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medical diagnosis support, uncertainty, imprecision, the Dempster-Shafer theory of evidence, the fuzzy set theory, expert systems.

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UNCERTAINTY AND IMPRECISION IN MEDICAL DIAGNOSIS SUPPORT

The paper concerns methods of representation of uncertainty and imprecision in successful medical support applications. Advantages of the methods are pointed out and some of their drawbacks are explained. A method of simultaneous representation of imprecision of symptoms and uncertainty of diagnostic rules is proposed. The method suggests an extension of the Dempster-Sahfer theory for fuzzy focal elements. An example of the method is given and their links as well differences from previous approaches are discussed. Conclusions about uncertainty and imprecision representation in medical diagnosis support are provided.

1. INTRODUCTION

Medical diagnosis is a very complex task since different kinds of information must be considered with various certainty and next combined. Answers from an interview with a patient are often ambiguous. Results of a primary examination are usually linguistically formulated. Outcomes of laboratory tests are judged in relation to their norms. Other diagnostic items like images, parameters of electrical signals etc., also require interpretations. Moreover, sometimes examinations cannot be done, for instance because of a patient's state, and then the diagnosis must be taken in the lack of evidence.

A result of an examination can be attached with a precision measure that indicates its accuracy of matching a symptom. For instance, the body temperature of 37°C matches 'fever' with less precision than the temperature of 39°C. If there is no thermometer available the 'fever' can be find out with low precision by touching a forehead. These are trivial examples, but indeed all accessible evidence should be used during a diagnosis. Simultaneously, the low precision of evidence should be taken into account.

Relations among symptoms and diseases generally are also uncertain. The same symptoms may occur with different diseases and one disease may have various manifestations. A headache may be a symptom of flu or migraine, while migraine may manifest by the headache or a partial vision loss. Of course, symptoms and diseases are related with different frequency of occurrence. The frequency of occurrence or belief that a symptom is relevant to a disease may be expressed by a certainty measure.

It might be concluded that two measures: imprecision and uncertainty should be used in diagnostic reasoning. Nevertheless, many researchers do not make distinction between precision and certainty and regard them the same concept. It happens particularly when one of the measures is less important in reasoning (e.g. diagnostic rules have equal significance) or reliable information about the measure is not available. Still, all diagnosis support tools use some confidence measure. Depending on an approach the measure is considered as probability, membership function, belief or plausibility. Although researchers work on diagnosis support for many years, they only partly solve the problem of a measure choice that is appropriate for a problem. The present work shows some approaches denoting their strong and week points and at the end suggests an original method of modeling imprecision and uncertainty measures in diagnosis support.

2. MODELING UNCERTAINTY OF A DIAGNOSIS

Let us consider uncertainty of a diagnosis as a measure of significance of symptoms in the diagnosis. It is often considered as a probability value or a membership function of a fuzzy set. Statistics

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are often used to evaluate probability of the diagnosis given symptoms. Information from statistics can be applied in the diagnosis support in two ways. Firstly, frequencies of occurrence of symptoms interpreted by experts are directly used to evaluate significance of the symptoms in the diagnosis. Secondly, necessary a priori and conditional probabilities are found by means of the frequencies and next the Bayes' formula is used. Let us discuss the first manner.

Frequencies of occurrence are not exclusive knowledge about relations among symptoms and diagnoses. They are usually supplemented by experts' heuristics. In this way medical indices were formulated. They were introduced into medical practice much earlier than computers entered hospitals and they are still in use, thus they are worthy of notice. Roughly speaking, the medical index is a table that concerns one disease, in which each symptom has an assigned score. The score is an integer positive or negative value. It can be given by means of a step function (Fig.1). The scores should be summed up for symptoms occurring with a patient. Next the sum is interpreted by means of limits that are established for the table and imply conclusions. These limits are determined according to statistics. The conclusions are usually of the form: ‘suspected disease’, ‘further investigation are necessary’ and ‘probably not ill’. Examples of such indices are Crooks Index [12] and Murray Index [19] for thyroid glad diseases or INFARCTEST [36] for a heart infarct risk estimation. The indices are simple and useful tool for quick evaluation of many symptoms at a primary

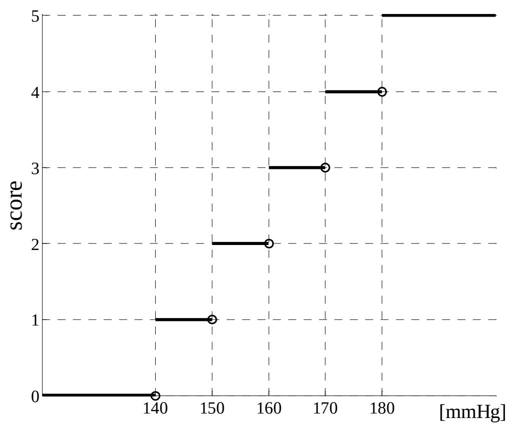

Fig. 1. Original score step function for the systolic blood pressure in INFARCTEST.

