of anesthesia. This structure is called as decision support system. As this system is dependent on experts' knowledge base, its performance depends on the expert's expertise which can be validated by comparison with other expert's knowledge base and finding maximum correlation among them. This paper demonstrates the application of prehistoric Gower's coefficient to validate the expert's expertise for fuzzy logic-based experts' system. Database is collected from ten experts. For the 80% level of confidence, eight experts are classified into one group leaving two aside. Database of these eight experts is used for the design of decision support system. A set of 270 results noted from decision support system is validated from the expert. Out of 270, expert declines 3 decisions accepting 98.88% result.

Keywords Intravenous anesthesia · Expert-based system · Fuzzy logic
Gower's coefficient · Decision support system

1 Introduction

In the framework of complex unclear processes that can be controlled by trained human operators, modeling an uncertainty is a great challenge. Within the processes, the exact level of accuracy can be expressed by the characterization and

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quantification of uncertainty. Imprecision and inexactness of information that we have to characterize heave with complexity of processes. It is pragmatic to have an indistinguishable relationship between precision, information, and complexity. However, for most of the processes, we can achieve a better control in accepting some level of imprecision. Mapping of imprecision and uncertainty with the help of experts to control a complex process is the wreath of fuzzy logic [1]. Fuzzy logic-based expert's system for intravenous anesthesia is designed and proved its usefulness in our previous publications [2–4]. This system is dependent on information provided by experts. To validate the knowledge base provided by experts, different similarity measures are used which includes metric-based, set theoretic-based, and implication-based measurements. Different distance-based measurements such as Hamming, Euclidean, and Raha's coefficients are used to find similarity among quantitative measures [5–7]. Lazlo Koczy with his fellows has proposed a methodology for distance measurement between two fuzzy sets [8]. Koczy's methodology generates an output which is denoted by an interval and it is not able to cover qualitative properties. Gower's coefficient is published in 1971. Gower has proven its effectiveness for the use of qualitative as well as quantitative similarity measures for different applications through different publications [9].

In this sequel, a sincere attempt has been made to use classify experts' database using Gower's coefficient to extract effective knowledge base for the expert-based system and use the strong expert's database only for further development. The proposed methodology is applied to designing and development of decision support system for intravenous anesthesia.

This paper is divided into five sections. Section 2 discusses fuzzy modeling where the structure of fuzzy model is explained. Section 3 focuses on similarity measure, describing the use of Gower's coefficient. Section 4 explains results and discusses them with the case study of design and implementation of decision support system for intravenous anesthesia. Section 5 concludes the work.

2 Fuzzy Modeling

Fuzzy modeling has wide applications and proven to be useful, especially in control engineering. There are two approaches to model using fuzzy logic: (a) based on data and (b) based on knowledge acquisition. Fuzzy model for intravenous anesthesia is built using experts' knowledge base. This knowledge is stored in terms of membership functions and rule base. Membership functions are nothing but the human interpretation of variable in linguistic term. For example, we say that today, temperature is low. In this case, temperature is variable and low is linguistic term. In country like India, range of low temperature may be around 7–12 °C. This interpretation is represented in terms of mathematics using membership function. Figure 1 shows the block diagram of fuzzy model.

Main nuts and bolts of fuzzy logic system are fuzzification which is based on antecedent membership functions, inference mechanism which is driven by rule

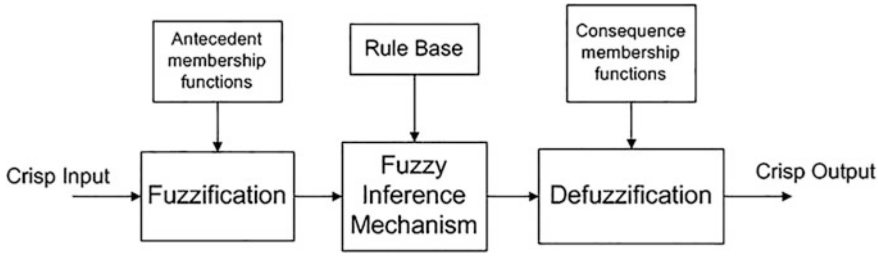


Fig. 1 Block diagram of fuzzy model

base, and defuzzification which is driven by consequence membership functions. Fuzzification is the process of representing human interpretation in terms of mathematical equations. This representation is called as membership function. Membership functions pursue different shapes such as triangular, trapezoidal, sigmoid, Gaussian and rely on the believability of occurrence of event/linguistic representation (e.g., when we say, antecedent is low, the plausibility of antecedent at typical condition will be highest which is considered as 1 whereas it decreases with upgradation or degradation of the antecedent). Membership functions are calculated for all linguistic variables. Next component of FLS is rule base where consequence mapping is stored in terms of if–then rules. This consequence mapping can be of expert-based or experiment-based. If system response is known, then consequence part of fuzzy rules is calculated from fuzzy patches. Fuzzy inference mechanism drives fuzzy rules for occurred antecedents' value and calculates fuzzified consequence which is defuzzified later by defuzzification method. Most famous and accurate defuzzification method is calculation of the center of mass or center of gravity (CG).

