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# Volume II: Applications


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# A choice of uncertainty and imprecision representation for diagnostic reasoning

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**Abstract**

Measures of confidence successfully implemented in selected medical diagnosis support tools are analyzed in this study. Reasons that limit their wide use in other problems of the diagnosis support are discussed. The analysis and the discussion lead to a representation of confidence as a combination of uncertainty of the diagnosis and imprecisions of symptoms. A method of a determination of certainty and imprecision measures in the framework of the Dempster–Shafer theory and fuzzy sets is suggested. Its particular properties that make it suitable for the primary diagnosis are shown on an example. Conclusions on a choice of uncertainty and imprecision representation are driven.

**Keywords:** uncertainty, imprecision, probability, Dempster–Shafer theory, fuzzy sets

## 1 Introduction

Decades have passed since first expert systems were introduced into a medical practice. Yet, several problems of diagnosis support remain unsolved. These problems become even more essential nowadays, when medical knowledge extends so rapidly that it is hardly possible for a physician to follow this progress being simultaneously an active practitioner. A comparison of methods and an analysis of implementation experiences [37] show that one of the crucial matters in the diagnosis support is the proper knowledge representation. Representation methods differ depending on the aim of the diagnosis: algorithms that are used to process or to analyze signals obtained from a patient are not necessary efficient in case of estimation of patient's subjective feelings or symptoms observed dur– ing a primary examination. The present work concerns the two latter elements of the diagnosis and focuses on confidence measures. An estimation of diagnosis confidence is difficult because medical databases gather incomplete information about numerous symptoms. In the present paper features of several methods of medical knowledge representation, with a special focus on certainty modeling, are discussed. An original approach to the latter problem is next proposed. Finally, conclusions on suitable representations of certainty and imprecision are provided.

## 2 Representation of diagnostic rules

The problem of representation of heuristic rules that are formulated by diagnosti– cians appears in all diagnosis support fields, but it is crucial in case of modeling reasoning about symptoms from an interview with a patient and a primary ex– amination. An analysis of these symptoms often decide of the right direction of further investigations, so it is crucial for patient's health. Thus, rules concerning these symptoms deserve special attention.

The first difficulty consists in a representation of uncertain relations among symp– toms and diseases. The same symptoms may occur with different diseases and one disease may have various manifestations. The second problem that needs so– lution is the imprecision that characterize symptoms. Patient's answers during an interview are often ambiguous. Primary investigation findings are usually lin– guistically formulated. Laboratory tests results are judged in relation to norms depending on a laboratory unit. Thus, imprecision of symptoms is an inevitable element of this stage of diagnosis. Therefore, two measures, i.e. imprecision and uncertainty, should be considered in the diagnosis.

However, many researchers do not make such a differentiation and regard preci– sion and certainty as a unique concept. Even though, all diagnosis support tools deal with the one or another measure. The certainty is usually considered as prob– ability, belief or plausibility, while imprecision is often modeled by fuzzy sets. Let us discuss different approaches to uncertainty and imprecision representation.

## 2.1 Uncertainty of a diagnostic rule

Let us consider uncertainty of a diagnostic rule as an evaluation of strength of a symptom–diagnosis link. The simplest way to express this strength is to assign a weight to the 'IF symptom THEN diagnosis' rule. It should be possible to aggregate weights of rules in such a way that the diagnosis certainty increases along with its confirmation by consecutive symptoms. If new evidence denies the diagnosis, twofold approaches are possible. Firstly, the certainty of the diagnosis may decrease, secondly, the certainty of a competing diagnosis may increase. The latter solution is closer to properties of aggregation operators defined for arguments in the $[0, 1]$ interval. The properties are: continuity, neutrality (commutativity), monotonicity, associativity and idempotency [22]. Since the weight of a single rule is often defined in this interval, the aggregation operators seem to fit exactly the process of updating certainty of the diagnosis during a consultation session. A variety of the operators should make it possible to choose one that is adequate for an implementation. Yet, counterexamples show that the aggregation may differ from human reasoning.

