MEDICAL FUZZY MODELS FOR E-HEALTH APPLICATIONS

Dragan Z. Šaletić   Milica Savić
School of Computing, University "Union", Belgrade, Serbia
Knez-Mihailova str. 6/VI
dsaletic@raf.edu.rs   savicmilica@yahoo.com

Abstract *— In the paper, a possible e-health application of fuzzy models of determining the severity of respiratory distress in a patient in an intensive care unit is considered. Models of fuzzy multi-criteria decision making are applied in two situations: the first, with all features of equal importance and without interaction between criteria, and the second, with interacting criteria. The practical usage of both approaches is considered. In the first case the Bellman-Zadeh's approach is used, and in the second case, the Choquet integral is used. Directions for possible further work on the telemedicine application considered are pointed out.*

1. INTRODUCTION

E-health technologies are part of Internet society technology and are dealing wiht healthcare practice supported by electronic processes and communication. E-health encompasses a range of services or systems that are at the edge of medicine/healthcare and information technology, including, among other technologies, a telemedicine. Telemedicine is a rapidly developing application of clinical medicine, where medical information is transferred through interactive audiovisual media for the purpose of consulting, and sometimes remote medical procedures or examinations. In the paper, we focus on evaluating the severity of respiratory distress in a patient in an intensive care on the base of fuzzy models, having in mind a telemedicine application. Disease severity is the focal point of medical interest. It reflects all symptoms and impairments caused by analysed disease. The goal of severity evaluation is to generate standardized indicators that are suitable for unified assessment of patients' condition. Diseasy severity is evaluated by medical examiners based on objective measurements and quantification of symptoms .

The severity rating scales used in clinical practice are regularly base on simplistic additive scoring. These scales enjoy wide acceptance because they are easy to administer. The additive scoring approach yields indicators of insufficient precision.

Current medical rating scales do not use graded logic functions and other useful features of soft computing decision models. The main goal of of this paper is to demonstrate how soft computing methods and corresponding software tools can be use as tools in medical evaluation.

Fuzzy sets theory offers lots of aggregation operators for combining membership values representing uncertain information. That is of importance not only for models expressed by fuzzy expert systems, but also for fuzzy decision-making systems, and wider.

In many applications of fuzzy sets theory, in order to model a complex and maybe not fully defined systems, fuzzy decision making systems are used. Thus, the aggregation process of fuzzy information is an important element of fuzzy decision making system.

A situation that requests fuzzy modelling exists in the process of determining the severity of respiratory distress. The idea of using fuzzy sets theory in modelling the decision-making process in determining the severity of respiratory distress was proposed in [1]. In [2], software implementation of fuzzy decision-making process in determining the severity of respiratory distress is described.

With intelligent medical systems, the status of a patient can be described by numerical values, text and image data, i.e. multimedia data. A patient with respiratory distress is described by a set of symptoms with numerical values assigned at approximate intervals, by a set of symptoms expressed verbally (*Breathing*), and by a set of symptoms presented by an image (chest radiograph -*Rö*). The appropriate model that can deal with all these kinds of data is a fuzzy model. Some variants of simplified fuzzy models for determining the severity of respiratory distress and the developed application have been reported in [2]. In this paper possibilities of further implementation and development of the application are discussed.

Considering nonadditive integrals in the discrete finite case defines a class of aggregation functions allowing criteria interaction modelling. For this the concept of fuzzy measure (or the Choquet capacity) is used. The Choquet integral has been proposed as an aggregation operator for information fusion and pattern classification [3]. An algorithm for discriminative training of Choquet-integral based fusion operators is described in [4]. This new algorithm is applied to a landmine detection problem, and compared to other techniques.

Fuzzy sets theory generated among other things, a widely accepted application, fuzzy-logic controllers , but also gives powerful motivation for aggregation operators research with results of importance not only for fuzzy modelling. Some results of that research have also been applied for evaluation of disease severity, for example in peripheral neuropathy [5].