3 Similarity Measure

Similarity coefficient measures the likeness between two individuals based on characters or distinct kind of information. These characters can be of two types, quantitative or qualitative. Quantitative characters can be arranged into ordered set for comparison but qualitative characters do not form an ordered set though they may have many levels. The similarity measures are classified into three categories: (1) metric-based measures, (2) set theoretic-based measures, and (3) implicator-based measures. While dealing with distance-based measure, every distance axiom is clearly violated by dissimilarity measures, particularly the triangle inequality and consequently the corresponding similarity measure disobeys transitivity. Even in case of set theoretic measures, the perceived similarities do not follow transitivity. Experts' knowledge base consists of membership functions as well as rule base. Membership functions can be compared by simply finding out correlation factor between two, but it does not cover the complete expertise. It lies within rule base also. For such applications, distance-based measurement fails. In 1971, J.C. Gower proposed a general coefficient which collectively compares quantitative as well as qualitative character. For example, if we want to compare two human beings, based on height, weight, and skin complexion, height and weight are quantitative measures whereas skin complexion is qualitative measure. In this case, Gower's coefficient finds out the similarity between two individuals. Similarly for expert-based system, Gower's coefficient is able to find out similarity between membership functions as well as rule base.

(a) Gower's coefficient

If two individuals i and j *are* compared for character k, then the assigned a score (Gower's coefficient) is S_{ijk}.
For qualitative characters S_{ijk} = 1, if the two individuals i and j agree in the kth character and S_{ijk} = 0 if differs.
For quantitative characters,

$$S_{ijk} = 1 - \frac{\left|X_i - X_j\right|}{R_k},$$

$R_k \rightarrow$ Range of character k.

The similarity between i and j is defined as the average score taken over all possible comparisons.

$$S_{ij} = \frac{\sum_{k=1}^{v} S_{ijk}}{\sum_{k=1}^{v} \delta_{ijk}},$$

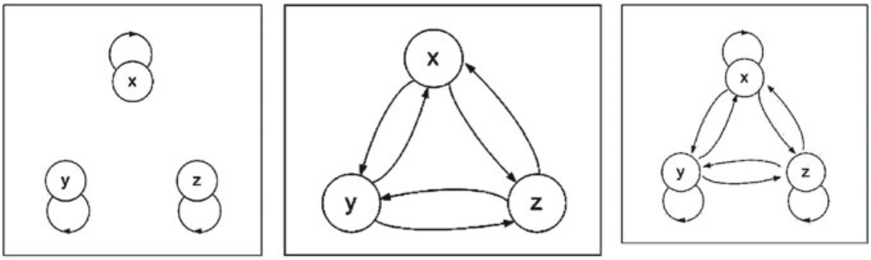
where δ_{ijk} is the possibility of making comparison.

$\delta_{ijk} = 1$ when character k can be compared for i and j.
$\delta_{ijk} = 0$ when character k cannot be compared for i and j.

(b) Properties of Fuzzy Relation [10]

An equivalence relation is the relation that holds between two individuals if and only if they are members of the same set that has been partitioned into different subsets such that every element of the set is a member of one and only one subset of the partition. The intersection of any two different subsets is empty; the union of all the subsets equals the original set. An equivalence relation follows three properties: (1) reflexive property, (2) symmetric property, and (3) transitive property.

(1) Reflexive Property



(a) Reflexive (b) Symmetric (c) Transitive

Fig. 2 Properties of equivalence relation

A relation R for all x, y, z € S is said to be reflexive, if $x \approx x$ as shown in Fig. 2a.

(2) Symmetric Property

A relation R for all x, y, z € S is said to be symmetric, if $x \approx y$ and $y \approx x$ as shown in Fig. 2b.

(3) Transitive Property

A relation R for all x, y, z € S is said to be transitive if $x \approx y$ and $y \approx z$, then it is true for $x \approx z$ as shown in Fig. 2c.

(c) Tolerance to Equivalence Relation

Tolerance relation is a relation who follows symmetry and reflexivity but not transitivity. For comparison, relation should be equivalence. Tolerance relation is converted into equivalence relation by self-composition of the relation. Two most familiar methods are max–min composition and max-product composition. For relation R, max–min composition is defined as

$$T = R^{\circ}R,$$

$$\chi_T = \vee(\chi_R(\mathrm{Col}, \mathrm{row}) \wedge \chi_R(\mathrm{row}, \mathrm{col})).$$

Max-product composition is defined as

$$\chi_T = \vee(\chi_R(\mathrm{Col}, \mathrm{row}) \cdot \chi_R(\mathrm{row}, \mathrm{col})).$$

In this paper, max–min composition is used.

