Fuzzy sets in modelling patient's disease states in medical diagnostic support algorithms

A. AMELJAŃCZYK[1]
andrzej.ameljanczyk@wat.edu.pl

T. AMELJAŃCZYK[2]
tameljanczyk@wim.mil.pl

[1]Military University of Technology, Faculty of Cybernetics
Institute of Computer and Information Systems
Kaliskiego St. 2, 00-908 Warsaw, Poland
[2]Military Institute of Medicine,
Szaserów St.128, 01-141 Warsaw, Poland

The article presents the concept of using fuzzy sets methodology in modelling patient's disease states for preliminary medical diagnosis. The preliminary medical diagnosis is based on the identified disease symptoms. The basis of the algorithm are descriptions of the patient's disease status and patterns of disease entities. These patterns were defined as fuzzy sets. The paper presents simple classifiers that allow he a preliminary diagnosis based on the analysis of fuzzy sets for the use of the general practitioner.

Keywords: fuzzy set, disease pattern, classifier, preliminary diagnosis.

DOI: 10.5604/01.3001.0054.1486

1. Introduction

The paper presents the concept of using pattern recognition methodology in the medical diagnostic support system based on fuzzy sets [8]. The essence of the proposed approach consists of two problems: a set of Disease Entity patterns (DE) and a adequately precise formula matching the medical data set of the patient (patient's health condition) to the DE patterns included in the medical repository. The pattern of the disease entity and the description of the patient's condition will be presented as properly defined fuzzy sets [1, 25, 28, 30]. The process of medical diagnosis is an extremely complex undertaking that determines the treatment method and the patient's final health condition. Generally, this is a task from the pattern recognition area. Such a task consists on determining from a set of patterns of disease entities, the disease unit most similar to an adequately defined (described) state of health of the patient. The specificity of recognition of diagnostic medical patterns is mainly due to the fact that the patient's health status (for various reasons) is difficult to reliably and accurately determine and the number of patterns of disease units reaches a few or even several thousand [2, 15, 16, 18, 19, 20, 24]. The patient's health status at a given moment may determine several symptoms and many risk factors as well as hundreds of other medical parameters, the values of which can often be determined as a result of time-consuming and expensive specialist tests carried out in medical laboratories. The degree of the severity of the occurrence of specific symptoms or risk factors is difficult to assess both by the physician and the patient, mainly due to the subjective perception and individual characteristics of the patient. In addition, the patient may be simultaneously ill with several concomitant diseases, whose symptoms may interfere with each other or even cancel each other out. In such case, the difficulty in recognizing medical patterns is mainly due to the fact that the similarity of the patient's health status to several diseases should be sought. Therefore, the diagnostic process is a sequential process, the beginning of which is the collection of medical history during the patient's first visit. The medical diagnosis resulting from it is generally the basis for further diagnostic steps involving the performance of additional specialist tests. The sequence of these medical tests, their number and scope are extremely difficult to determine correctly. This is undoubtedly a very responsible, complex and difficult optimization task that must be carried out by a doctor. It has an impact on the effectiveness of further treatment, treatment time and cost. Very often the diagnostic procedure is interrupted by treatment attempts. The ineffectiveness of the therapy is generally a signal of misdiagnosis. This naturally raises the problem of optimization the specialist set of tests ordered by the doctor. A wide-ranking set of prescribed, additional specialist tests is more likely to make a correct diagnosis (and protects the doctor), but it lengthens the time to the diagnosis, increases the cost of diagnosis and burdens the Health Care System (by lengthening the queue for medical services). Less numerous sets of specialist tests are generally less effective when it comes to making a correct diagnosis. It can also significantly prolong the diagnostic process although – it is probably much cheaper and less aggravating for the Health Care System. Determining the optimal set of specialist tests (from a mathematical and formal point of view) is undoubtedly a very ambitious task of multi-criteria optimization. This paper presents a new concept of supporting the diagnostic process, based on classification procedures drawn from the pattern recognition theory [11, 14, 15]. In this case, the classifier is a properly defined (designed) model of similarity of the input data set to disease entity patterns (DE). The set of patterns of disease entities can be developed by expert doctors [2, 21, 26, 27] or "learned" on training data and properly validated. It is also possible (in the hybrid variant) to "improve" an expert set of DE patterns on training data or even synthetic data. This is an approach that is significantly different from other approaches to classical classification such as linear classifiers, artificial neural networks, k-NN models, decision trees, Bayes networks or hidden Markov models.

