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A fuzzy model of determining severity of respiratory distrees and possibilities of implementation

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The paper presents the research results which can be applied in medicine: the fuzzy model of determination of severity of respiratory distress in a patient in an intensive care unit, based on the usage of a kind of fuzzy aggregation operator, the Choquet integral. The determination of the degree of respiratory distress is of extreme clinical relevance. The approach proposed in the paper is the improvement of existing models, due to the fact that the application of fuzzy measures can take into account the interaction between criteria. Possibilities of Web-based model implementation are considered. The results are given and the directions for possible further work are pointed out.

Key words: **fuzzy model, respiratory disturbance, decision-making, Choquet integral, application, health care, implementation, Web-based system**

List of notation and symbols

ARDS	– acute respiratory distress syndrome
Rö	– chest radiograph
PaO_2 ,mm Hg	– (1 mm HG = 133.322 Pa) the arterial partial tension of oxygen
$PaCO_2$,mm Hg	– the arterial partial tension of carbon dioxide
$\mathbf{x}_i, i = 1,2,...,N,$	– feature vectors of objects considered in a decision-making process
$C_j, j = 1,2,...,m$	– decision-making criteria
$\mu_{ij}(\mathbf{x}_i),$ $i = 1,2,...,N,$ $j = 1,2,...,m$	– scores
$D_i, i = 1,2,...,N$	– decisions
D^*	– decision about which of object $\mathbf{x}_i$ is the best according to all criteria $C_j, j = 1,2,...,m$
M	– averaging operator (mean)
Φ_i	– weight functions
F	– strictly monotone function
$\mathbf{R}$	– set of real numbers
$\mathbf{p} = [p_1,...,p_n]^T$	– vector
$\mathbf{w} = [w_1,...,w_n]^T$	– vector
$\mu_{ij}(\mathbf{x})$	– membership degrees for a phase

Introduction

RESHEARCH results in the theory of fuzzy sets may have military and non-military applications. Fuzzy sets theory [2] was tested in the domain of medicine soon after it was introduced, [3], and has since been extensively used, [16]. In determining the severity of respiratory distress both numerical and linguistic imprecision may appear in the available data. This necessitates the application of fuzzy models, based on the theory of fuzzy sets.

The idea of using the theory of fuzzy sets for modelling decision-making in determining the severity of respiratory distress has been proposed in [4]. In [5], the creation and evaluation of a knowledge-based computer system is meant to support clinical decisions concerning patients with severe ARDS. In [1] the problem of determining the severity of respiratory distress in a patient in an intensive care unit is modeled as a fuzzy multicriteria decision-making one and the computer implementation of the model is considered. In this paper the use of fuzzy measures [6], and of the Choquet integral [10] are considered in order to get improvement of results from [1], and this approach is a novelty introduced in the fuzzy modeling of ARDS. The improvement is due to the fact that the application of fuzzy measures can take into account the interaction between criteria.

In intelligent medical systems the status of a patient can be described by numerical, textual and image data, i.e. by multimedia data. The patient with respiratory distress is described by a set of symptoms assigned numerical values at approximate intervals, by a set of symptoms expressed verbally (breathing), and by a set of symptoms presented by image (Rö).

In Section 2 of the paper, the fuzzy aggregation operators overview is given. The considered problem is described in Section 3. The theoretical foundation of the model is given in Section 4, based on the theory of fuzzy measures and representations of interactions. Section 5 deals with the results. The possibilities of Web-based system implementations are discussed in Section 6. Finally, conclusions are given and directions for possible further work are pointed out.

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The fuzzy aggregation operators overview

The problem of determining the severity of respiratory distress in a patient in an intensive care unit is modeled as a fuzzy multicriteria decision making one, Fig.1.