stage of a diagnosis. Unfortunately, computerization of indices is worthless for diagnosis support because it is very difficult to add a new symptom to an existing set of findings or to change an evaluation of a medical procedure. In both cases the change of the algebraic sum is difficult to assess. Hence, updating each time requires a new statistical investigation. Obviously, complexity of the investigation increases along with the final number of symptoms. Thus, it may happen that the performance of an enlarged index in worse than that of the previous version [31]. Therefore, medical indices are not a suitable tool for computer diagnosis support. They can be suitable for formulating fuzzy rules, though we cannot expect that in each case a fuzzy conclusion will be exactly the same as the conclusion indicated by the original score [31].

The second way to use statistical information consists in a determination of conditional and a priori probabilities which are next used in Bayes' formula. In the diagnosis support the formula is used in the following form [15, 16]:

$$P(D/S) = \frac{P(S/D)P(D)}{P(S/D)P(D) + P(S/ND)P(ND)}, \tag{1}$$

where *ND* stands for lack of the disease, hence $P(D)+P(ND)=1$. Bayesian approach is important in early medical diagnosis support [22], but it is not free from substantial drawbacks. Some of necessary probability values are available, but the other are difficult to obtain. Calculation of the $P(D/S)$ requires the $P(D)$ value which is usually available because frequencies of occurrence of diseases in the population are often known. The P(S/D) is determined on the basis of examinations done in hospitals or outpatient clinics. The matter is much more complicated with the $P(S/ND)$. In practice it is not found for a population of healthy people, but for a 'control group' in which there are patients who do not suffer from the D disease, but generally are not healthy. This may result in a false evaluation of the probability. Moreover, the S symbol in (1) stands both for set of symptoms or a single symptom (one-element set). Thus, to be exact, the P(S/D) and the $P(S/ND)$ should be determined individually for each possible combination of symptoms. It is practically impossible. Conditions of a statistic research are very strict and often impossible to sustain. Because of all these drawbacks the diagnosis support based on the Bayes' formula (1) is either simplified to trivial cases or used in rather a flexible manner, ignoring mathematical constraints. For instance in Iliad expert system an iterative Bayes' formula is proposed [15]:

$$\begin{aligned} &P(D/S_{i+1}) := \frac{P(S_i/D)P(D)}{P(S_i/D)P(D) + P(S_i/ND)P(ND)}, \\ &P(D) := P(D/S_{i+1}), \\ &P(ND) = 1 - P(D), \\ &i = 1,\ldots,n. \end{aligned} \tag{2}$$

The Iliad authors assume that a posteriori probability of the disease calculated for one symptom becomes a priori probability of the disease when the next symptom is considered. This formula solves the problem of calculation complexity, but do not works satisfactory for many symptoms because the change of the final $P(D)$ value decreases along with the number of symptoms [32]. A human diagnostician do not make distinction between e.g. $P(D)$=0.9901 and $P(D)$=0.9999 and may disregard subsequent symptoms. In order to prevent it, Iliad presents differential diagnosis that makes it possible to sort possible hypotheses according to their probability. This opportunity is known already from earlier medical expert systems, like for instance INTERNIST [2], [16] and is convenient if the list of hypotheses is relatively short. A comparison between Iliad and INTERNIST is justified, as both are expert systems in the domain of internal diseases. It is also interesting that INTERNIST employs positive and negative score of hypotheses.

Another well-known expert system in which probability measures are used is MYCIN [30]. Perhaps it is the most successful medical expert system, thus its uncertainty representation deserves discussion. MYCIN's certainty factor (CF) is defined in as [5]:

$$CF(h,e) = \begin{cases} 1 & P(h) = 1, \\ MB(h,e) & P(h/e) > P(h), \\ 0 & P(h/e) = P(h), \\ -MD(h,e) & P(h/e) < P(h), \\ -1 & P(h) = 0, \end{cases} \tag{3}$$

where h denotes a hypothesis and e – evidence, MB is called the measure of belief and MD – the measure of disbelief. The latter are calculated in the following way [5]:

$$\begin{aligned} MB(h,e) &= \begin{cases} \dfrac{P(h/e) - P(h)}{1 - P(h)} & P(h/e) > P(h), \\ 0 & otherwise, \end{cases} \\ MD(h,e) &= \begin{cases} \dfrac{P(h) - P(h/e)}{P(h)} & P(h/e) < P(h), \\ 0 & otherwise. \end{cases} \end{aligned} \tag{4}$$

