# On an Intuitionistic Fuzzy Approach for Decision Making in Medicine: Part 2 

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#### Abstract

An idea presented in [6, 7] has been developed further, and the patients readiness for weaning form long-term mechanical ventilation has been determined in the sense of intuitionistic fuzzy logic [1]. In the present paper it is solved as pattern recognition problem. As a final estimate of the classification an estimate aggregated from four estimates, obtained by four different procedures: Stepwise discriminant analysis (SDA), stepwise logistic regression (SLR), "intuitionistic fuzzy" Voronoi diagrams (IFVD) and nonpulmonary weaning index (NPWI), is taken. The aggregation of estimates is executed by the application of the second algorithm, proposed in [7]. A comparison between the two algorithms has been made.


Keywords: Intuitionistic fuzzy sets, Pattern recognition, Mechanical ventilation, Weaning, Readiness to weaning.

## Introduction

In [6] the first algorithm is applied in the solution of the pattern recognition problem for prognosticating the moment for beginning the weaning from long-term mechanical ventilation. In the present paper the second algorithm is applied, which consists of the following:

Let us have a set of images, and for each of them the pattern recognition problem be solved by no more than k in number classification methods. Let the result of the classification from each of the methods is a number in the interval $[0,1]$. We shall denote by $\sigma_{s}$ the value of the estimate of the $s$-th method for a particular image ( $s=1,2, \ldots, k$ ). Then we have k in number fuzzy estimates $\sigma_{1}, \sigma_{2}, \ldots, \sigma_{k}$, whose values we input in the interval [0, 1]. It is possible for some of these estimates to coincide. The task that we set before us is to produce a common estimate based on the estimates of the values generated by the individual methods, and that would also reduce the degree of indeterminacy.

Let us denote

$$
\begin{align*}
\sigma_{\min } & =\min \left\{\sigma_{1}, \sigma_{2}, \ldots, \sigma_{m}\right\}  \tag{1}\\
\sigma_{\max } & =\max \left\{\sigma_{1}, \sigma_{2}, \ldots, \sigma_{m}\right\} \tag{2}
\end{align*}
$$

The algorithm in the cases $k=2$ and $k=3$ looks like:

1. For $k=2$ the values of the degree of membership $\mu$, degree of nonmembership $v$ and the degree of indeterminacy $\pi$ are calculated by the formulas:
$\mu=\sigma_{\text {min }}$
$v=1-\sigma_{\text {max }}$
$\pi=\sigma_{\text {max }}-\sigma_{\text {min }}$
2. For $k=3$ we determine the interior point $\sigma$ of the three points, i.e. the point for which:
$\sigma_{\text {min }}<\sigma<\sigma_{\text {max }}$.

Using the formula:

$$
\begin{equation*}
\sigma^{\prime}=\sigma_{\min }+\sigma_{\max }-\sigma, \tag{7}
\end{equation*}
$$

we find point $\sigma^{\prime}$, that we will call "conjugated point of $\sigma$ ". Obviously this point is symmetric to $\sigma$ with respect to the middle point of the interval $\left[\sigma_{\min }, \sigma_{\max }\right]$.

Then $\mu, v$ and $\pi$ will be determined according to the formulas:

$$
\begin{align*}
& \mu=\min \left(\sigma, \sigma^{\prime}\right)  \tag{8}\\
& v=1-\max \left(\sigma, \sigma^{\prime}\right)  \tag{9}\\
& \pi=\max \left(\sigma, \sigma^{\prime}\right)-\min \left(\sigma, \sigma^{\prime}\right) \tag{10}
\end{align*}
$$

3. For $\mathrm{k}>3$ :
3.1. We sort the sequence $\sigma_{1}, \sigma_{2}, \ldots, \sigma_{k}$ by increasing value.

We put $\mu=0, v=0$ and $\pi=1$;
And we put $q=1$.
3.2. We give to $\mu, v$ and $\pi$ respectively the values:
$\mu:=\mu+\sigma_{q} \pi$
$v:=v+\left(1-\sigma_{k-q}\right) \pi$
$\pi:=\left(\sigma_{k-q}-\sigma_{q}\right) \pi$

We put $q:=q+1$.