Section 2 of this paper considers a practical problem, the problem of determining the severity of respiratory distress in a patient in an intensive care unit. The theoretical basis of the model in which the Choquet integral is used, is given in Section 3. The model is based on fuzzy measures theory and interaction representation. Section 4 treats the results. In Section 5, the problem of Internet implementation of considered problem is discussed. Finally, the conclusions are given, and possible further work is pointed out.

2. PROBLEM CONSIDERED

A medical application of a fuzzy multicriteria decision-making model is considered. Criteria used for an early diagnosis of ARDS (acute respiratory distress syndrome), [1], [2] include:

-clinical aspects of breathing (*Breathing*);

-chest radiograph (*Rö*);

-the arterial partial tension of oxygen (PaO_2, mmHg);

-the arterial partial tension of carbon dioxide ($PaCO_2$, mmHg);

-alveolar-arterial oxygen tension difference ($A\text{-}aDO_2$, mmHg).

Those criteria are used as an example. It is obvious that an implementation of a real medical system requires an extension of a number of considered criteria.

The progression of changes through various phases of ARDS is given by Table I.

In Table I., in column "*Phase*", N is the normal condition of a patient, I – is the first (the least severe) phase of respiratory distress (injury and resuscitation), II – the second phase of respiratory distress (subclinical), III – the third phase (established respiratory distress), and IV – the fourth phase of distress (severe respiratory failure), which, due to medical reasons is not considered in the paper.

The features *Breathing* and *Rö* are expressed verbally, and are given a subjective membership degree (fuzzy sets theory). Other features are characterized by approximate intervals of numerical values. For these features to be interpreted as fuzzy sets, such as 'x is approximately in the interval [b, c]', they can be characterized by an ordered quadruple $A = (a, b, c, d)$, a fuzzy trapezoidal number, [1].

Note that features *Breathing* and *Rö,* having in mind an implementation of usable medical system and in order to get an adequate score for a patient for those criteria, require the development of two pattern recognition systems. The first of these systems would be used for describing *Breathing*, and the other one (a kind of computer vision system) for providing data to a fuzzy model about the feature *Rö*.

Characteristic values of the criteria for determining the severity of respiratory distress, given by Table I, represented by fuzzy intervals formed on the basis of experience, are given in Table II.

When considering ARDS syndrome in [1], all the criteria (symptoms) are of equal importance. Then Bellman-Zadeh`s decision-making principle, [6], can be applied,: for m criteria C_j, $j = 1, \dots, m$, and object $\mathbf{x}$, described by the sequence of feature values (performances), the overall performance of an object is determined by its weakest manifestation. From the set of these alternatives D_i, $i = 1, \dots, N$, the alternative

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TABLE I. DECISION-MAKING PARAMETERS FOR DETERMINING THE SEVERITY OF ARDS

Phase	*Breathing*	*Rö*	PaO_2	$PaCO_2$	$A\text{-}aDO_2$
N	-	-	80 – 100	35 – 45	5 – 10
I	normal	no changes	70 – 90	30 – 40	20 – 40
II	mild to moderate tachypnea	minimal infiltrates	60 – 80	25 – 35	30 – 50
III	increasing tachypnea	confluence of infiltrates	50 – 60	20 – 35	40 – 60
IV	obvious respiratory failure	generalized infiltrates	35 – 55	40 – 55	50 – 80

TABLE II. FUZZY DECISION PARAMETERS FOR DETERMINING THE SEVERITY OF ARDS

Phase	PaO_2	$PaCO_2$	$A\text{-}aO_2$
N	(70,80,100,110)	(30,35,45,50)	(0,5,10,15)
I	(50,70,90,110)	(25,30,40,45)	(10,20,40,50)
II	(40,60,80,100)	(20,25,35,40)	(20,30,50,60)
III	(40,50,60,70)	(10,20,35,45)	(30,40,60,70)
IV	(30,35,55,60)	(30,40,55,65)	(40,50,80,90)

(decision) D^* is chosen, where an object **x** has maximal overall performance taking into account all of the criteria. In a fuzzy case, the membership degree value $\mu_j(\mathbf{x}) \in [0,1]$, $j = 1,2, \dots m$, indicates the point at which a criterion C_j is fulfilled by an object **x**, i.e., by the object's j-th performance. The value $\mu_j(\mathbf{x})$ represents the score for j-th criteria.