2. Modelling of patient's disease states

Let us therefore say $\mathcal{M} = \{1,...,m,...,M\}$ – a set of numbers of disease entities in the diagnostic repository. We will mark the set of patients as follows: $X = \{x_1,...,x_k,...,x_K\}$, where K is the number of considered patients. The set of possible occurrence of symptoms (for simplicity their numbers) will be presented in the form: $S = \{1,...,s,...,S_L\}$, where L is the number of recognizable symptoms. Let e_s^m means the point value determined by the expert for the symptom $s \in S$ in the disease $m \in \mathcal{M}$ ($1 \le e_s^m \le 10$). The symbol $\bar{e}_s^m$ means their normalized values $\bar{e}_s^m = \frac{e_s^m}{10}$ (interval from 0 to 1). Numerical values e_s^m are the subjective assessments of experts in the field of medical diagnostics. They can be treated as some approximation of real values obtained on the basis of a suitably large set of training data such as: (confirmed symptoms, disease entity), in the process of learning under supervision mode.

The patient's $x \in X$ health status, during the visit to the primary care physician is assessed as a result of physical examination and interview. The doctor identifies the set of symptoms and the severity of them. Additional diagnostic information are findings regarding risk factors. Taking the identified symptoms into consideration, the patient's disease state can also be described in the form of a fuzzy set:

$$W(x) = \left\{\left(s, \mu_{W(x)}(s)\right) \middle| s \in S\right\} \tag{1}$$

where S as before, the set of symptoms and the $\mu_{W(x)}(s)$ membership function of belonging symptoms $s \in S$ to the set $W(x)$. Data from the sample of medical history of the patient $x \in X$, is provided in Table 1.

Tab. 1. Data from the medical history

SYMPTOMS OF DISEASE		
No. (s)	**Name of identified symptom**	e_s^x
1	fever	8
2	myalgia	8
3	headache	6
4	sore throat	5
5	dry cough	6
6	fatigue	8
7	shivers	7
8	rhinitis	8
9	lack of appetite	4

In the third column of the table subjective values (scale from 1 to 10) of the doctor's (and the patient's) assessment regarding the degree, severity of the symptoms (stored in the second column), have been recorded. After normalization, we can save the function of belonging symptoms to the fuzzy set $W(x)$ as follows:

$$\mu_{W(x)}(s)=\overset{-x}{e_s} \quad s\in S \tag{2}$$

The disease state of the examined patient thus presents a fuzzy set:

$$W(x)=\left\{\left(1,8/10\right),\left(2,8/10\right),\left(3,6/10\right),\left(4,5/10\right),\ldots,\left(9,4/10\right)\right\}$$

In this case, the diagnostic task consists of matching the most similar pattern of disease $W\left(\overset{*}{m}\right)$ to the established disease state of the patient $W(x)$ from the Repository containing all patterns of disease entities

$$REP=\left\{W(m)\middle|\ m\in\mathcal{M}\right\} \tag{3}$$

This amounts to the task of determining such $\overset{*}{m}\in\mathcal{M}$, that

$$p\left(W(x),\ W\left(\overset{*}{m}\right)\right)=\max_{m\in\mathcal{M}} p\left(W(x),\ W(m)\right) \tag{4}$$

where $p\left(W(x),\ W(m)\right)$ the function of the similarity (adjustment) of a fuzzy set $W(x)$ to a fuzzy set $W(m)$ [1, 28, 30].