A weight of the IF–THEN diagnostic rule can be considered as conditional probability of disease given symptoms. This method known as the Bayesian approach is important in early medical diagnosis support [24]. Unfortunately, the diagnostic rule is usually formulated in the form 'IF symptom(s) THEN disease', while conditional probability illustrates dependence of symptom(s) on the disease. This inversion of the conclusion and the premise complicates a calculation of disease probability by means of the Bayes formula. This formula is used in the diagnosis support as follows [16], [17]:

$$P(D|\,S) = \frac{P(S|\,D)P(D)}{P(S|\,D)P(D) + P(S|\,ND)P(ND)}, \qquad (1)$$

where $D$ denotes a disease, $ND$ the absence of the disease, thus $P(D) + P(ND) = 1$, and $S$ is either a single or a set of symptoms. Several probability values are required to calculate the $P(D|\,S)$. They are:

- $P(D)$ – a priori probability of the disease – relatively easy to obtain since a frequency of disease occurrence in a population is often known.
- $P(S|\,D)$ – determined on the basis of examinations done in hospitals or outpatient clinics for patients with the confirmed $D$ disease. Still, the patients may simultaneously suffer from other diseases.
- $P(S|\,ND)$ – often found for a 'control group' including patients who undergo therapy for diseases different than $D$. Yet, such patients are not healthy.

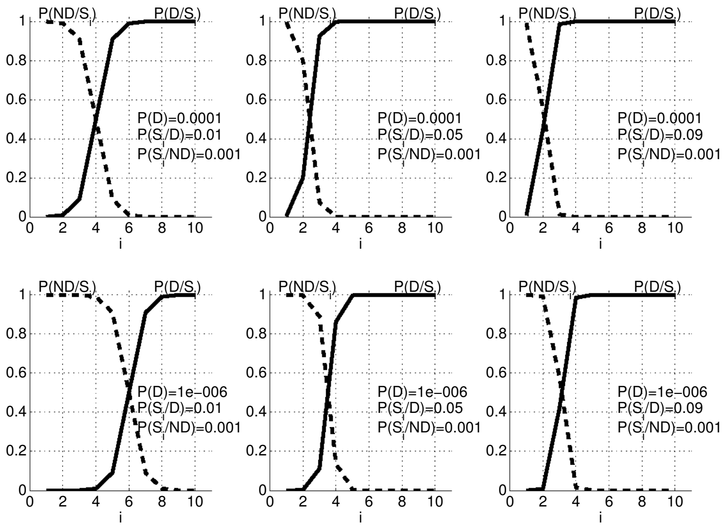


Figure 1: Values of $P(D|S)$ and $P(ND|S)$ depending on number of considered symptoms

The above mentioned circumstances of a determination of a priori and con– ditional probabilities indicate that results of $P(D|S)$ calculations may be faulty. Moreover, as $S$ in (1) is either a single symptom or a set of symptoms, $P(S|D)$ and $P(S|ND)$ probabilities should be determined individually for each possible subset of symptoms. It is practically unfeasible. Therefore, the diagnosis support based on the Bayes' formula (1) often ignores dependence of symptoms. Further– more, this formula should be re–calculated whenever a new symptom is observed, which increases the number of computations. Thus, implementations avoid it us– ing methods that are close to the original Bayes formula, e.g. Bayesian networks [28], [29]) or use the formula in rather a flexible manner, ignoring some math– ematical constraints. It is also questionable if we should aim at using classical probability in reasoning by means of heuristic rules while human thinking does not follow exactly the classical probability principles [24]. Thus, a flexible way of probability use should not be the only reason to criticize the methods. For instance in Iliad expert system Bayes formula is modified as follows [16]:

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

In formula (2) a posteriori probability of the disease calculated for the $i-th$ symp–tom becomes a priori probability of the disease when the $(i+1)-th$ symptom appears. This formula seems to be convenient for calculations, but it is awkward in case of simultaneous consideration of many symptoms because a posteriori prob–ability value approaches 1 for few symptoms. Hence, from the point of view of a human diagnostician succeeding symptoms have little influence on the diagnosis evaluation [34]. In Fig.1 values of $P(\,D|\,S)$ and $P(\,ND|\,S)$ probabilities obtained for three $P(\,S|\,D)$ values are presented. The $P(D)$ stands for the starting a priori probability of the disease and $P(\,S_i|\,D)$ is the same for each symptom. Calcula–tions follow formula (2) for $i = 1, \ldots, 10$. Significant changes of $P(\,D|\,S)$ are observed at most for 6 symptoms for the small value of $P(\,S_i|\,D) = 0.01$ and $P(D) = 0.0001$ (the first row, leftmost diagram). Results for greater $P(\,S_i|\,D)$ are even worse. Outcomes are not much better if $P(D)$ decreases (the second row). For the very low value of $P(D) = 10^{-6}$ a differentiation of the disease probability values is not clear already for 10 symptoms, while the Crooks index [13], a guideline for primary diagnosis of hyperthyroidism, includes 25 symp–toms. Thus, this approach is not valid for a great number of symptoms. This problem was noticed by the expert system creators, while in this system as well as in INTERNIST [2], and other expert systems [17] a facility was introduced that allows for differential diagnosis. In this kind of the diagnosis hypotheses are sorted according to their probability. It is noticeable that in INTERNIST positive and negative score of hypotheses are possible and in CASNET additional score of hypotheses is added depending on the number of symptoms that they cover [27]. Thus, diagnosis support systems rather use probability measures based on classi–cal probability than strictly this probability. Another example of such an approach is the certainty factor in MYCIN. MYCIN [31] is perhaps the most successful medical expert system with well defined and relatively narrow domain of exper–tise [6] as well as mechanisms like contexts and backward chaining that make its reasoning clear, consistent and effective. Its knowledge base includes rules of the following form [31]:

$$\begin{aligned} \text{IF } 1)&\ \text{The stain of the organism is gramneg, and} \\ 2)&\ \text{The morphology of the organism is rod, and} \\ 3)&\ \text{The aerobicity of the organism is aerobic} \\ \text{THEN}&\ \text{There is strongly suggestive evidence } (.8) \\ &\ \text{that the class of the organism is enterobacteriae}. \end{aligned} \tag{3}$$

The conclusion of this rule is related to the premise with the strength that is rep–resented by the linguistic certainty factor 'There is strongly suggestive evidence' which is evaluated by the number $0.8$. It is worth to notice that this rule is abduc–tive, i.e. the above mentioned inversion of the conclusion and the premise role in comparison to cause–effect link is observed. Thus, if the certainty factor is defined in terms of probability, it cannot be estimated just as a frequency of occurrence of the conclusion, given the premise. Indeed, in MYCIN the certainty factor, denoted as $CF$, is calculated in a sophisticated manner [4]:

$$CF(h,e) = \begin{cases} 1 & P(h) = 1, \\ \frac{P(h/e)-P(h)}{1-P(h)} & P(h/e) > P(h), \\ 0 & P(h|e) = P(h), \\ \frac{P(h)-P(h/e)}{P(h)} & P(h/e) < P(h), \\ -1 & P(h) = 0, \end{cases} \tag{4}$$

where $h$ denotes a hypothesis, $e$ – evidence and $CF \in [-1,1]$. If evidence does not carry information (i.e. $P(h|e) = P(h)$) the certainty factor is equal to zero, if it denies a hypothesis ($P(h/e) < P(h)$) it is negative. This may indicate that the $[0,1]$ interval of classical probability values is insufficient to represent a diag–nostic conclusion. This approach can be compared with the idea of the medical index with positive and negative weights [13]. Still, even MYCIN's certainty fac–tor is not free from inconsistency. In Fig.2 plots of $CF$s as functions of $P(h|e)$ for different $P(h)$ values are presented. Let us assume that we evaluate two hy–potheses with the same conditional probability: $P(h_1|e_1) = P(h_2|e_2)$ and with different a priori probabilities, e.g. $P(h_1) = 0.2$ and $P(h_2) = 0.7$. In the diagram we see that $CF(h_1, e_1) > CF(h_2, e_2)$, which disagrees with our intuition. This inconsistency was shown and criticized by several researchers [6], [17]. Reliable reasoning by means of the $CF$ is possible only if values of a priori probability of competing hypotheses are equal. However, in medicine a priori probability of a disease is usually smaller than probability of health. As the result the disease risk can be exaggerated. Certainly, considering a disease in priority to health is safer,

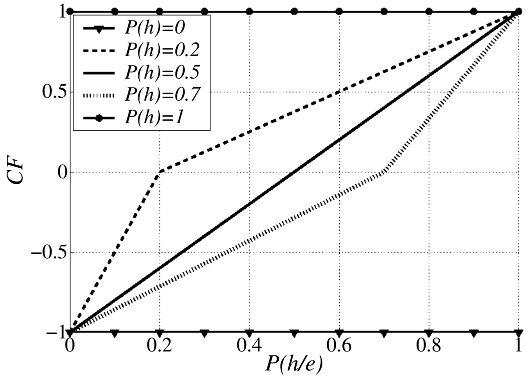


Figure 2: Values of the $CF$ for various $P(h|e)$ to $P(h)$ values relations.