The certainty factor equals: $CF = MB - MD$ and since $MB, MD \in [0,1]$ then $CF \in [-1,1]$. Thus, in terms of the certainty factor a situation in which evidence does not carry information can be represented by $CF = 0$. This is an important indication that the probability in its classical form may be insufficient to represent a diagnostic conclusion. A success of MYCIN is sometimes explained by its narrow and well-defined domain of expertise [7]. MYCIN's rules are considered in contexts [30], which means that a relatively small number of highly adequate rules are fired at each stage of inference. This ensures the great robustness and makes easier updating certainty factors. However, the *CF* is not free from deficiencies.

Figures 2 – 4 concerns two hypotheses: h_1 and h_2 when evidence e is given and for the both hypotheses $P(h_i/e)>P(h)$ as well as probability values are different form 0 and 1. In such conditions $CF(h_i, e)=MB(h_i, e)$, according to (3), (4). In Fig.2 six cases of a priori and conditional probability values are presented as well as *MB* values calculated for the cases. A priori probabilities are equal: $P(h_1)=P(h_2)$ and for conditional probabilities $P(h_1/e)<P(h_2/e)$. Values of measures $MB_1 \equiv MB(h_1, e)$ and $MB_2 \equiv MB(h_2, e)$ preserve the conditional inequality, i.e. $MB(h_1, e) < MB(h_2, e)$ which agrees with common sense. The cases in Fig.3 for which $P(h_1)>P(h_2)$ and $P(h_1/e)>P(h_2/e)$ with resulting $MB(h_1, e) > MB(h_2, e)$ are also judged intuitively right. However, in Fig.4 we observe that $P(h_1/e)=P(h_2/e)$, $P(h_1)>P(h_2)$ and $MB(h_1, e) < MB(h_2, e)$, which is counterintuitive.

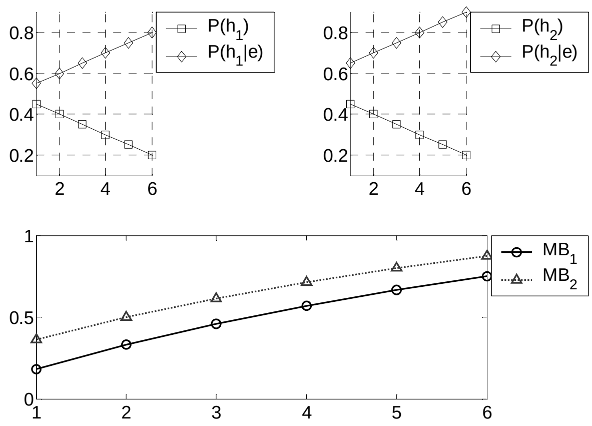

Fig. 2. Values of the belief measure for two hypotheses with $P(h_1)=P(h_2)$ and $P(h_1/e)<P(h_2/e)$.

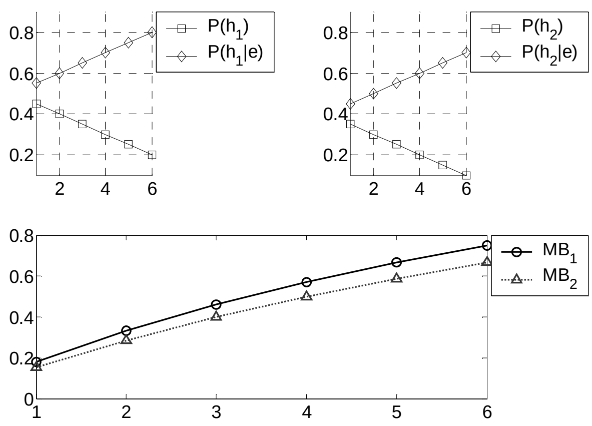

Fig. 3. Values of the belief measure for two hypotheses with the same $P(h_i/e)$-$P(h_i)$ difference.

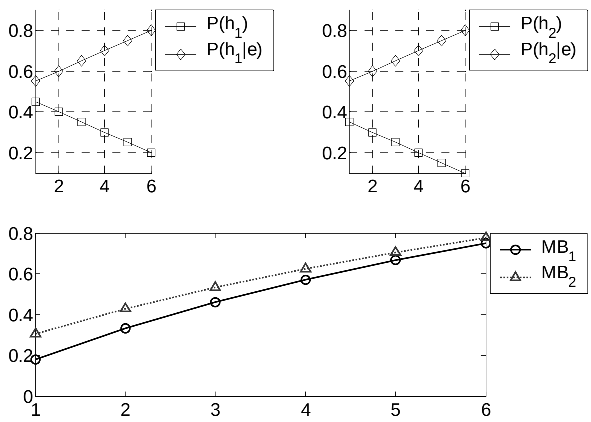

Fig. 4. Values of the belief measure for two hypotheses with $P(h_1/e)=P(h_2/e)$ and $P(h_1)>P(h_2)$.