3. Algorithm for determining the initial medical diagnosis based on the set of identified symptoms

The work will present the possibility of selecting the formula of matching fuzzy patterns in the framework of the simplest similarity scheme which is the determination of a part of the common features of the studied sets [30].

In the version of the simplest binary model of the similarity of sets $W(x)$ and $W(m)$ can be determined by a modified Jaccard index [28, 30]:

$$p_1\left(W(x),W(m)\right)=\frac{\left|supp\left(W(x)\cap W(m)\right)\right|}{\left|supp\left(W(m)\right)\right|}, \tag{5}$$

It seems more interesting to designate a set $W(x,m)$, as a common part of fuzzy sets $W(x)$ and $W(m)$.

$$W(x,m)=W(x)\cap W(m)=\left\{\left(s,\mu_{xm}(s)\right),\ s\in S\right\}, \tag{6}$$

where

$$\mu_{xm}(s)=\min\left\{\mu_x(s),\mu_m(s)\right\} \tag{7}$$

is the membership function of belonging symptoms to the common part [25, 26, 28].

For simplification we will write instead of $\mu_{W(m)}(s)$, $\mu_{W(x)}(s)$ respectively $\mu_m(s)$, $\mu_x(s)$. Analogous to (5) the characteristic of the fuzzy common part is the index:

$$p_2\left(W(x),\ W(m)\right)=\frac{\sum_{s\in S^m}\mu_{xm}(s)}{\left|\mathrm{supp}\left(W(m)\right)\right|} \tag{8}$$

To simplify let's introduce the symbol

$$S^m=\left\{s\in S\middle|\mu_m(s)>0\right\} \tag{9}$$

the set of symptoms in the support of $W(m)$ set of the disease pattern $m\in\mathcal{M}$.

Analogously:

$$S^x=\left\{s\in S\middle|\mu_x(s)>0\right\} \tag{10}$$

the set of symptoms in the support of $W(x)$ set of the patient's disease state $x\in X$. The third indicator of a fuzzy common part may be the following index [10]:

$$p_3\left(W(x),\ W(m)\right)=\frac{\sum_{s\in S^m}\mu_x(s)\mu_m(s)}{\left|\mathrm{supp}\left(W(m)\right)\right|} \tag{11}$$

An interesting diagnostic interpretation in terms of the metric similarity of sets $W(x)$ and $W(m)$ may have generalized Minkowski's distance characteristics with parameter $p\geq 1$ [5], which we write as follows:

$$\mathrm{dist}_p\left(W(x),\ W(m)\right)=\left(\sum_{s\in S}\left(\left|\mu_x(s)-\mu_m(s)\right|\right)^p\right)^{1/p} \tag{12}$$

For example, for $p=1,2,\infty$ we get respectively [5]:

1) Hamming distance

$$\mathrm{dist}_1\left(W(x),\ W(m)\right)=\sum_{s\in S}\left(\left|\mu_x(s)-\mu_m(s)\right|\right) \tag{13}$$

2) Euklides distance

$$\mathrm{dist}_2\left(W(x),\ W(m)\right)=\sqrt{\sum_{s\in S}\left(\left|\mu_x(s)-\mu_m(s)\right|\right)^2} \tag{14}$$

3) Chebyshev distance

$$\mathrm{dist}_\infty\left(W(x),\ W(m)\right)=\max_{s\in S}\left\{\left(\left|\mu_x(s)-\mu(s)\right|\right)\right\} \tag{15}$$

These indicators (each separate) in simple way can be used to define typical diagnostic classifiers [6, 9] of the type: $C_n : X\to 2^{\mathcal{M}}$ in the following form:

$$C_n(x)=\arg\max_{m\in\mathcal{M}} p_n\left(W(x),W(m)\right) \tag{16}$$

The above formula presents the essence of the diagnostic algorithm in the form of a classification task [11, 12, 13]. It can also be used to build metaclassifiers (conferences, teams, e.t.c.).