but it does not justify an inaccuracy of the $CF$ definition. The definition also in–volves complex computations, particularly for chain of rules [4]. Thus, although the $CF$ works good in MYCIN, it cannot be advised for other applications.
In cases when data sets are insufficient to estimate probability values necessary for calculations two solutions are possible. The first is to use subjective probabilities [11] given by experts [17]. However, these probability values strictly concern a chosen diagnostic task, hence they have to be acquired with knowledge rules and hardly express population trends. They also depend on an expert [7]. Therefore a diagnosis support system cannot be transferred into different diagnostic condi–tions. The second idea is to use certainty representation that is close to human evaluation and to support heuristics by available training data. This is possible in the fuzzy set theory [40]. Fuzzy sets are used to represent medical knowledge almost from the beginning of the theory. Their use solves many problems of di–agnosis support. The CADIAG expert system [1], [21] is an example of their successful use. In this system knowledge is represented by following rules [17]:

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

where $O$ denotes occurrence, $C$ –confirmation, $\lambda$ –linguistic values and $\mu$ –nu–merical values. The rule includes linguistic values: 'elevated', 'often', 'strong' which have fuzzy representations. However, conclusion of this rule is crisp ('pan–creatic cancer'), which is typical for diagnosis and so it cannot be concerned a classical fuzzy rule. For this reason it is hardly applicable in a classical fuzzy in–ference performed by means of the compositional rule of inference or using fuzzy

implication [22]. In this case the inference must base on imprecision of premises usually represented by minimum membership of their conditions, which can be observed in CADIAG and other applications [26], [38].
Formulation of fuzzy rules and designing membership functions allow for an easier combining of information from knowledge and data than the probability calculation. Still, rules are again abductive which sometimes results in ambiguous conclusions. The conclusions are more accurate when evidence better fits a rule premise. Thus, often thresholds are used to eliminate rules which premises are not enough precisely confirmed. Even though, the inference is not easy because individual conclusions finally have to be aggregated. The maximum is the worst aggregation operator as it admits a priority of the conclusion with the greatest membership. A choice of the right aggregation operator is difficult and application–oriented, but it is crucial for robustness. Although we can choose among many operators which properties are described in a number of papers (e.g. [30], [10]), the selected model of reasoning is usually suitable for only one diagnostic problem [34].

## 2.2 Representation of symptom imprecision

Besides uncertainty of the link from symptoms to diagnosis, the symptoms themselves can be expressed with some imprecision. For instance, the symptom 'fever' more precisely describes a patient with 39°C than the patient with 37°C. Laboratory tests concern strict norms, still their results are interpreted by in linguistic categories [15]. A representation of imprecision is even more important for symptoms that are difficult to evaluate, for instance pain [14]. Not only knowledge, but also evidence may be imprecise [12], [19], [25]. The fuzzy set theory is convenient for the representation of such imprecision. A symptom is defined by means of its membership function. For instance, the body temperature is a medical parameter and only if the membership function of the high body temperature is built we can talk about the fever. Thus, designing membership functions for symptoms become an important problem of diagnosis support [35]. A shape of the membership function does not need to be strictly determined [5], yet several requirements should be fulfilled. The following problems are essential:

- determination of a domain for which all membership functions of a chosen medical parameter will be defined
- deciding on the number of membership functions for the medical parameter
- determination of crucial points; these are usually values of the support in which the membership function has 0, 0.5 or 1 values, as well as points of

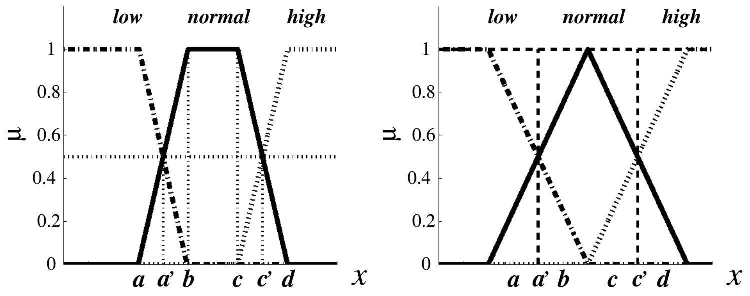


Figure 3: Construction of membership functions of symptoms

intersections with other functions.