This phenomenon was noticed and criticized by several researchers [16] because a priori probability values for all hypotheses should be equal to keep consistence of *CF*. Another disadvantage of this factor is a complicated and inconsistent calculation of *CF* for chain of rules [5]. However, it cannot be denied that the introduction of the *CF* started new trends in diagnosis support. It has been accepted that a priori probabilities which are necessary for calculations can be subjective probabilities [10] given by experts [16]. Yet, experts determine values of subjective probabilities in different ways [8]. Thus, inquiries about these probabilities must be repeated for each application.

There is a number of methods of diagnosis support based on Bayes' formula in which calculations are performed in a network [25, 26]. Their aim is to make easier and clearer calculations, particularly updating probability values. Still, disadvantages of acquiring knowledge remain. Hence, there are good reasons to look for different methods of diagnosis support, particularly as it is confirmed that humans use uncertain concepts in a diagnostic inference, but they do not follow exactly the classical probability principles [22].

A probability theory that avoids the condition which is the most unfortunate for the diagnostic inference is the Dempster-Shafer theory of evidence [9]. In this theory focal elements are defined as predicates with assigned basic probability values. The dependence condition is absent in the definition of the assignment. Its values can be obtained from experts. This makes the theory convenient for diagnosis support [3]. The way of its use will be shown in the fourth section.

Another approach to diagnostic inference modeling makes use of the fuzzy set theory [37]. Fuzzy sets were recognized a good tool for human knowledge representation and soon after their introduction began trials of their application in medicine. Although designing membership functions for medical parameters and modeling diagnostic inference by means of fuzzy rules turned out to be more complex than researchers supposed, expert systems, like for instance CADIAG [1, 20], were finally built. A rule in CADIAG-2 is for instance [16]:

$$\begin{array}{ll} \text{IF} & \text{elevated pancreatic oncofetal antigen (POA) in serum} \\ \text{THEN} & \text{maybe pancreatic cancer} \\ \text{with} & \lambda_O = \text{often}, [\mu_O = 0.8], \lambda_C = \text{strong}, [\mu_C = 0.7] \end{array} \tag{5}$$

In (5) O denotes occurrence, C - confirmation, λ – linguistic values and μ – numerical values. Linguistic descriptions: 'elevated', 'often', 'strong' can be represented by membership functions. Yet, this rule is not exactly a fuzzy rule because its premise is fuzzy ('elevated'), but its conclusion is crisp ('pancreatic cancer'), unless the conclusion is assumed to be the disease risk with the linguistic evaluation 'maybe'. If 'maybe' is understood as certainty of the rule then it is difficult to include its membership function in the fuzzy inference. In such a situation the classical fuzzy inference based on a fuzzy relation or a fuzzy implication is questionable. Hence, fuzzy inference in this system consists in operating on membership functions of the premises and on memberships μ_O and μ_C. A similar rule model appears also in other applications [24, 35], in which classifiers rather than inference systems are used to support the diagnosis.

Another deviation from classical fuzzy inference is an abductive formulation of rules: 'IF symptom(s) THEN diagnosis'. A diagnostic rule that represents causal dependence which is used in classical probability approach is 'IF disease THEN symptom(s)'. In the CASNET expert system based on semantic networks such rules are also used [34]. Logically the same rule should be used in fuzzy inference, since the scheme of reasoning is the generalized modus ponens: $(a' \wedge (a \Rightarrow b)) \Rightarrow b'$. However, heuristics are usually formulated in an opposite manner and so are the fuzzy rules. The violation of logics influences inference effects.

Results of the first stage of fuzzy inference are membership functions of conclusions which next need to be aggregated. A choice of an aggregation operator is both crucial and difficult. The aggregation operator cannot be maximum since then conclusion of the greatest membership becomes the final conclusion. This is false as such a conclusion results from few considered symptoms. The choice of the right aggregation operator is application-oriented. These problems, briefly mentioned here, are wider explained in [32]. Hence, it seems that the fuzzy set theory is convenient for representing knowledge in diagnosis support but is not ready for straightforward use in the diagnostic inference.