Having (see (5)) the function of similarity (matching) $p(W(x),\, W(m))$ of a fixed fuzzy set $W(x)$ to the fuzzy set $W(m)$ we can define in a similar way a fuzzy diagnosis $D_p(x)$ (fuzzy diagnosis) of the patient $x \in X$ in the form of a fuzzy set:

$$D_p(x) = \{(m, \mu_{px}(m)),\ m \in \mathcal{M}\} \qquad (17)$$

where: $\mu_{px}(m) = p(W(x), W(m)),\ m \in \mathcal{M}$

is the membership function of disease nr $m \in \mathcal{M}$ to the diagnosis $D_p(x)$.

4. An example of determining the initial diagnosis

The example below illustrates the operating of the diagnostic algorithm (16) for selected variants of the matching index of patient's disease status to the patterns of disease entities included in the diagnostic repository system. The result of the patient's x interview is a description of the patient's condition in the form of a fuzzy set $W(x)$. The data from the interview are recorded in the table below:

Tab. 2. Data from the patient's medical history

SYMPTOMS		
No. (s)	**Name of identified symptom**	e_s^x
1	fever	8
2	myalgia	6
3	headache	5
4	chest pain	6
5	dry cough	7
6	fatigue	5
7	shivers	5
8	enlarged lymph nodes	7

In a set of DE patterns there are ten types of diseases. Their fuzzy patterns are presented in the table below (matrix). The rows of this matrix correspond to the numbers of symptoms and the columns correspond to the numbers of disease entities. Numbers in the appropriate fields of the table indicate the severity of the symptom (row number) in the diagnosis of the disease entity (column number) on a scale from 1 to 10. For example column 1 describes the fuzzy set being the reference of influenza – the second column describes the pattern of Lyme borreliosis and so on.

Table 4 contains (for technical reasons) only fragmentary, representative descriptions of disease entity patterns REP in the form of fuzzy sets $W(m),\ m \in \mathcal{M}$.

REP = {flu, borreliosis, type 1 diabetes, hepatitis B, pneumonia, prostate cancer, chicken pox, gallstones, tuberculosis, heart attack}.

Tab. 3. Repository (set) of disease patterns

s/m	1	2	3	4	5	6	7	8	9	10
1	8	0	0	5	8	0	7	0	5	0
2	4	0	0	0	0	0	4	0	0	0
3	6	7	0	6	0	0	5	0	0	0
4	5	0	0	0	0	0	4	0	0	0
5	5	0	0	0	6	0	0	0	0	0
6	6	0	7	0	5	0	7	0	5	5
7	3	0	0	0	5	0	0	0	0	0
8	4	0	0	0	0	0	3	0	0	0
9	7	0	0	8	0	0	6	0	0	0
10	0	10	0	0	0	0	0	0	0	0
11	0	7	0	0	0	0	0	0	0	0
12	0	7	0	0	0	0	0	0	0	0
13	0	7	0	0	0	0	0	0	0	0
14	0	5	0	0	0	0	0	0	0	0
15	0	5	0	0	0	0	0	0	0	0
16	0	5	0	0	0	0	0	0	0	0
17	0	5	0	0	0	0	0	0	0	0
18	0	3	0	0	3	0	0	0	0	0
19	0	3	0	0	6	0	0	0	4	0
20	0	3	0	0	3	0	0	0	0	0
21	0	3	5	0	0	0	0	0	0	0

The next Table 4 presents the results of calculations of selected matching index:

$$p_n(W(x), W(m)) = p_n(x, m),\ n = 1, \ldots, 5$$

a) $p_1(x,m)$ – Jaccard index (5)

b) $p_2(x,m)$ – intersection index (8)

c) $p_3(x,m)$ – intersection (*) index (11)

d) $p_4(x,m)$ – Hamming index (13)

e) $p_5(x,m) = \frac{1}{4}\sum_{n=1}^{4} w_n p_n(x,m)$ – sum weight index [4, 9, 12, 30].