The degree by which an object **x** maximally satisfies all the criteria, is the wanted decision (the phase of syndrome), for $i = 1, 2, \dots, N$:

$$D^*(\mathbf{x}) = \max_i \{\min[\, \mu_1(\mathbf{x}), \dots, \mu_m(\mathbf{x})]\}. \qquad (1)$$

In the considered problem, the criteria are, Table I: C_1 – *Breathing*, C_2 – *Rö*, C_3 – PaO_2, C_4– $PaCO_2$, and C_5 – $A\text{-}aDO_2$, $j = 1, 2, \dots, 5$. According to considered features (symptoms) with respect to the established criteria, and using the described procedure, a patient's condition is classified into one of the following phases (alternatives): D_1 – *N* (normal conditions), D_2 - *I*, D_3 - *II*, D_4 - *III*, (and D_5 - *IV*), i.e. $i = 1, \dots, 5$.

Membership degrees $\mu_j(\mathbf{x})$, $j = 1, 2, \dots, 5$, for a phase, for the given numerical values of symptoms, indicated by Table I, are determined by using trapezoidal membership function, [1], and given by Table II.

3. THE FOUNDATION OF THE ALTERNATIVE APPROACH

As an alternative to the usage of the Bellman-Zadeh's decision making principle, a nonadditive set function on a finite set of criteria can be used. This allows weight defining, not only on each criterion, but also on each subset of criteria, allowing criteria interaction modelling. For this the concept of fuzzy measure (or the Choquet capacity) is used.

A fuzzy measure (or the Choquet capacity) on $C = \{C_1, \dots, C_m\}$ is a monotonic set function $\mu : P(C) \to [0,1]$, where $P(C)$ is the power set of the set C, with $\mu(\emptyset)=0$ and $\mu(C)=1$. Monotonicity means that $\mu(S) \le \mu(T)$, whenever $S \subseteq T \subseteq C$. An interpretation of $\mu(S)$ can be that it is the weight related to the subset S of criteria.

For this situation, a suitable aggregation operator is the discrete Choquet integral [3], [7].

Given μ, the Choquet integral of $\mathbf{x} \in (\mathbf{R}^+)^m$ with respect to μ is defined by

$$Ch_\mu(\mathbf{x}) := \sum_{i=1}^{m} (x_{(i)} - x_{(i-1)})\,\mu(\{(i),\dots,(m)\}). \qquad (2)$$

In (2) $(\cdot)$ in indices means a permutation of the elements of C such that $x_{(1)} \le \dots \le x_{(m)}$ and $x_{(0)} = 0$. Given patient's symptoms, using the Choquet integral, the rank of phases can be obtained, and the phase with the maximum global evaluation is the ARDS phase of the considered patient. The Choquet integral allows expressing physician's preferences.

4. THE EXAMPLE

For a patient whose condition is described by data given in Table III, decision-making table is given by Table IV. Using the model from [1], (1), respiratory distress is determined as being in phase II.