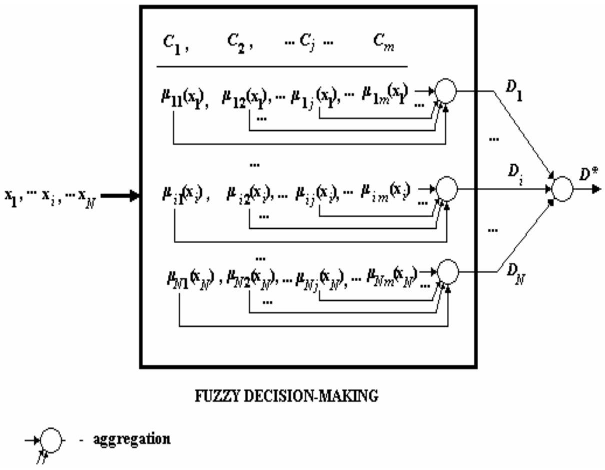

Figure 1. Fuzzy multi-criteria decision-making system

Denotations in Fig. 1. are:

$\mathbf{x}_i$, $i = 1,2,...,N$, are feature vectors of objects considered in a decision-making process; C_j, $j = 1,2,...,m$, are decision-making criteria; $\mu_{ij}(\mathbf{x}_i)$, $i = 1,2,...,N$, $j = 1,2,...,m$, are scores–degrees by which an object $\mathbf{x}_i$ (or some of its features) fulfills a criterion C_j. In the case of fuzzy decision-making systems, it holds: $\mu_{ij}(\mathbf{x}_i) \in [0,1]$. D_i, $i = 1,2,...,N$, are decisions (performance indices) of object $\mathbf{x}_i$ related to all criteria C_j. Decisions D_i are obtained through an aggregation of information $\mu_{ij}(\mathbf{x}_i)$, using some of aggregation operators. Decision D^* about which of objects $\mathbf{x}_i$ is the best according to all criteria C_j, $j = 1,2,...,m$, is obtained by the aggregation of decisions D_i, - using the specified aggregation operator, selected according to a problem considered. Hence, the process of fuzzy information aggregation is an important step of the fuzzy decision-making process.

In an aggregation process, one value, aggregated value, is assigned to a collection of values, also called aggregation arguments. An aggregation process appears not only in fuzzy decision-making systems, but in fuzzy expert systems as well, i.e. in fuzzy systems in general [12]. An information aggregation process appears in many applications, which are in connection with development, not only fuzzy systems, but also with development of other uncertainty processing systems, and other intelligent systems, for example, in neural networks, in robotics, knowledge acquisition systems and in multi-criteria decision-making systems. Aggregation (also known as: information fusion, information integration, data fusion, information synthesis) is present in a sensor information fusion, in distribution detection, as well as in economic models, biological, and education models. The aim of aggregation in artificial intelligence is decision-making support, or all-inclusive representation of expert domain. Processes of decision-making and information fusion in general, are embedded in most of artificial intelligence systems applications, for example, in applications in commercial electronics or at Internet. Furthermore, aggregation methods represent the basic tools of some well-founded artificial-intelligence techniques (some methods of machine learning). Aggregation is present also in IF part of a rule in fuzzy expert systems, if more premises exist. As aggregation operators, *t*-norms or *t*-conorms can be used in the context of interpretation of AND and OR conjunctions, but other operators can be used as well. The class of operators important for fuzzy systems in general, is the class of compensation operators, introduced in [8]. Namely, fuzzy sets theory provides a host of attractive aggregation operators for integrating membership values representing uncertain information. These operators can be categorized into the following three classess: union, intersection and compensation operators.

Union produces a high output whenever any of the input values representing degrees of satisfaction of different features or criteria is high. Intersection operators produce a high output only when all of the inputs have high values. Compensative operators have a property that a higher degree of satisfaction of one of the criteria can compensate for a lower degree of satisfaction of another criteria to a certain extent.

In a word, union operators provide full compensation while intersection operators provide no compensation.

In the presence of conflicting goals, a compensation between the corresponding compatibilities is allowed.