Tab. 4. Value of matching index

p_n / m	p_1	p_2	p_3	p_4	p_5
1	0,666	0,311	0,207	0,800	0,496
2	0,154	0,077	0,046	0,200	0,119
3	0,100	0,050	0,035	0,200	0,096
4	0,125	0,063	0,050	0,300	0,135
5	0,500	0,300	0,200	0,300	0,325
6	0	0	0	0	0
7	0,272	0,145	0,095	0,400	0,228
8	0	0	0	0	0
9	0,429	0,214	0,014	0,400	0,264
10	0,050	0,025	0,015	0,100	0,048

The values of the above-mentioned indexes were calculated according to appropriate formulas, based on data describing fuzzy sets being descriptions of the patient's disease state and relevant patterns of disease entities included in the repository.

Depending on the adopted index $p_n\left(W(x),\ W(m)\right) = p_n(x,m),\ n = 1,\ldots,5$ we can determine a fuzzy diagnosis of the patient in the form of:

$$D_{p_n}(x) = \left\{\left(m, \mu_{px}(m)\right), m \in \boldsymbol{\mathcal{M}}\right\}$$

and a number of other characteristics that demonstrate the quality (reliability) of the diagnosis in the form of a fuzzy set, such as [8]:

a) diagnosis support

b) diagnosis core

c) height of diagnosis

d) sharpness of diagnosis

e) fuzziness of diagnosis.

Table 4 also allows calculating on the basis of fuzzy diagnoses (obtained with different matching indexes), diagnostic proposals in the form of a typical classification [6, 9, 29] using type classifiers (16) and in the form of rankings for appropriate matching indicators (more useful for the general practitioner).

$$p_n\left(W(x), W(m)\right) = p_n(x,m),\ n = 1,\ldots,5$$

For example, for the Jaccard index (11) we get the classification:

$$C_1(x) = \arg\max_{m \in \boldsymbol{\mathcal{M}}} p_1\left(W(x), W(m)\right) = \{1\} =$$
$$= \{flu\}$$

The Jaccard index leads to the following ranking $r(p_1)$ of diagnoses (see Table 4):

$$r(p_1) = \langle 1,5,9,7,2,4,3,10,6,8 \rangle$$

The following diseases in the ranking (after flu) are: pneumonia, tuberculosis, chickenpox etc. The remaining rankings have (Table 5) the following form:

$$r(p_2) = \langle 1,5,9,7,2,4,3,10,6,8 \rangle$$
$$r(p_3) = \langle 1,5,7,4,2,3,10,9,6,8 \rangle$$
$$r(p_4) = \langle 1,5,9,7,2,4,3,10,6,8 \rangle$$
$$r(p_5) = \langle 1,5,9,7,4,2,10,3,6,8 \rangle$$

In all five cases, the first place was flu and the second pneumonia. Discrepancies in the next places in the rank are increasingly bigger. The two last positions are identical – this is due to the fact:

$$W(x,m) = W(x) \cap W(m) = \varnothing,\ m \in \{6,8\}.$$

For the completeness of the results, the quality characteristics of the diagnosis will be determined, using as an example, those obtained for the Jaccard index:

$$\mathrm{supp}\left(D_1(x)\right) = \{1,2,3,4,5,7,9,10\}$$
$$\mathrm{core}\left(D_1(x)\right) = \varnothing$$
$$\mathrm{hgt}\left(D_1(x)\right) = 0,666$$
$$\mathrm{sharp}\left(D_1(x)\right) = 0,287$$
$$\mathrm{fuzze}\left(D_1(x)\right) = 0,713$$

Attention is drawn to the fact that the $D_1(x)$ diagnosis has a big fuzziness and (despite this), indicates flu with great certainty (in first place).