If the physician's preferences are: "features *Breathing* and *Rö* are less important than others, and features PaO_2 and $PaCO_2$ must be favored", a synergy between the criteria exists. Symptoms PaO_2 and $PaCO_2$, when considered together, have greater importance than when considered separately. Expressed by a fuzzy measure these preferences could be:

For the first preference:

μ (*Breathing*)= μ (*Rö*)=0.1
$\mu(PaO_2)$= $\mu(PaCO_2)$= $\mu(A\text{-}aDO_2)$=0.2

TABLE III. SYMPTOMS (FEATURES) FOR A PATIENT

Breathing	Ro	PaO2	PaCO2	A-aDO2
increasing tachypnea	confluence of infiltrates	50	32	31

TABLE IV. DECISION-MAKING TABLE FOR A PATIENT

Phase	Breathing	Ro	PaO2	PaCO2	A-aDO2
N	0	0	0	0.4	0
I	0	0	0	1	1
II	0.2	0.3	0.5	1	1
III	1	1	1	1	0.1

For the second preference:

$$\mu(PaO_2,PaCO_2)=0.5>\mu(PaO_2)+\mu(PaCO_2)=0.4$$

The idea is that superadditivity of the fuzzy measure implies synergy between criteria, and subadditivity implies redundancy.

Note that it is up to the physician to scale these values to the extent that he feels they express the importance and interaction. For instance, for the first preference, he also could have increased $\mu(PaO_2)$, $\mu(PaCO_2)$, $\mu(A\text{-}aDO_2)$ above average instead of decreasing $\mu(Breathing)$ and $\mu(Rö)$, or he could have done both.

Back to the example: for the Choquet integral for each phase to be calculated, it is also necessary to define *v* for the required subsets of criteria: $\mu(Breathing, Rö, PaO_2, PaCO_2)$, $\mu(Rö, PaO_2, PaCO_2, A\text{-}aDO_2)$, $\mu(PaO_2, PaCO_2, A\text{-}aDO_2)$, $\mu PaCO_2, A\text{-}aDO_2)$. Here, the superadditivity of the fuzzy measure is also used to imply synergy between criteria, and subadditivity to imply redundancy.

Preferences in the example imply that there is only synergy between criteria PaO_2 and $PaCO_2$. Additivity implies no synergy or redundancy between criteria.

Respiratory distress is determined as being in phase III (Ch_μ(III)=0.73) what is different from the case when symptoms maximally satisfy all the criteria.

A physician, a specialist for ARDS would say which model is more adequate.

5. FUZZY MEASURE IDENTIFICATION

The *ARDS Advisor* application based on the previous discussion was developed, [2]. The first step in using the application (Fig. 2) is entering the values for the 5 criteria widely used for determining the phase of respiratory distress syndrome: clinical aspects of breathing (*Breathing*); chest radiograph (*Rö*); the arterial partial tension of oxygen (PaO_2); the arterial partial tension of carbon dioxide ($PaCO_2$); alveolar-arterial oxygen tension difference ($A\text{-}aDO_2$, mmHg). The first two symptoms are described verbally, and the physician is required to enter the degree of truth for the given statements on a scale 0 to 1 (zero being absolutely false, one being absolutely true).

For the three remaining symptoms, the measured values for a patient are to be entered.

Phases of respiratory failure are modeled as fuzzy trapezoidal numbers. For input values, membership degree to each phase for each symptom is calculated. By clicking the *Submit* button (Fig. 2), user gets the first result computed using the Bellman-Zadeh`s decision-making principle. By clicking the *Next* button, the user is taken to the next step, where the input of additional parameters, which are needed for the Choquet integral, starts.

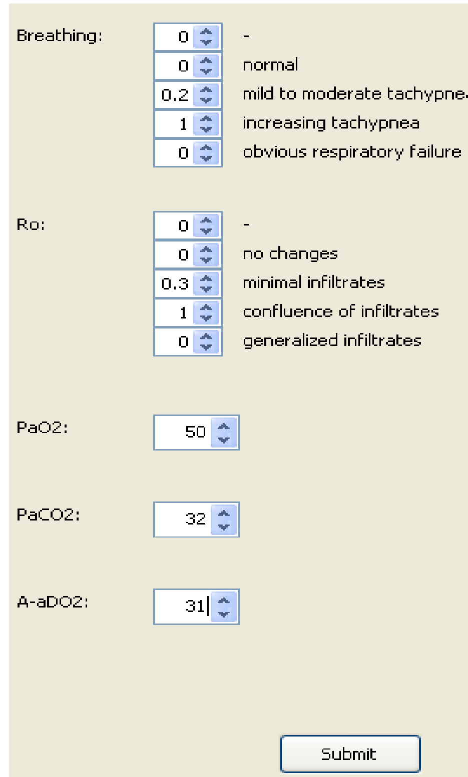

Figure 1. The first step : (Table 3 entrees)