3. IMPRECISION OF SYMPTOMS

Probability-based methods of inference generally ignore the problem of unknown symptoms or manifestations that partly match disease symptoms. However, these problems are common in medical practice and without their solution diagnosis support tool will always be awkward. The fuzzy set theory is much more convenient because matching a symptom and evidence can be evaluated in the [0,1] interval. It is also possible to express values of linguistic variables by means of membership functions. This is particularly important for symptoms which are difficult to estimate, for instance pain, that is evaluated by means of the visual analog scale (VAS) [13]. Nevertheless, the majority of symptoms is linguistically formulated. Even laboratory test results are interpreted by in linguistic categories [14]. Linguistic expressions can be represented by membership functions. The membership function becopmes the characteristic function if the symptom is represented in two-valued logic (e.g. 'struma'). Membership functions may be determined for a numerical scale (laboratory test result), for a generally assumed scale ('great pain'), as well as for an occasionally chosen scale ('normal appetite').

A shape of the membership function is not crucial as during inference numerical rather than symbolic calculations are done. A minor change in membership function does not change its interpretation [6]. Still, results of applications may strongly depend on several important points. They can be determined by means of descriptive statistics of data [28], neural networks [29] or/and experts' opinions [21]. Triangular functions can result from fuzzy identification [33] similar to procedures used for control [31]. An extended discussion on membership function shapes is provided in [27]. Let us assume trapezoidal shape of the membership function. Its formula is [4]:

$$\mu(x) = \begin{cases} 0, & x \le x_\alpha, \\ \dfrac{x - x_\alpha}{x_\beta - x_\alpha}, & x_\alpha < x \le x_\beta \\ 1, & x_\beta < x \le x_\gamma \\ \dfrac{x_\delta - x}{x_\delta - x_\gamma}, & x_\gamma < x \le x_\delta \\ 0, & x > x_\delta. \end{cases} \tag{6}$$

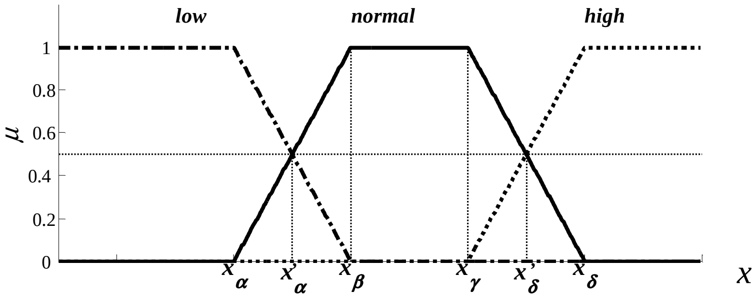

Fig. 5. Crucial points for membership functions.

This formula shows that crucial points are values of the domain in which the function changes its values from zero (x_α, x_δ) and from one (x_β, x_γ) (see Fig.5). If the function represents 'normal' values of a laboratory test then (x_α, x_δ) are usually norms of the test. Still, in [32] points in which the membership function has 0.5 values, i.e. (x'_α, x'_δ) are suggested for the norm limits. The latter reference points are in better agreement with intersection points of probability distributions for low, normal and high results of a laboratory test [32]. In medical applications the 'normal' function is often the basic function for a parameter and the other two, i.e. 'low' and 'high' can be constructed as its complements. Nevertheless, if membership functions represent experts' knowledge, the functions that represent abnormal values of a parameter may be individually created as an average opinion of several experts. It is doubtful if step functions included in medical indices are a good basis to define the functions since it is not known if an upper or lower approximation of the steps should be made. In this case training data are helpful and a kind of identification should be performed [31].

Evidence is matching a symptom to the extent that is minimum between the membership function of the symptom and the function of evidence, which is usually a singleton. Yet, evidence represented by the proper membership function will certainly be of use, as it is pointed out in [18] and fuzzy input information is already proposed in [11] and [23]. However, a method of creating membership functions for any linguistic value entered by a computer user should be elaborated to use fuzzy sets both as symptoms and evidence.

4. THE DEMPSTER-SHAFER THEORY WITH FUZZY FOCAL ELEMENTS

Many researchers agree that joining probability-based and fuzzy approaches can solve complex problems [8]. It possible to combine the Dempster-Shafer theory (DST), which represents uncertainty of the rule 'IF symptom(s) THEN disease', with the fuzzy set theory that describe imprecision of symptoms. In the DST focal elements are defined for which the basic probability assignment (BPA) is determined as [17]:

$$m(f) = 0, \qquad \sum_{a \in S} m(a) = 1, \tag{7}$$

where m is the BPA, f stands for the false predicate and S is a set of focal elements a. Focal elements are predicates, so they can describe symptoms. The focal element may concern one or several symptoms, i.e.:

$$a_l \equiv s_l \quad \text{or} \quad a_l = \{s_i\}, i = 1,\ldots,n_l, \tag{8}$$

where l is the rule and i is its condition index. The BPA is determined for a chosen diagnosis and can represent correlations, frequency of occurrence or experts' evaluations. When a patient is consulted, several up to all focal elements are confirmed by his/her manifestations. The manifestations are evidence in the diagnostic inference. The belief and plausibility measures are calculated for the evidence in the following way [17]:

$$Bel(d) = \sum_{(a \Rightarrow d) = t} m(a) \tag{9}$$

$$Pl(d) = \sum_{(a \Rightarrow d) \neq f} m(a) \tag{10}$$

where *d* stands for the disease and *t* for truth. The right arrow $\Rightarrow$ in (9) and (10) does not denote an implication, but an assignment. Thus, the set of focal elements and the BPA are knowledge and *Bel* and *Pl* results of a consultation. If all focal elements are single-symptom then always $Bel(d)=Pl(d)$, otherwise $Bel(d)\leq Pl(d)$. If manifestations do not confirm symptoms at all, then $Bel(d)=Pl(d)=0$. The truth of the assignment $a \Rightarrow d$ can be interpreted by means of a precision measure which has values in the [0,1] interval. This measure can be the membership of evidence in fuzzy sets representing symptoms. Hence, membership functions are constructed for each focal element and each symptom in the element is confirmed by evidence at the level [32]:

$$\eta_i = \sup_{x \in \mathbf{X}} [\mu_i(x) \wedge \mu_i^*(x)], \tag{11}$$

where $\mu_i(x)$ is the membership function of the *i*-th symptom in the focal element and $\mu_i^*(x)$ is the membership function of the appropriate piece of evidence. The latter can be the characteristic function, the singleton or the proper membership function. The matching level for the whole focal element is calculated in different ways for the belief or plausibility measures because of various formulations of summation conditions in (9) and (10). When the belief measure is considered then the level is [32]:

$$\eta^{(l)} = \min_{1 \leq i \leq n_l} \eta_i, \tag{12}$$

while for the plausibility measure [32]:

$$\theta^{(l)} = \max_{1 \leq i \leq n_l} \eta_i, \tag{13}$$

where n_l stands for the number of symptoms in the a_l focal element. The $\eta^{(l)}$ indicate to which extent evidence confirms the focal element and $\theta^{(l)}$ the amount of available information about the focal element.

Such matching is done for all focal elements and elements for which $\eta^{(l)}$ is greater than an assumed *T* threshold are selected. The threshold can be evaluated using the value of the plausibility measure [32], but in simple cases it can be deduced on the basis of membership functions. It should correspond their cross-points. After the selection, the BPA values for the chosen focal elements are summed up. This process is done for several diagnoses – at least for two: ‘healthy’ and ‘ill’. Belief values for the diagnoses are compared and the greatest value, if it is unique, indicate the winning diagnosis. If the greatest value occurs for more than one diagnosis, there is no valid conclusion. Let us present an example that shows similarities and differences of the presented method to other probability-based approaches.

4.1. EXAMPLE

Let us consider three diagnoses (e.g. diseases d_1, d_2 and health *h*) for which rules of two-condition premises are formulated. The conditions refer to linguistic values *A*, *B* and *C* (for instance: ‘low’, ‘medium’ and ‘high’) of two symptoms (e.g. laboratory tests) *X* and *Y*. The rules are listed in Tab.1. The first column of the table should be read as follows: IF *X* is *A* and *Y* is *A* THEN diagnosis is d_1. The other columns make analogical rules, except for columns with ‘–‘ instead of the diagnosis – these rules are not formulated. Thus, the knowledge base is not complete, which often happens in medical diagnosis. Moreover, various diagnoses have different number of rules. Membership functions for the *X* and *Y* symptoms are presented in Fig.6.

Table 1. Rules for three diagnoses and two symptoms.