### 3.3. If $q<k-q$, we return to 2 .

When solving the classification problem for prognosticating the moment of weaning from long-term mechanical ventilation, in order to preserve objectivity in the comparison of the results, the same contingent of 151 patients, described in [5] was used.

Each patient is represented by a vector of $n$ indices (in our particular case $n=17$ ), i.e.
$x=\left(x_{1}, x_{2}, \ldots, x_{n}\right)$
where: $x_{1}$ - fever; $x_{2}$ - hemoglobine; $x_{3}$ - hematocrit; $x_{4}$ - Leuc; $x_{5}$-RUE; $x_{6}$ - total blood protein (tbp); $x_{7}$ - blood albumin (alb); $x_{8}$ - blood sugar (bs); $x_{9}$ - lactate; $x_{10}$ - fraction of inspired oxygen $\mathrm{FiO}_{2} ; x_{11}$ - arterial oxygen partial pressure $\mathrm{PaO}_{2} ; x_{12}$ - arterial carbon dioxide tension $\mathrm{PaCO}_{2} ; x_{13}$ - ratio $\mathrm{PaO}_{2} / \mathrm{FiO}_{2} ; x_{14}$ - heart rate (Ps); $\mathrm{x}_{15}$ - systolic arterial pressure (RRs); $x_{16}$ - diastolic arterial pressure (RRd); $x_{17}$ - mean arterial pressure (RRm).

Two classes were considered. The first one is the class to which we assign each patient who is not ready to begin the process of weaning, and we may agree upon calling it "sick". The second class consists of all the patients ready to begin weaning procedures and we may refer to them as "healthy".

The problem is solved with four classification methods: Stepwise discriminant analysis (SDA) and stepwise logistic regression (SLR) [2, 8]; "intuitionistic fuzzy" Voronoi diagrams (IFVD) [3, 4] and nonpulmonary weaning index (NPWI) [5].

All of them determine the membership of a patient to one of the two considered classes. The results are represented by a fuzzy estimate. This estimate is obtained as follows:

- For the method using SDA
$\sigma_{i}=\frac{1}{2}\left(1-\left(1-\operatorname{sign}\left(p_{i}\right)\right) \frac{p_{i}}{p_{\text {min }}}+\operatorname{sign}\left(p_{i}\right) \frac{p_{i}}{p_{\text {max }}}\right), 0 \leq \sigma_{i} \leq 1$
i.e.
$\sigma_{i}=\left\{\begin{array}{l}\frac{p_{i}}{2}\left(\frac{1}{p_{\text {min }}}+\frac{1}{p_{\text {max }}}\right), p_{i} \geq 0 \\ 0, p_{i}<0\end{array}\right.$
- For the method using stepwise logistic regression
$\sigma_{i}=\frac{1}{2}\left(1-\operatorname{sign}\left(f_{i}\right) \frac{f_{i}}{f_{\text {min }}}+\left(1-\operatorname{sign}\left(f_{i}\right)\right) \frac{f_{i}}{f_{\max }}\right), 0 \leq \sigma_{i} \leq 1$
i.e.
$\sigma_{i}=\left\{\begin{array}{l}\frac{f_{i}}{2}\left(\frac{1}{f_{\text {min }}}+\frac{1}{f_{\text {max }}}\right), f_{i} \geq 0 \\ 0, f_{i}<0\end{array}\right.$
- For the method using the index NPWI
$\sigma_{i}=\frac{1}{2}\left(1-\left(1-\operatorname{sign}\left(g_{i}\right)\right) \frac{g_{i}}{g_{\min }}+\operatorname{sign}\left(g_{i}\right) \frac{g_{i}}{g_{\text {max }}}\right), 0 \leq \sigma_{i} \leq 1$
i.e.
$\sigma_{i}=\left\{\begin{array}{l}\frac{g_{i}}{2}\left(\frac{1}{g_{\text {min }}}+\frac{1}{g_{\text {max }}}\right), g_{i} \geq 0 \\ 0, g_{i}<0\end{array}\right.$

$$
\begin{equation*}
\sigma_{i}=\frac{k_{i}^{\prime \prime}}{k_{i}^{\prime}+k_{i}^{\prime \prime}}, 0 \leq \sigma_{i} \leq 1 \tag{21}
\end{equation*}
$$