An averaging operator (mean) is a function

$$M : [0,1] \times [0,1] \to [0,1]$$

satisfying the following properties:

- idempotency : $M(x,x) = x, \forall x \in [0,1]$
- commutativity: $M(x,y) = M(y,x), \forall x, y \in [0,1]$
- external conditions: $M(0,0) = 0,\ M(1,1) = 1$
- monotonicity: $M(x,y) \le M(x',y')$, if $x \le x'$ and $y \le y'$

M is continuous.

All means satisfy the fundamental compensation property:

$$\min\{x,y\} \le M(x,y) \le \max\{x,y\}, \forall x,y \in [0,1]$$

The theory of means offers a wide spectrum of candidate mathematical models for compensation operators. The most suitable are those means that have adjustable parameters enabling easy adjustment of orness/andness and continuous transition from the pure conjunction to the pure disjunction. This problem was investigated in [8] using a general framework of the Losonczi means:

$$M(x_1,...,x_n,\ \Phi_1,...,\Phi_n) = \\ = F^{-1}\left(\sum_{i=1}^{n} \Phi_i(x_i) F_i(x_i) \Big/ \sum_{i=1}^{n} \Phi_i(x_i) \right)$$

The mean uses weight functions Φ_i: $[0,1] \to \{0\} \cup \mathbf{R}^+$, and the strictly monotone function F: $[0,1] \to \mathbf{R}$. In a special case of constant weights $\Phi_i = W_i$, $W_i > 0$, $i=1,...,n$, $W_1+...+W_n=1$, the Losonczy mean is reduced to the weighted quasi-arithmetic mean:

$$M(x_1,...,x_n) = F^{-1}\left(\sum_{i=1}^{n} W_i F_i(x_i) \right)$$

The simplest form of the F function is the power function $F(x) = x^r$, $r \in \mathbf{R}$, and andness and orness are introduced as functions of the parameter r [8].

Fuzzy aggregation operators are quantitative or qualitative, according to the nature of aggregation arguments: numeric (quantitative operators) or linguistic (qualitative).

Quantative aggregation operators encompass weighted average operators, (weighted) ordered weighted averaging operators ((*W*)*OWA*) [9], [10] and the Choquet integral [11].

An Ordered Weighted Averaging (OWA) operator of the dimension n is a mapping F: $\mathbf{R}^n \to \mathbf{R}$, that has an assosiated vector $\mathbf{w} = [w_1,...,w_n]^T$ such as $w_i \in [0,1]$, $1 \le i \le n$, $w_1 + ... + w_n = 1$. Furthermore $F(a_1,...,a_n) = \sum_{j=1}^{n} w_j b_j$, where b_j is the j-th largest element of the bag[1] $< a_1,...,a_n >$, [9].

An Weighted *OWA* (*WOWA*) operator of the dimension n is a mapping F: $\mathbf{R}^n \to \mathbf{R}$, that has associated weighting vectors $\mathbf{p}=[p_1, ..., p_n]^T$, $\mathbf{w}=[w_1, ..., w_n]^T$, such as $p_i \in [0,1]$, $p_1+...+p_n=1$, $w_i \in [0,1]$, $w_1+...+w_n=1$, $1 \le i \le n$. Furthermore $F(a_1,..., a_n; p_1,...,p_n; w_1,...,w_n) = \sum_{j=1}^{n} \omega_j a_{\sigma(j)}$, where $\{\sigma(1),..., \sigma(n)\}$ is the permutation of $\{1,..., n\}$ such that $a_{\sigma(j-1)} \ge a_{\sigma(j)}$ for all j=2, ..., n (i.e. $a_{\sigma(1)}$ is the largest element in the collection (the bag!) $< a_1,...,a_n >$,). The weight ω_j is defined as

$$\omega_i = w^*(\sum_{j=0}^{i} p_{\sigma(j)}) - w^*(\sum_{j=0}^{i-1} p_{\sigma(j)})$$

where w^* is a monotone increasing function that interpolates the points (i/n, $\sum_{j=0}^{i} w_j$) together with the point (0,0), [10].