4 Results and Discussion

Gower's coefficient between each expert is calculated which shows similarity between the pair of experts. Similarity matrix is obtained by calculating similarity index between each pair of experts. This matrix is then converted into equivalence

Table 1 Equivalence relational matrix obtained from database given by ten experts

Expert No.	1	2	3	4	5	6	7	8	9	10
1	1	0.779	0.871	0.9	0.9	0.779	0.9	0.9	0.9	0.9
2	0.779	1	0.779	0.779	0.779	0.9	0.779	0.779	0.779	0.779
3	0.871	0.779	1	0.871	0.871	0.779	0.871	0.871	0.871	0.871
4	0.9	0.779	0.871	1	0.904	0.779	0.904	1	0.904	0.96
5	0.9	0.779	0.871	0.904	1	0.779	0.928	0.904	0.928	0.904
6	0.779	0.9	0.779	0.779	0.779	1	0.779	0.779	0.779	0.779
7	0.9	0.779	0.871	0.904	0.928	0.779	1	0.904	0.966	0.904
8	0.9	0.779	0.871	1	0.904	0.779	0.904	1	0.904	0.96
9	0.9	0.779	0.871	0.904	0.928	0.779	0.966	0.904	1	0.904
10	0.9	0.779	0.871	0.96	0.904	0.779	0.904	0.96	0.904	1

matrix for comparison. Equivalent relational matrix of all experts is as shown in Table 1. We can observe that this matrix follows reflexivity, symmetry, and transitivity, hence satisfying conditions for classification. For expert-based system, if 80% level of confidence is considered, then Table 2 shows relational matrix after applying α-cut at 0.8. From this table, we can observe that expert No. 2 and 6 are not satisfying the 80% level of confidence. Hence, while considering the database for expert-based system, these two experts can be neglected, in view of other 8 experts. Database of these 8 experts is used to design fuzzy logic-based decision support system for intravenous anesthesia [11, 12], and it is implemented using National Instruments LabVIEW software. Screenshot of the same is as shown in Fig. 3. A set of 270 results noted from decision support system is validated from the expert. Out of 270, expert declines 3 decisions accepting 98.88% result.

Table 2 Relational matrix after applying α-cut at 0.8

Expert No.	1	2	3	4	5	6	7	8	9	10
1	1	0	1	1	1	0	1	1	1	1
2	0	1	0	0	0	1	0	0	0	0
3	1	0	1	1	1	0	1	1	1	1
4	1	0	1	1	1	0	1	1	1	1
5	1	0	1	1	1	0	1	1	1	1
6	0	1	0	0	0	1	0	0	0	0
7	1	0	1	1	1	0	1	1	1	1
8	1	0	1	1	1	0	1	1	1	1
9	1	0	1	1	1	0	1	1	1	1
10	1	0	1	1	1	0	1	1	1	1

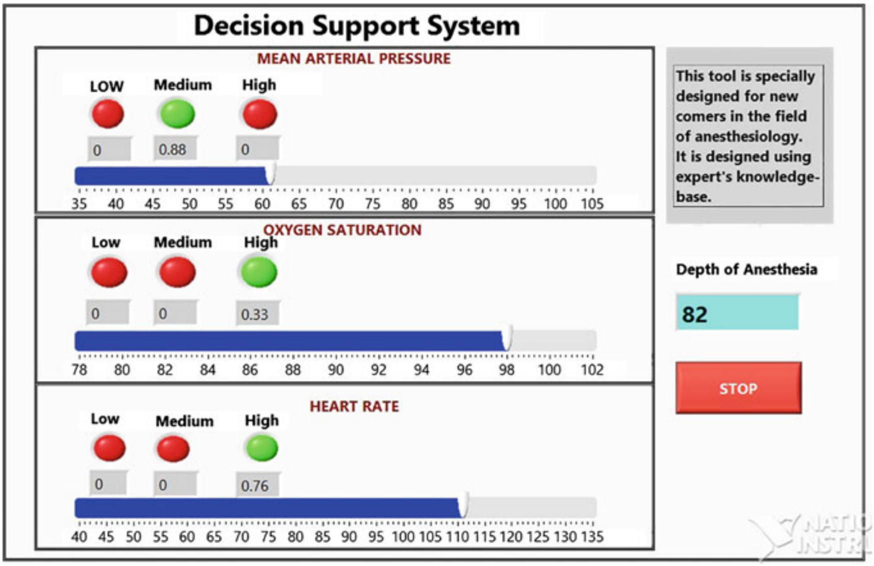


Fig. 3 Decision support system for intravenous anesthesia

5 Conclusion

For applications such as anesthesia, quality of control is based on expert's skill and experience. Being biological control, accuracy is most important here. For such applications, to design decision support system, uncertainty from the experts' knowledge base can be reduced by classification of experts' knowledge base. For fuzzy logic-based experts' system, where knowledge base is in terms of quantitative as well as qualitative measures, Gower's coefficient satisfies the need of comparison. Selecting strong experts out of comparison matrix gives strong knowledge base for decision support system for intravenous anesthesia.

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