## Example

The results obtained by the realization of the described above algorithm are given in Table 1.
Table 1

| $\sigma$ - SDA | $\sigma$ - SLR | $\sigma$ - NPWI | $\sigma$ - IFVD | $\mu \mathrm{I}$ | $\checkmark$ I | $\pi$ I | $\mu \mathrm{II}$ | $\checkmark$ II | $\pi$ II |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 0.37332 | 0.41096 | 0.44789 | 0.51230 | 0.39022 | 0.52082 | 0.08896 | 0.31477 | 0.52082 | 0.16411 |
| 0.34003 | 0.38534 | 0.38737 | 0.42333 | 0.35235 | 0.58809 | 0.05956 | 0.24213 | 0.58809 | 0.16978 |
| 0.31066 | 0.34172 | 0.38176 | 0.43381 | 0.31414 | 0.60320 | 0.08266 | 0.18960 | 0.60320 | 0.20720 |
| 0.29184 | 0.27983 | 0.3444 | 0.27487 | 0.25067 | 0.67476 | 0.07457 | 0.18203 | 0.67476 | 0.14321 |
| 0.33422 | 0.40662 | 0.28331 | 0.36044 | 0.30729 | 0.62806 | 0.06465 | 0.23463 | 0.62806 | 0.13731 |
| 0.37087 | 0.39355 | 0.18724 | 0.28203 | 0.24110 | 0.60655 | 0.15235 | 0.12064 | 0.60655 | 0.27281 |
| 0.29641 | 0.31470 | 0.29088 | 0.45405 | 0.29602 | 0.65290 | 0.05108 | 0.22617 | 0.6529 | 0.12093 |
| 0.35844 | 0.42365 | 0.30742 | 0.44309 | 0.29094 | 0.57024 | 0.13882 | 0.23272 | 0.57024 | 0.19704 |
| 0.31298 | 0.36784 | 0.28525 | 0.33666 | 0.29024 | 0.61044 | 0.09932 | 0.13987 | 0.61044 | 0.24969 |
| 0.26354 | 0.32124 | 0.57720 | 0.35334 | 0.30035 | 0.58900 | 0.11065 | 0.21103 | 0.589 | 0.19997 |
| 0.25837 | 0.29683 | 0.61545 | 0.48048 | 0.29420 | 0.53389 | 0.17191 | 0.25149 | 0.53389 | 0.21462 |
| 0.30473 | 0.33482 | 0.60035 | 0.50952 | 0.32307 | 0.48277 | 0.19416 | 0.26451 | 0.48277 | 0.25272 |
| 0.29243 | 0.35198 | 0.68437 | 0.50143 | 0.34308 | 0.50581 | 0.15111 | 0.25623 | 0.50581 | 0.23796 |
| 0.39693 | 0.43308 | 0.73336 | 0.52250 | 0.41373 | 0.46250 | 0.12368 | 0.36923 | 0.46259 | 0.16818 |
| 0.29209 | 0.35479 | 0.79121 | 0.51404 | 0.33465 | 0.46708 | 0.19827 | 0.27393 | 0.46708 | 0.25899 |
| 0.57289 | 0.65525 | 0.70386 | 0.63417 | 0.59980 | 0.31758 | 0.08262 | 0.49281 | 0.31758 | 0.18961 |
| 0.47893 | 0.52707 | 0.72972 | 0.61820 | 0.49239 | 0.34709 | 0.16052 | 0.42259 | 0.34709 | 0.23032 |
| 0.63078 | 0.72127 | 0.64446 | 0.71925 | 0.62805 | 0.29342 | 0.07853 | 0.47416 | 0.29342 | 0.23242 |
| 0.70973 | 0.81464 | 0.70195 | 0.69857 | 0.68817 | 0.21276 | 0.09907 | 0.53009 | 0.21276 | 0.25715 |
| 0.65149 | 0.71822 | 0.72999 | 0.69738 | 0.62245 | 0.24917 | 0.12838 | 0.56963 | 0.24917 | 0.18120 |
| 0.72471 | 0.81739 | 0.64235 | 0.68330 | 0.68600 | 0.23522 | 0.07878 | 0.57797 | 0.23522 | 0.18681 |
| 0.66640 | 0.8003 | 0.69921 | 0.72191 | 0.66793 | 0.24582 | 0.08625 | 0.56927 | 0.24582 | 0.18491 |
| 0.71054 | 0.82933 | 0.65196 | 0.63285 | 0.66133 | 0.23958 | 0.09909 | 0.53203 | 0.23958 | 0.22839 |
| 0.65988 | 0.76567 | 0.59599 | 0.46883 | 0.58683 | 0.29714 | 0.11603 | 0.41533 | 0.29714 | 0.28753 |
| 0.62853 | 0.71468 | 0.33484 | 0.50351 | 0.50581 | 0.35073 | 0.14346 | 0.29171 | 0.35073 | 0.35756 |
| 0.70389 | 0.80727 | 0.22914 | 0.50973 | 0.47771 | 0.27962 | 0.24267 | 0.22914 | 0.27962 | 0.49124 |
| 0.68593 | 0.79431 | 0.36997 | 0.52798 | 0.53445 | 0.25684 | 0.20871 | 0.28042 | 0.25684 | 0.46274 |
| 0.62824 | 0.72428 | 0.29870 | 0.43532 | 0.45363 | 0.33973 | 0.20664 | 0.24023 | 0.33973 | 0.42004 |
| 0.56298 | 0.64530 | 0.36190 | 0.39737 | 0.45476 | 0.41894 | 0.12630 | 0.27226 | 0.41894 | 0.30880 |
| 0.52666 | 0.60633 | 0.39265 | 0.45810 | 0.43756 | 0.43318 | 0.12926 | 0.28424 | 0.43318 | 0.28258 |