The domain is usually a scale of parameter's values within limits of expected data. The limits are meaningless if membership functions are acquired from experts, but if they are determined from data then too wide domain may cause needless numerical burden. For instance in a fuzzy identification process [36] many superfluous functions can be built [32]. The number of membership functions is usually equal to the number of diagnostic hypotheses that concern the medical parameter. If we consider three diagnostic categories for thyroid gland diseases: hyperthyroidism, hypothyroidism and euthyroidism (health) then 3 membership functions will be sufficient to evaluate results e.g. of a laboratory test.

The number and place of crucial points of the membership function is a more complex problem. Let us consider trapezoidal functions as an example. For these functions usually four points are determined, which are denoted as $a$, $b$, $c$, $d$ for the 'normal' function in the left diagram of Fig.3. Adjacent functions do not always cross at the level of $0.5$ if the functions are designed by experts. When the crossing value is different for various functions, reasoning might be confusing since a final diagnosis can be obtained for different levels of precision depending on a symptom [34]. Thus, it might be suggested that the functions always cross at $0.5$, but their slopes are modified (see Fig.3 the right diagram) from triangles up to characteristic functions (dashed lines). In this way the functions can be tuned according to data. Simultaneously, the requirement of strict norms, which often is substantial for physicians, can be satisfied without resigning from the generality of fuzzy interpretation. The norms can determine the cross points and if a more flexible reasoning is required, test results for which membership is smaller than $0.5$ can be considered. In [34] it was shown that such an approach can be effective.

# 3 The Dempster-Shafer theory with fuzzy focal elements

From the analysis provided in the previous sections it may be concluded that we have to combine the measures of rule uncertainty and premise imprecision. The necessity of such a combination is noticed by many researchers, among others by [9], [23], [39]. The study [20] is particularly interesting as it concerns medicine, still it does touches on medical diagnosis. The combination is possible if we extend the Dempster–Shafer theory of evidence (DST) [3], [8], [18] for fuzzy focal elements [34]. Focal elements in the DST are predicates with an assigned information. They do not need to be independent. Thus, they can represent symptoms. The information is provided by means of the basic probability assignment (BPA) that is determined by two formulas [18]:

$$m(f) = 0, \sum_{s \in S} m(s) = 1. \tag{6}$$

In (6) $m$ denotes the BPA, $f$ is the false predicate and $S$ is the set of focal elements $s$. If $s$ are symptoms included in rule premises then $s = \{s_i\}$, $i = 1, \ldots, n_l$, where $n_l$ is the number of symptoms in the $l - th$ rule. We do not have to care if $s_i$ and $s_j$ are independent while determining $m(s)$. The BPA value may be the rule certainty measure. On the other hand, the predicate can employ fuzzy concepts, so membership functions may represent imprecision of symptoms. This idea of fuzzy focal elements in the DST is explained in [33], [34], [35]. In this approach membership functions of symptoms are data driven or are designed by experts. Next the BPA is calculated separately for each diagnostic hypothesis. Let us assume that the BPA is data–driven. Because it is calculated for fuzzy symptoms, it must be decided whether the symptoms are true or false. Therefore, in (6) a threshold for membership is introduced and finally [34]:

$$m(f) = 0, \sum_{\substack{s_i \in S, i=1,\ldots,n \\ \eta_i > \eta_{BPA}}} m(s_i) = 1. \tag{7}$$

where $\eta_{BPA}$ is the minimal level of precision for which a symptom is considered as carrying information and $\eta_i$ is the actual precision of a symptom found for training cases. When membership functions and BPAs for all diagnostic hypotheses are determined, the knowledge base is ready. Then belief and plausibility of the hypotheses can be calculated. The plausibility measure evaluates an amount of information [34], while the belief measure estimates confidence in the diagnosis. Let us concentrate on the latter. It is calculated as [34]:

$$Bel(d, \eta_T) = \sum_{\substack{s_i \in S \\ \eta_i > \eta_T}} m(s_i), \tag{8}$$