Qualitative aggregation operators in wide sense are grouped in two classes: the first of them, the class of interpretative aggregation operators when the qualitative values are interpreted numerically, and then some quantitative average operator is applied, and the second, one the class of qualitative aggregation operators, when aggregation processes are strictly in a qualitative domain.

The Problem Considered

Widely used criteria for an early diagnosis of acute respiratory distress syndrome include, [13]:

- clinical aspects of breathing (*Breathing*);
- chest radiograph (Rö);
- the arterial partial tension of oxygen (PaO_2, mmHg, 1mmHg=133.322 Pa);
- the arterial partial tension of carbon dioxide ($PaCO_2$, mmHg);
- alveolar-arterial oxygen tension difference ($A\text{-}aDO_2$, mmHg).

Table 1 gives the progression of changes through various phases of ARDS. In Table 1, in the column "Phase", N is the normal condition of a patient, I – is the first (least severe) phase of respiratory distress (injury and resuscitation), II – the second phase of respiratory distress (sub clinical), III – the third phase (established respiratory distress), and IV – the fourth phase of distress (severe respiratory failure), which, due to the medical reasons, is not considered in the paper.

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

Membership degrees $\mu_{ij}(\mathbf{x})$ for a phase, for the given numerical values of symptoms, indicated by Table 1, are determined by using trapezoidal membership functions [1] and Table 2. By utilising the principle of fuzzy decision-making indicated here by expression (1), the distress phase most compatible with all the symptoms may be determined [1].

Table 1. Decision-making parameters for determining the severity of ARDS

Phase	Breathing	Rö	PaO₂	PaCO₂	A-aDO₂
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	5 – 35	30 – 50
III	increasing tachypnea	confluence of infiltrates	50 – 60	20 – 35	40 – 60
IV	obvious respiratory failure	generalised infiltrates	35 – 55	40 – 55	50 – 80

Table 2. Fuzzy decision parameters for determining the severity of ARDS

Phase	PaO₂	PaCO₂	A-aDO₂
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)

Characteristic values of the criteria for determining the severity of respiratory distress, given by Table 1, are represented by fuzzy intervals formed on the basis of experience, and given by Table 2. In considering the syndrome in [1], all features have the same importance. Then Bellman-Zadeh's decision- making principle, [7] is applied:for m criteria C_j, j = 1,...,m, an object $\mathbf{x}_i$, i= 1,2,...,N, is described by the sequence of feature values (performances) with respect to the criteria, μ_{ij}. The alternative (decision) D^*, from the set of alternatives D_i, i = 1,…,N, is needed to fulfil the condition of maximum overall performance for a considered object. In a fuzzy case, the membership degree value $\mu_{ij}(\mathbf{x}_i) \in [0,1]$ indicates the point at which a criterion C_j is fulfilled by the object's j-th performance x_{ij}.

The alternative (phase) by which an object $\mathbf{x}_i$ maximally satisfies all the criteria for providing the desired decision (phase, the degree of severity of ARDS) is, for i=1,2,...,N:

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

In the problem considered, the criteria are, Table 1.: C_1–*Breathing,* C_2–Rö, C_3–PaO_2, C_4–$PaCO_2$, and C_5 – $A\text{-}aDO_2$. According to such 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 condition), D_2-*I,* D_3-*II,* D_4-*III,* (and D_5-*IV*), i.e. i =1,…,5.

[1] Assume *A* is a set of elements. *A bag* drawn from *A* is any collection of elements contained in *A*. A bag is different from a subset in that it allows multiple copies of the same element.

The Theoretical Foundation of the Novelty Introduced in the Model

An alternative to Bellman-Zadeh's decision-making principle, where all features have the same importance, is to use as aggregation operator for a set of m aggregation arguments $a_1,...,a_m$, the weighted arithmetic means (for a weighting vector **w** such that $w_i \in [0,1]$ and $\sum_{i=1}^{m} w_i = 1$):

$$D_w(\mathbf{a}_i) = \sum_{j=1}^{m} w_j a_{ij} \qquad (2)$$

and then to find $\max_i D_w$. In that way the different importance of features is introduced, that is, a decision making process can be adapted to a patient's status and a physician's preferences.