Here, the user is first asked to enter the importance of each individual symptom. For this, a scale of 0 to 5 is proposed as intuitively most suitable, and all the values are initially set to 1 (the average value of equally important symptoms). An equally valid result will be obtained by using some other scale, for instance, from 0 to 1. By clicking on the *Next* button, indices of importance of individual symptoms which the user has entered are shown, as well as indices of importance of all the possible combinations of symptoms, calculated by using the ordinary addition operation. (Case when there is no interaction between symptoms: importance of criteria *A* and *B* combined = importance *A* + importance *B*) (Fig. 3).

User scales these values in order to express interaction between criteria using the following principle: if the symptoms are redundant to some degree, then the index of their combined importance is to be decreased; if the symptoms have some degree of synergy, then the index of their combined importance is to be increased.

It is up to the user of the application to scale these values to the extent he feels they express the interaction. If the user submits parameters incorrectly (for instance: submitted importance of parameters PaO_2 and PaO_2 combined is smaller than individual importance of one of them), a prompt will be issued to correct these parameters.

Although the user is given the calculated values for the non-interacting criteria, and is asked to scale them in order to express interaction, this is still a tedious task. Also, if the number of symptoms for *ARDS Advisor* application was to grow, rather than improving the application, this could lead to an unusable application instead – that is, the task of scaling alone would be too much to grasp.

The first improvement that deals with this problem could come from the fact that representation through interaction indices is closer to the decision maker's mind than the usual measure representation.

Interaction index between any number of criteria was defined by Grabisch , [10], [11], based on [9]:

$$I^{\mu}(K) := \sum_{L \subset [m] \setminus K} \frac{(m-|L|-|K|)!|L|!}{(m-|K|+1)!} \sum_{L' \subset K} (-1)^{|K|-|L'|} \mu(L' \cup L), \quad \forall K \subset [m], \tag{3}$$

where $[m]$ is the index set $[m] = [1,2, ..., m]$, $m \setminus K$ is a difference between sets $[m]$ and K , a coalition of elements from $[m]$ that does not include elements from K, $|L|$ is a cardinal number of a set L , and other notations are obvious.

The second, perhaps more significant improvement could come from use of algorithm for identifying fuzzy measures. Attempts in this direction already exist: algorithm of Mori and Murofushi [12], and algorithm developed by Grabisch [8]. In [8], algorithm which takes advantage of the lattice structure of the coefficients (Figure 4) is introduced.

For the description of the algorithm, the following terminology is used:

The lattice of a fuzzy measure is made from nodes related by links. The lattice has $n + 1$ horizontal layers, numbered from 0 (for the layer containing only $\mu_{\varnothing}$) to n (for the layer containing only μ_X). A path is a set of chained links, starting from the node $\mu_{\varnothing}$ and arriving to the node u_X (on figure 4, the path passing through μ_3, μ_{23}, and μ_{234} is emphasized). For a given node in layer l, its lower neighbors (resp. upper neighbors) are the set of nodes in the layer l-1 (resp. l + 1) linked to it. There are l lower neighbors and n – l upper neighbors.

The author of the algorithm describes it in 2 steps as follows:

step 1: for a given datum x, we modify only the coefficients on the path involved by x in order to decrease the error, as in a gradient descent algorithm. The modification is done in order to preserve the monotonicity property *on the path*. Also, monotonicity is checked for neighboring nodes. This is done for all learning data, several times.

step 2: if there are too few learning data, then some nodes may have been left unmodified. These nodes are modified here in order to have the most equilibrated lattice, i.e. distance from neighbors should be as equal as possible.