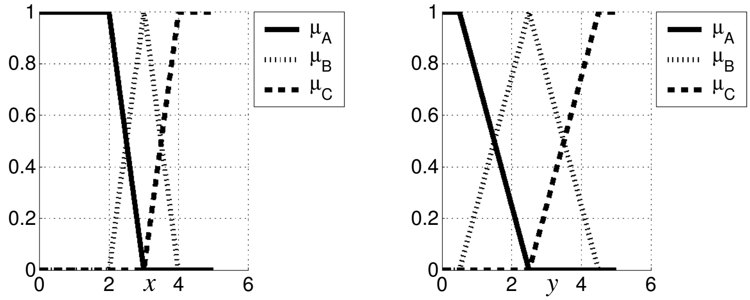


Figure 4: Membership functions for $X$ and $Y$ domains

where $d$ stands for the diagnosis and $\eta_T$ is the precision threshold of reasoning. For crisp patient observations $\delta^*_{x_i}$ and fuzzy symptoms $\mu_i(x_i)$ [34]:

$$\eta_i = \sup_{x \in \mathbf{X}} \left[\mu_i(x_i) \wedge \delta^*_{x_i}\right] = \mu_i\left(x^*_i\right). \tag{9}$$

Thus, the belief measure sums up weights of symptoms that fit patient's obser– vations at least with the $\eta_T$ precision. During the diagnosis no less than two hypotheses have to be differentiated since in medicine usually data are incom– plete, so belief in a hypothesis is rarely close to 1. All in all, both imprecision and uncertainty of knowledge and evidence are considered. Such a combination of probability and fuzziness may bring interesting results as it is shown in the following example.

### 3.1 Example

Let us use membership functions provided in Fig.4 to define rules of the form 'IF $A(x)$ and $B(y)$ THEN $d_1$' which are listed in Table 1. The table of rules is in– complete that often happens in medical diagnosis. Focal elements are premises of the rules, i.e. $s^{d1}_1 = \{A(x), A(y)\}$, $s^{d1}_2 = \{A(x), B(y)\}$ make the set of focal el– ements for the $d_1$ diagnosis: $S_{d1} = \left\{s^{d1}_1, s^{d1}_2\right\}$, for which the BPA is $m_{d1}(s^{d1}_1) = m_{d1}(s^{d1}_2) = \frac{1}{2}$. Similarly, $s^{dh}_1 = \{B(x), A(y)\}$, $s^{dh}_2 = \{B(x), B(y)\}$, $S_{dh} = \left\{s^{dh}_1, s^{dh}_2\right\}$, $m_{dh}(s^{dh}_1) = m_{dh}(s^{dh}_2) = \frac{1}{2}$; and $s^{d2}_1 = \{B(x), C(y)\}$, $s^{d2}_2 = \{C(x), B(y)\}$, $s^{d2}_3 = \{C(x), C(y)\}$, $S_{d2} = \left\{s^{d2}_1, s^{d2}_2, s^{d2}_3\right\}$, $m_{d2}(s^{d2}_1) = m_{d2}(s^{d2}_2) = m_{d2}(s^{d2}_3) = \frac{1}{3}$. Now, let us simulate a diagnosis for $x$ and $y$ symp– tom values generated in the $[0, 5]$ intervals with the 0.05 step. The $Bel(d_1, \eta_T)$, $Bel(d_h, \eta_T)$ and $Bel(d_2, \eta_T)$ are calculated and then compared. If one of the be– lief values is greater than the others, it indicates the final diagnosis, otherwise the

Table 1: Diagnostic rules

| | $A(y)$ | $B(y)$ | $C(y)$ |
|---|---|---|---|
| $A(x)$ | $d_1$ | $d_1$ | – |
| $B(x)$ | $d_h$ | $d_h$ | $d_2$ |
| $C(x)$ | – | $d_2$ | $d_2$ |

diagnosis cannot be stated. Simultaneously, let us repeat this experiment for fuzzy reasoning performed in such a way that a rule is fired when minimal membership of conditions in its premise exceeds the $\eta_T$ threshold. Diagnoses obtained in both manners are illustrated by diagrams in Fig.5.

In the left column diagnoses for the proposed extension of the DST are pre–sented, while the right column shows diagnoses for fuzzy reasoning. If the pre–cision threshold is $\eta_T \geq 0.5$, results of the both methods are almost identical. However, if symptoms are less precise, fuzzy reasoning extrapolate diagnoses, while the extended DTS do not provide diagnosis showing 'no decision' areas. This feature can be either advantage or deficiency of the proposed method. Nev–ertheless, it is an interesting property that helps to detect unreliable diagnoses. It is also possible to construct additional rules which can improve diagnosis in dubi–ous conditions. These rules will have a minor importance in clear cases. Anyway, for the proposed method an influence of an ignorance level on reasoning is ob–servable.