In order to have a flexible representation of complex interaction phenomena between criteria, it is useful to substitute the weights in (2) for a nonadditive set function on a finite set of criteria, allowing defining a weight not only on each criterion, but also on each subset of criteria, thus allowing modeling criteria interaction. For this purpose the concept of fuzzy measure [6] has been used.

A *fuzzy measure* (or *Choquet capacity*) on $C=\{C_1,...,C_m\}$ is a monotonic set function $\mu : P(C) \to [0,1]$, where $P(C)$ is the power set of the set C, with $\mu(\varnothing)=0$ 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 described as the weight related to the subset S of criteria. It should be noticed that the usual definition of a measure is generalized by replacing the usual additivity property for probability measures ($\mu A \cup B) = \mu A) + \mu B)$, $A \cap B = \varnothing$), by a weaker requirement, i.e. the monotonicity property with respect to set inclusion, (see also [15]).

Now a suitable aggregation operator, able to represent in some understandable way an interaction between criteria, is the discrete Choquet integral [11], [6]. As the Choquet integral is considered here as an operator on $[0,1]^m$, its definition is restricted to [0,1] valued function [11]: given μ, a fuzzy measure on the set of criteria C, and a function a: $[0,1]^m \to [0,1]$, the *Choquet integral* of a with respect to μ is defined by

$$Ch_\mu(a_1,...,a_m) := \sum_{j=1}^{m} (a_{(j)} - a_{(j-1)}) \mu(A_{(j)}) \qquad (3)$$

where $_{(j)}$ indicates that the indices have been permuted so that, for monodimensional functions a_i, constituents of a, it holds: $0 \le a_{(1)} \le ... \le a_{(m)} \le 1$, $a_{(0)} = 0$, and $A_{(j)} := \{C_{(j)}, ..., C_{(m)}\}$.

The non-additivity of fuzzy measures enables the modelling of interaction between criteria.

For 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 patient in question. The Choquet integral allows expressing physician's preferences relation in connection with the patient.

The Example

For the patient whose condition is described by data given in Table 3., a decision-making table is given by Table 4. By the model in [1], respiratory distress is determined as being in phase II. If physician's preferences are: features *Breathing* and Rö are less important than the others, and features PaO_2 and $PaCO_2$ must not be favoured, these preferences, expressed by fuzzy measure, are:

$$\mu(Breathing) = \mu(\text{Rö}) = 0.3; \mu(\text{PaO}_2 = \mu(\text{PaCO}_2) = \\ = \mu(A\text{-}aDO_2) = 0.5$$

for the first preference, and:

$$\mu(PaO_2,\ PaCO_2) = 0.8 < \mu(PaO_2) + \mu(PaCO_2)$$

for the second one. Having those preferences in mind, and using (3), respiratory distress is determined as being in phase I (C_μ(I) = 0.5) as opposed to the result from [1] (phase II).

Table 3. Symptoms (features) for a patient

Breathing	Rö	PaO_2	$PaCO_2$	A-aDO_2
mild to moderate tachypnea	minimal infiltrates	42.72	36.54	29

Table 4. Decision-making table for a patient

Phase	Breathing	Rö	PaO_2	$PaCO_2$	A-aDO_2
N	0	0	0	1	0
I	0	0	0	1	1
II	0.8	1	0.14	0.7	0.9
III	0.2	0	0.3	0.85	0

Possibilities of Computer Implementation

There are many options for Web-based system implementations, [14], all viable and likely to meet needs. Most of architectural decisions would be based on two things: access to tools and technology, and development team skill set.