In this table in the columns are given the following:

- In the first column are given the values of $\sigma$ for SDA, calculated by Eq. (15).
- In the second column are given the values of $\sigma$ for SLR, calculated by Eq. (17).
- In the third column are given the values of $\sigma$ for NPWI, calculated by Eq. (19).
- In the fourth column are given the values of $\sigma$ for IFVD, calculated by Eq. (21).
- In the fifth, sixth and seventh columns are given the values of the degree of membership, degree of non-membership and degree of indeterminacy for each of the patients, calculated by the first algorithm.
- In eighth, ninth and tenth columns are given the values of the degree of membership, degree of non-membership and degree of indeterminacy for each of the patients, calculated by the second algorithm.

Based on the values of $\mu$ and $v$ from Table 1 Figs. 1 and 2 were constructed. The images from class 1 are denoted with circle, and that of class 2 with asterisk.


Fig. 1


Fig. 2

As a comparison between the two algorithms the minimal, maximal and average value of the degree of non-membership, obtained by the two algorithms have been calculated and normalized over the whole set. They are shown in Table 2.

Table 2

|  | Maximal value of $\boldsymbol{\pi}$ | Minimal value of $\boldsymbol{\pi}$ | Average value of $\boldsymbol{\pi}$ |
| :--- | :---: | :---: | :---: |
| I algorithm | 0.7566 | 0.0001 | 0.1248877 |
| II algorithm | 0.8281 | 0.0036 | 0.243742 |

## Conclusion

The application of the proposed algorithm allows the results of all the applied procedures used in the solution of a particular pattern recognition problem to be taken under consideration thus improving its objectivity. Because of that its use looks promising. In future work the authors will apply a second algorithm for the aggregation of the values received from the individual procedures. The results obtained from the two algorithms will be analyzed and compared.

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