5. Conclusions

The paper presents the diagnostic support algorithm (21) as a diagnostic classifier based on the fuzzy set approach as a natural basis for modeling medical diagnostic processes. The basis for the proposed diagnostic decision is the product of the fuzzy set which is the patient's health condition determined by the doctor and the fuzzy set which is the pattern of the disease entity The basis of the diagnostic decision is the degree of similarity of these two sets. The following models of similarity of fuzzy sets were analyzed:

– Jaccard similarity index
– common part index
– Hamming index
– similarity metric
– Chebyshev index.

The presented concept of determining the initial medical diagnosis is illustrated by an extensive numerical example. For each medical diagnosis obtained in this way, it is possible to define a number of its qualitative characteristics, such as: diagnosis support, the core of the diagnosis, clarity of diagnosis or its fuzzyness. These characteristics have the obvious value of additional information providing on the credibility of the diagnostic process. Additional diagnostic information is the possibility of presenting a ranking of diagnostic indications for individual models of the similarity of fuzzy sets.

6. Bibliography

[1] Albin M., *Fuzzy sets and their applications to medical diagnosis*, University of California, Berkeley, USA, 1975.

[2] Allan M., Spencer J., *Crash Course – wywiad i badania przedmiotowe*, Elsevier Urban & Partner, Wrocław 2005.

[3] Ameljańczyk A., *Optymalizacja wielokryterialna w problemach sterowania i zarządzania*, Ossolineum, Wrocław 1984.

[4] Ameljańczyk A., „Multicriteria similarity models in medical diagnostics support algorithms", *Bio-Algorithms and Med--Systems*, Vol. 9, No. 1, 1–7 (2013).

[5] Ameljańczyk A., „Metryki Minkowskiego w tworzeniu uniwersalnych algorytmów rankingowych", *Biuletyn WAT*, Vol. LXIII, Nr 2, 29–44 (2014).

[6] Ameljańczyk A., „Property analysis of multi-label classifiers in the example of determining the initial medical diagnosis", *Computer Science and Mathematical Modelling*, No. 1, 11–16 (2015).

[7] Ameljańczyk A., „Analiza wpływu przyjętej koncepcji modelowania systemu wspomagania decyzji medycznych na sposób generowania ścieżek klinicznych", *Bliuletyn Instytutu Systemów Informatycznych*, Nr 4, 1–8 (2009).

[8] Ameljańczyk A., "Fuzzy sets in modeling of patient' disease states", *Computer Science and Mathematical Modelling*, No. 9, 1–7 (2019).

[9] Ameljańczyk A., „Pareto filter in the process of multi-label classifier synthesis in medical diagnostics support algorithms", *Computer Science and Mathematical Modelling*, No. 1, 3–10 (2015).

[10] Ameljańczyk A., Długosz P., "Properties of the Algorithm for Determining an Initial Medical Diagnosis Based on a Two-Criteria Similarity Model", *Biuletyn Instytutu Systemów Informatycznych*, Nr 8, 9–16, (2011).

[11] Ameljańczyk A., „Wielokryterialne mechanizmy wspomagania podejmowania decyzji klinicznych w modelu repozytorium w oparciu o wzorce", POIG.01.03.01-00-145/08/2009, WAT, Warszawa 2009.

[12] Ameljańczyk T., Ameljańczyk A., „The problem of thresholds determination in ranking classifiers applied in medical diagnostic", *Journal of Health Policy and Outcomes Research*, Vol. 9(1), 20–29 (2016).

[13] Acid S., Campos L.M., "A comparison of learning algorithms for Bayesian Networks: a case study based on data from an emergency medical service", *Artificial Intelligence in Medicine*, 30(3), 215–232 (2004).