Rule	$R_{d1}^{(1)}$	$R_{d1}^{(2)}$	–	$R_{d1}^{(3)}$	$R_h^{(1)}$	$R_h^{(2)}$	–	$R_{d2}^{(1)}$	$R_{d2}^{(2)}$
X	A	A	A	B	B	B	C	C	C
Y	A	B	C	A	B	C	A	B	C
Diagnosis	d_1	d_1	–	d_1	d_h	d_h	–	d_2	d_2

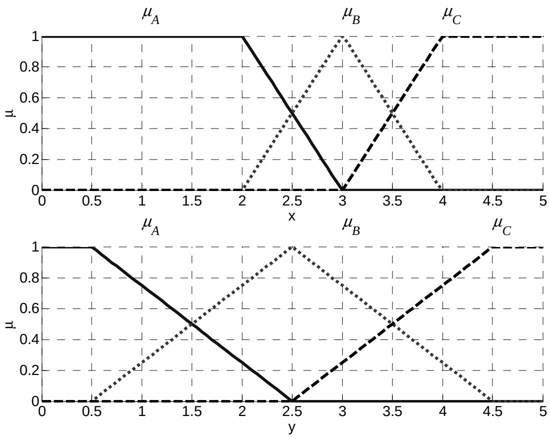

Fig. 6. Membership functions for linguistic values of rule premises.

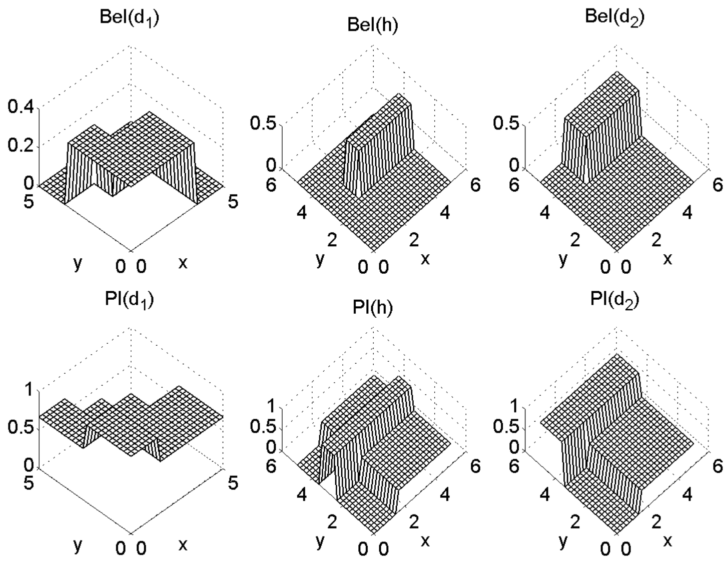

Fig. 7. Belief and plausibility values for $\{x_i,y_k\}$ changed with 0.05 step in the [0, 5] interval.

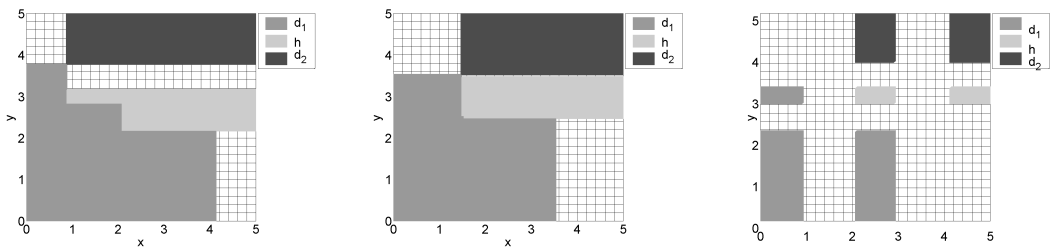

Fig. 8. Belief and plausibility values for $\{x_i,y_k\}$ changed with 0.05 step in the [0, 5] interval.

The BPA values for the rules are assumed equal for each rule in the diagnosis, so, $m_{d1}(R_{d1}^{(i)})$=1/3, i=1,2,3, $m_h(R_h^{(i)})$=1/2, i=1,2, $m_{d2}(R_{d2}^{(i)})$=1/2, i=1,2. Thus, an increase of the belief and plausibility values is not equal for each diagnosis if evidence confirms its premise. Yet, not the *Bel* and *Pl* values themselves make diagnosis, but their comparison for different diagnoses.

Now, let us test the knowledge base, i.e. rules and their BPAs, for various values of X and Y simulating patient's observations. The values make couples $\{x_i, y_k\} \in [0,5] \times [0,5]$, i, k=1,…,101. Although the *Bel* and *Pl* values are not easy to interpret (see Fig.7), results of *Bel* comparison make consistent diagnoses if the right threshold is chosen (Fig.8). The threshold value depends on membership functions and in this example the most appropriate value is T=0.5. If the threshold in too low (e.g. T=0.2 for the leftmost diagram in Fig.8) then diagnoses may faulty overlay each other or areas without the final diagnosis occur due to diagnoses conflict. If the threshold corresponds cross-points of membership functions then the diagnoses are the most appropriate (T=0.5 for the diagram in the center). If T is too high then areas of lack of diagnosis are large (T=0.8 in the rightmost diagram).