The idea behind the step 2 is that in the absence of any information for some nodes, they should be arranged into the lattice in order to get a lattice as homogeneous as possible.

In case of *ARDS Adviser* application [2], the use of this (or a similar) algorithm for identifying fuzzy measures could lead to more 'user-friendly' application, especially when considering the possibility of improving *ARDS Adviser* application by adding even more symptoms to be considered when determining ARDS phase for the patient.

6. CONCLUSIONS

The application of fuzzy systems gives formal basis for modelling and developing decision-making systems based on soft computing, that can use verbally expressed experience in the considered area. In this paper, the practical implementation of fuzzy systems, that deals with independent, equally important information (the Bellman-Zadeh approach), and, also, with interacting, not equally important information (the Choquet integral), is described. Possible use of the considered approaches in telemedicine is shown. This may be an application of interest for considering some other aggregation functions.

Including interaction among criteria gives more flexible model of ARDS, and allows expressing physician's preferences in connection to the complex phenomena of criteria and subsets of criteria interaction.

ARDS Advisor can be further improved, the first by enlarging the number of considered parameters, and then by using it on larger number of cases. Other improvements are also possible, for instance, improvements can be obtained by including interaction indices, as well as identification of fuzzy measures. Intelligent medical computer aid in case of ARDS is welcome in clinical practice. It can alarm the physician, remind him of the possibility of patient developing ARDS, and signal the degree of respiratory distress. The final decision remains with the physician. To make considered application closer to clinical practice, pattern recognition systems for *Breathing* and chest radiograph images should be implemented.

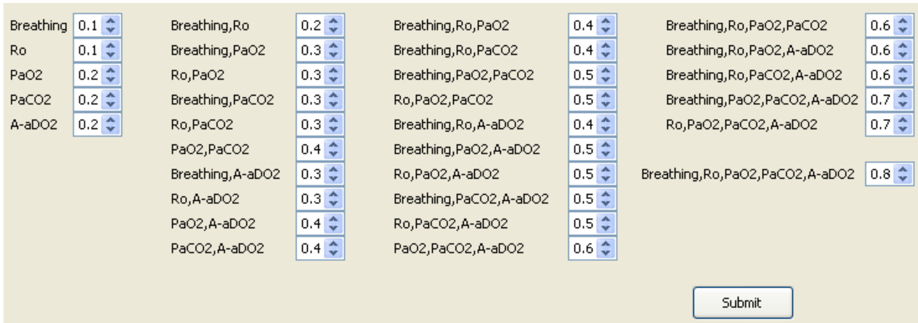

Figure 2. Indices of importance.

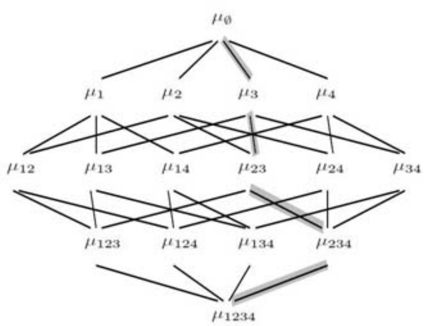

Figure 3. Lattice of the coefficients of a fuzzy measure (n=4)

The application of fuzzy systems offers a mathematical basis for developing medical systems more attuned to human cognitive processes – i.e., systems of soft computing which can make use of verbally expressed medical experience in the domain.

Reconciling and delivering relevant medical knowledge to practitioners using Internet technology are issues of universal importance. Within this context, the Java programming language is a candidate for developing distributed intelligent application, e-health application available on a variety of computing platforms, and enabling the users to make use of the (multimedia) information they have access to. The presented fuzzy models enables a distribution of not-so-well-structured information.

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