[14] Błaszczykowski J., Krawiec K., Słowiński R., Stefanowski J., Wilk Sz., *Wspomaganie decyzji i komunikacji w systemach telemedycznych*, Politechnika Poznańska, Poznań 2006.

[15] , 2006.

[16] Collins R.D., *Algorytmy interpretacji objawów klinicznych*, Medipage, Warszawa 2010.

[17] Kokot F., *Diagnostyka różnicowa objawów chorobowych*, PZWL, Warszawa 2007.

[18] Kokot F., Hyla-Klekot L., Kokot S., *Badania laboratoryjne: Zakres norm i interpretacja*, PZWL, Warszawa 2011.

[19] Makal J., Nazarkiewicz A., Oniśko A., Orzechowski P., „System ekspertowy do wspomagania diagnozy łagodnego przerostu prostaty", *Pomiary Automatyka i Robotyka*, 7(7–8), 193–196 (2004).

[20] Medyczne Systemy Ekspertowe, http://www.computer.priveteweb.at/judith/links3.htm.

[21] Oniśko A. i inni, „HEPAR I HEPAR II – komputerowe systemy wspomagania diagnozowania chorób wątroby", *XII Konferencja Biocybernetyki i Inżynierii Biomedycznej*, Warszawa 2001.

[22] Pawlak Z., "Rough Sets", *International Journal of Computer and Information Sciences*, Vol. 11, 341–356 (1982).

[23] Pawlak Z., *Systemy informacyjne. Podstawy teoretyczne*, WNT, Warszawa 1983.

[24] Resultmaker, "Workflow patterns of the Online Consultant", version 1.1, Kopenhaga 2006.

[25] Sanchez E., "Inverses of fuzzy relations. Application to possibility distributions and

medical diagnosis", *Proc. IEEE Conference Decision and Control*, USA, 1977.
[26] Sanchez E., "Medical diagnosis and composite fuzzy relations", [in:] *Advances in fuzzy sets theory and applications*, M.M. Gupta, R.K. Ragade, R.R. Yager (Eds.), pp. 437–444, North-Holland Publishing Company, 1979.
[27] Siegenthaler W., *Rozpoznanie różnicowe w medycynie wewnętrznej*, Tom 1–2, Medipage, Warszawa 2009.
[28] Smets P., "Medical diagnosis: Fuzzy sets and degrees of belief", *Fuzzy sets and Systems*, Vol. 5(3), 259–266 (1981).
[29] Strawa M., „Koncepcja modułu wspomagania podejmowania decyzji klinicznych w modelu repozytorium z wykorzystaniem metod sieci bayesowskich", POIG.01.03.01-00--145/08/2009, WAT, Warszawa 2009.
[30] Seung-Seok Choi, Sung-Hyuk Cha, Tappert Ch.C., "A Survey of Binary Similarity and Distance Measures", *Journal of Systemics Cybernetics and Informatics*, 8(1), 43–48 (2010).

Zbiory rozmyte w modelowaniu stanów chorobowych pacjenta w algorytmach wsparcia diagnostyki medycznej

A. AMELJAŃCZYK, T. AMELJAŃCZYK

W artykule przedstawiono koncepcję wykorzystania metodologii zbiorów rozmytych w modelowaniu stanów chorobowych pacjenta w algorytmach wstępnej diagnostyki medycznej. Wstępna diagnoza lekarska opiera się na rozpoznanych objawach choroby. Podstawą algorytmu są opisy stanu chorobowego pacjenta i wzorce jednostek chorobowych.Wzorce te zostały zdefiniowane jako zbiory rozmyte. W artykule przedstawiono proste klasyfikatory, które pozwalają na wstępną diagnozę na podstawie analizy zbiorów rozmytych do użytku lekarza pierwszego kontaktu.

Słowa kluczowe: zbiór rozmyty, wzorzec choroby, klasyfikator, diagnoza wstępna.