The type of system needed will have a significant middle tier. A formal middle tier should be defined. If the application would be deployed on a Windows machine, the option exists of implementing a COM (*Component Object Model*) and MTS (*Microsoft Transaction Server*) - based middle tier. The main advantages of this type of architecture are in the strength of its tools (Visual Studio). It is expected that the simple COM objects with minimum transaction support directly from the database when necessary should do the job. A database can be chosen for the purpose of prototyping beforehand.

On the MS route, the presentation tier should be Active Server Pages. On the Java route, there are information [14], that server side Java has nearly the same performance as traditional C++ or COM. Free and open source middleware exists (Apache, etc.).

As important as the selection of technology, is the selection of the logical topology of the system. The presentation tier would be separated from the middle and data tiers. There are many options for possible computer implementation. Given the scope and basic requirements of application, obviously, there is a lot of flexibility in choosing an implementation route.

Conclusions

In the paper the use of fuzzy measures, and of the Choquet integral are considered in order to get improvement of results from [1], and this approach is the novelty introduced in fuzzy modeling of ARDS. The improvement is due to the fact that the application of fuzzy measures can take into account the interaction between criteria, so a more flexible model of ARDS is obtained, allowing expressing physician's preferences in connection with complex interaction phenomena between criteria and also on each subset of criteria.

The model considered in the paper can be further improved, first by increasing the number of parameters considered. In the case considered, knowledge acquisition was performed by the expert consulting. The expert relied on extensive analysis of clinical data. Further improvements can be obtained by introducing multimedia data mining or Knowledge discovery from Multimedia at the Internet.

Reconciling and delivering relevant medical knowledge to practitioners using Internet technology are issues of universal importance. The considered fuzzy model enables a distribution of not-so-well-structured information by distributed intelligent application available on a variety of computing platforms.

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Model određivanja težine respiratornog poremećaja zasnovan na rasplinutim skupovima i mogućnosti njegove računarske realizacije

Rad razmatra problematiku primene rasplinutih sistema odlučivanja. Razmatra se primena u oblasti medicine, ali prikazani postupak odlučivanja je i od šireg značaja. Dat je rasplinuti model određivanja stepena respiratornog poremećaja. Model rasplinutog odlučivanja se zasniva na korišćenju Šokeovog integrala u postupku agregacije. pristup predložen u radu predstavlja novost u modeliranju stepena respiratornog poremećaja, i poboljšanje je postojećih modela. Novost se sastoji u tome što primena rasplinute mere i Šokeovog integrala omogućava uzimanje u obzir interakcije između kriterijuma za ocenu težine respiratornog poremećaja. U radu su razmatrane i mogućnosti računarske realizacije modela sa aspekta Internet programiranja. Dati su rezultati primene opisanog pristupa i ukazano je na pravce mogućeg daljeg rada.

Ključne reči: **rasplinuti model, respiratorni poremećaj, donošenje odluka, Šokeov integral, primena,medicina, računarska realizacija, Web-sistem.**

Модель определения сильности дыхательного нарушения, обоснованного на размытыми моделями и на возможности его реализации на вычислительных машинах

В этой работе рассмотрена проблема применения размытых моделей принятия решений.Здесь рассматривается применение в области медицины, но показаный поступок принятия решений имеет более широкое значение. Здесь дана размытая модель определения сильности дыхательного нарушения. Модель размытого принятия решений основывается на пользовании интервала Шоке в поступке группирования. Предложенный подход в работе представляет новизну в моделировании сильности дыхательного нарушения и улучшение существующих моделей. Новизна состоится в том, что применение размытой модели и интеграла Шоке дает возможность принять во внимание взаимодействие между критериями для оценки сильности дыхательного нарушения. В работе рассматриваны и возможности реализации модели на вычислительных машинах со стороны программирования системы Интернета. Здесь приведены результаты применения описанного подхода и указаны направления возможных дальнейших работ.

Ключевые слова: размытая модель, дыхательное нарушение, принятие решений, интеграл Шоке, применение, медицина, реализация на вычислительных машинах, система Интернета.