## 3.2 Discussion

The proposed method employs fuzzy sets as focal elements in the Dempster–Shafer theory. Fuzzy sets are useful for medical knowledge representation and the basic probability can express population characteristics by means of rule weights. Membership functions represent imprecision while the belief measure concerns uncertainty of the diagnosis. Moreover, ideas suitable in previous diagnosis sup–port approaches are applied in a modified and improved way in the suggested method. Values of belief measures are algebraic sums, similarly to classical prob–ability for independent symptoms. Yet, the sum is changed proportionally to the weights of rules, thus the growth of belief values does not decrease along with the number of consider symptoms. A dependence of symptoms does not need to be determined. Rule premises are formulated correspondingly to fuzzy rules and membership functions make it possible to represent linguistic values that are inevitable for medical diagnosis. However, disadvantages of an aggregation of fuzzy conclusions are avoided.

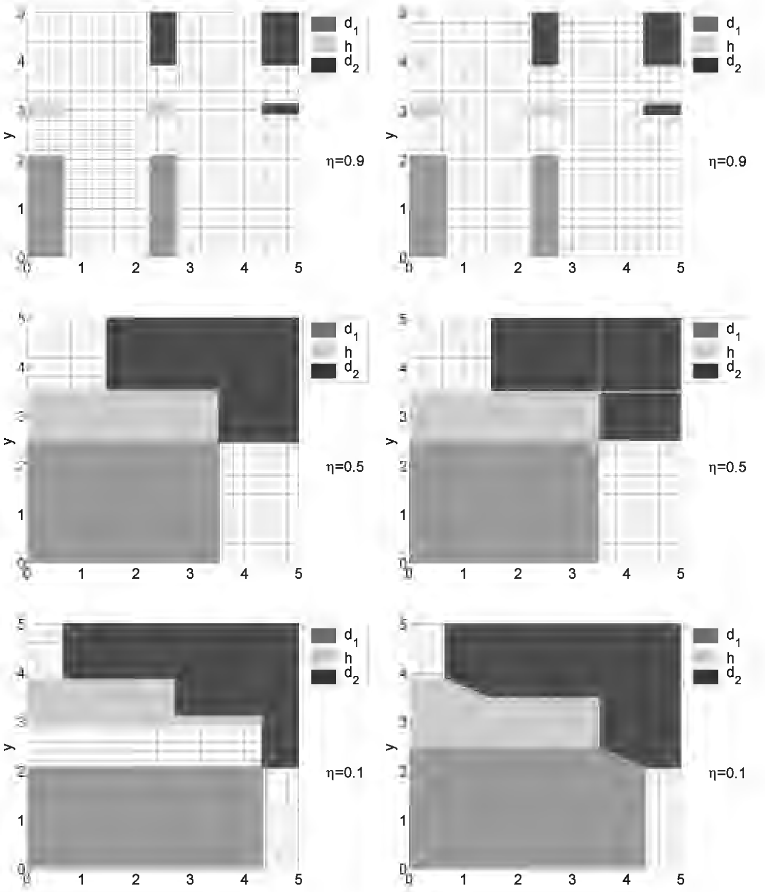


Figure 5: Comparison of diagnoses for the extended DST method (left) and a fuzzy reasoning (right) for different precision thresholds.

Reasoning in the medical diagnosis must often base on incomplete and confusing symptoms, so a determination of its ignorance level is necessary to evaluate its reliability. Diagnostic hypotheses may not be clearly differentiated. Therefore, a decisive diagnosis is risky and additional information showing actual changes of the hypotheses priority along with the change of the threshold would be important. In this way any kind of evidence may be used in reasoning in the lack of more reliable data, but information about the low precision of inference is always provided.
Revealing areas for which reasoning is less reliable creates an opportunity to complete knowledge or even to use different sets of rules in dubious diagnostic cases. Hence, it would be possible to relate knowledge, i.e. a choice of the rule set, to the level of ignorance, which could be equivalent to the change of contexts – the procedure works well in expert systems.
Membership functions as well as the BPA can be determined by means of training data and belief measures can be effortless calculated. Results of reasoning presented as beliefs in several hypotheses, are intuitively clear for a human user. The proposed method also make it possible to combine the basic probability assignments determined for various populations or by experts [35]. The Dempster–Shafer theory extended for fuzzy focal elements was tested for a number of benchmark databases. Results are described in details in [34], [35] and other publications of the author.