Thus, in this method, like in indices or probability-based approaches, the values of the BPA are summed up, but the introduction of the imprecision measure makes it possible to decide when a symptom influences the diagnosis. The threshold can be changed during diagnostic process and in this way unknown or not clear symptoms can be included in the diagnosis in a lack of better evidence. The comparison of the belief values correspond with hypotheses ordering in well-known expert systems. Calculations for databases confirmed good robustness of the method [32].

4.2. DISCUSSION

The proposed extension of the Dempster-Shafer theory and its use for medical diagnosis support combines probability and fuzzy approaches and makes it possible to represent knowledge and to perform inference in a manner that agrees with human intuition. Weights of diagnostic rules are represented by the BPA values, while fuzzy sets describe linguistic values of symptoms. The method follows suitable patterns of previous approaches to the diagnosis support. The sum of the BPA values is calculated to obtain belief values, which is similar to solutions used in described probability-based support tools. Premises are formulated correspondingly to fuzzy rules. Simultaneously, the proposed method introduces improvements. The belief and plausibility measures represent uncertainty whereas levels of matching symptoms and observations evaluates imprecision of the diagnosis. Hence, both certainty and precision of the diagnosis is considered at the same time. The opportunity to use imprecision measure to represent symptoms is very convenient if linguistic variables or visual analog scale have to be used. Thus, advantages of the fuzzy approach are preserved and drawbacks of fuzzy conclusion aggregation are avoided. Calculations are simple and a human user in not forced to interpret directly the belief or plausibility values. The method is easy to explain for a medical user, which is very important, since physicians are very cautious about diagnoses obtained from 'black-boxes'. It makes opportunity to use any kind of evidence if more reliable examinations cannot be performed, but maintains information about the low precision of inference. Furthermore, any kind of evidence, crisp or fuzzy can be used.

By means of the proposed method it is also possible to combine basic probability assignments determined for various populations or by experts. The method is extensively presented and results of numerous tests are provided in [32].

5. CONCLUSIONS

This study presents several approaches to determining measures of uncertainty or imprecision that have been practically implemented and proved useful in practice. Achievements of these solutions should be appreciated, but disadvantages should be kept in mind in case of new implementations. It is worth to search for new methods of uncertainty and imprecision representations using experience of the previous diagnosis support tools.

Medical knowledge is changing rapidly so a diagnosis support system should be easy to update and cannot use built-in values of certainty factors because a small change in laboratory procedure or a different interpretation of examination results must be possible to include immediately in such a system. The system should be also user-friendly and work according to intuitively clear and understandable principles.

The diagnosis support system should be designed for a very well-determined domain with consistent knowledge. A rule-based system seems to be the most convenient framework. However, it is probably impossible to cover a wide scope of medical problems, for instance the whole knowledge about internal diseases, by one set of rules and use only certainty factors to select rules suitable for a consultation. The rules have to be organized in some subsets which frequently are called contexts. Human experts often subconsciously use the context when they see a patient - sex, appearance, habits and environment influence the diagnosis. These subsets are not disjunctive and symptoms included in rules are not independent, so the classical probability axioms will be always violated in attempts of conditional probability use in diagnosis support. Simply, the necessary conditional probabilities cannot be obtained in the lack of training data. On the other hand, subjective probabilities can be used in theories avoiding classical probability limitations, like the Dempster-Shafer theory of evidence. Thus, such theories should be explored for new implementations.

It is inevitable to use both uncertainty and imprecision measures in medical inference. Imprecision is typical for representation of human knowledge which is always a part of medical knowledge bases. It can be modeled by fuzzy sets, still designing of their membership functions is not a trivial task. Fuzzy sets may need corrections if they are used to evaluate results of slightly different medical procedures or they are used in diagnosis support for various populations. Modifications are also advantageous for basic probability assignments. Hence, uncertainty measures that are assigned to the rules and imprecision measures corresponding rule premises should be calculated for a database. Therefore, it is beneficial to implement diagnosis support systems in a hospital information system and update the measures by population characteristics. The proposed method of diagnosis support that uses the extended Dempster-Shafer theory creates such an opportunity. Rules can be formulated and afterwards provided with appropriate values of the basic probability assignment and membership functions can be found for a database during training. If some rules are not applicable for selected populations, they are automatically pruned out by the zero values of the probability assignment. It is easy to introduce a new symptom and calculations are clear and effortless. It is possible to include both statistical information and heuristic knowledge and combine them into the common basic probability assignment. Fuzzy evidence can be input during inference. A threshold of imprecision can be assumed, so less relevant symptoms can be considered if the most reliable observations do not allow for elaborating a diagnosis. Therefore, the proposed method may solve some important problems of the diagnosis support

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