# 4 Conclusions

In the present paper several approaches to representation of uncertainty or imprecision are discussed. These ideas were implemented in diagnosis support tools which proved to be suitable in medical practice. However, they have also weak points. Examples that are provided in the present study show reasons why the approaches are not followed by other successful implementations. This review of the approaches aims at pointing out ways of their improvement and a suggestion of a new method that would benefit from previous experiences.
First of all, it should be noticed that a diagnosis support tool cannot exist without a representation of reasoning confidence. It is advisable to apply both representation of uncertainty and imprecision. In previous methods the representations are often combined into one measure, but these methods were used is diagnostic circumstances that admitted priority for one kind of confidence. For instance, in case of MYCIN, imprecision of laboratory tests is much less significant that uncertainty of rules. On the other hand, in CADIAG, in which many symptoms are described by their linguistic values, an imprecision measure is crucial for rea–

soning. Thus, the separate representations which yet are combined in reasoning should be used in a more universal approach.
Secondly, the discussed implementations operate on imprecision or certainty factors determined for specific diagnostic tasks and populations, which cannot be used in other diagnostic situations. Thus, objective methods of their determination, e.g. based on training data should be proposed. It would be also valuable to formulate principles of expert's knowledge representation. Moreover, medical knowledge is continuously updated, hence the proposed method should make it possible to change the rule set, modify membership function, as well as recalculate rules weights.
The proposed method based on the Dempster–Shafer theory and using fuzzy focal elements solves majority of the above mentioned problems. Uncertainty of diagnostic rules is evaluated by the basic probability assignment and imprecision of symptoms is represented by means of membership functions. During reasoning belief and plausibility of the diagnosis is determined. The final conclusion is found by a comparison of belief values for different hypotheses, or it is undetermined, if the maximum of belief occurs for several diagnoses. Simultaneously, the level of ignorance is assumed as the threshold membership above which symptoms are considered as precise enough to be considered in the diagnosis. In case of undetermined diagnosis this threshold can be changed or a set of diagnostic rules can be supplemented. Since the basic probability assignment can be determined for training data, rules that are irrelevant with the chosen population are eliminated by their low (or zero) weights. It is also possible that if the diagnosis is undetermined, another set of rules is used particularly prepared for dubious cases. In such a way this method approaches the idea of rules fired with a context that work well in previous applications.
The proposed algorithm of diagnosis support is user–friendly and intuitively clear for physicians, thus it should have good chances to be accepted in implementations. The general conclusion of the present study is that approaches that are successful in selected problems can be improved and it is beneficial to investigate them to find hints for a better representation of diagnosis confidence. It is also worth to search for new methods as diagnosis support will certainly remain a hot topic in future.

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The papers presented in this Volume 2 constitute a collection of contributions, both of a foundational and applied type, by both well-known experts and young researchers in various fields of broadly perceived intelligent systems.
It may be viewed as a result of fruitful discussions held during the Eleventh International Workshop on Intuitionistic Fuzzy Sets and Generalized Nets (IWIFSGN-2012) organized in Warsaw on October 12, 2012 by the Systems Research Institute, Polish Academy of Sciences, in Warsaw, Poland, Institute of Biophysics and Biomedical Engineering, Bulgarian Academy of Sciences in Sofia, Bulgaria, and WIT - Warsaw School of Information Technology in Warsaw, Poland, and co-organized by: the Matej Bel University, Banska Bystrica, Slovakia, Universidad Publica de Navarra, Pamplona, Spain, Universidade de Tras-Os-Montes e Alto Douro, Vila Real, Portugal, Prof. Asen Zlatarov University, Burgas, Bulgaria, and the University of Westminster, Harrow, UK:

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The consecutive International Workshops on Intuitionistic Fuzzy Sets and Generalized Nets (IWIFSGNs) have been meant to provide a forum for the presentation of new results and for scientific discussion on new developments in foundations and applications of intuitionistic fuzzy sets and generalized nets pioneered by Professor Krassimir T. Atanassov. Other topics related to broadly perceived representation and processing of uncertain and imprecise information and intelligent systems have also been included. The Eleventh International Workshop on Intuitionistic Fuzzy Sets and Generalized Nets (IWIFSGN-2012) is a continuation of this undertaking, and provides many new ideas and results in the areas concerned.

We hope that a collection of main contributions presented at the Workshop, completed with many papers by leading experts who have not been able to participate, will provide a source of much needed information on recent trends in the topics considered.

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