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DOI: 10.1016/S0950-7051(01)00123-X · Source: dx.doi.org

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Knowledge-Based Systems 15 (2002) 77–84
Knowledge-Based SYSTEMS
www.elsevier.com/locate/knosys

A framework for intelligent medical diagnosis using the theory of evidence

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Abstract

In designing fuzzy logic systems for fault diagnosis, problems can be encountered in the choice of symptoms to use fuzzy operators and an inability to convey the reliability of the diagnosis using just one degree of membership for the conclusion. By turning to an evidential framework, these problems can be resolved whilst still preserving a fuzzy relational model structure. The theory of evidence allows for utilisation of all available information. Relationships between sources of evidence determine appropriate combination rules. By generating belief and plausibility measures it also communicates the reliability of the diagnosis, and completeness of information. In this contribution medical diagnosis is considered using the theory of evidence, in particular the diagnosis of inadequate analgesia is considered. © 2002 Elsevier Science B.V. All rights reserved.

Keywords: Evidence-based reasoning; Medical diagnosis; Treatment of incomplete information

1. Introduction

Fault detection and diagnosis (FDD) can proceed on a number of bases, both analytical and knowledge-based [1]. Generally, fault detection via inference rules is suitable for applications with any or all of the following characteristics:

- there is little numerical data available;
- human experts can adequately express domain-specific knowledge in the form of rules;
- the ability to represent knowledge analytically is deficient;
- the system is required only to reason within a predefined context.

Rule-based FDD is particularly suitable where an expert system is designed to mimic a human operator. In complex processes, rule-based reasoning may be the most practical (or easily implemented) form of FDD. However, for such a system to operate well, it is necessary that the antecedent parts of rules capture the meaning intended by the rule. For rules derived in linguistic form, one common representation of this knowledge is fuzzy logic.

Three deficiencies have been identified in fuzzy logic when it is used in certain FDD applications. These are related to the

- uncertainty as to which symptoms should be used in antecedent expressions;
- inability to convey (reliability) information (that indicates the uncertainty of the diagnosis) [2];
- specification of fuzzy operators [3].

The first two points may be partially addressed by using a relational fuzzy model in which alternative rules map the same diagnosis. In this way different combinations of symptoms (including 'redundant information') can be used to form diagnoses. The weights in the relation matrix can then be used to limit the conclusion (fault existence) to less than some measure of reliability.

The CADIAG-2 system [4] developed for medical diagnosis uses multiple fuzzy relations to hold information related to the certainty and reliability of diagnoses. These relations may be found by equating weights with linguistic terms such as *always* and *often*. The system copes with unspecified relations by assigning a nominal weight of 0.5.

This paper proposes that the problems encountered while

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PII: S0950-7051(01)00123-X

using fuzzy logic for FDD can be addressed by a more rigorous treatment of information. That is, the choice of symptoms on which to base diagnoses is a question of the amount of information they provide. Reliability is related to the characteristics of the sources of the information. Likewise, combination operators should be determined by the relationships between the sources of information. In order to provide appropriate axioms, we have turned to the mathematical theory of evidence [5].

In general, the use of evidence-based reasoning for diagnosis is not a new idea. Belief measures can be considered a development on certainty factors (as used in MYCIN [6]) which have since been shown to be inconsistent [7] in that their axiomatic properties do not correlate with real-world phenomena. Other applications that use theories of evidence of various types also exist. However, belief and plausibility methods for FDD in engineering circles have almost always been rejected in favour of fuzzy logic techniques because they are much easier to apply. A closely related use of belief measures is given by Smets [8] who acknowledges that information necessary for diagnoses may be unavailable. However, Smets uses an adaptation of Bayes' rule for determining the degree of belief in a diagnosis, precluding any analogy with linguistic or relational fuzzy models. Kuncheva [9] addresses the idea of having supporting and contradicting evidence as determinants of belief but proposes a neural network based approach for reasoning.

Dexter [10,11] also draws upon evidence theory. In this work, the belief and plausibility of a diagnosis are calculated using fuzzy similarity relations between the antecedent expressions of fuzzy rules. Although this provides information as to ambiguity in diagnoses, it does not address the indicated deficiencies in fuzzy logic.

This paper considers the use of the theory of evidence for FDD, especially for use in medical diagnosis. Two main issues are addressed for the use of evidential reasoning in this environment, namely the:

- treatment of incomplete evidence, and
- combination of evidence.

An example shows how the framework can be applied for the possible diagnosis of inadequate analgesia (involuntary physiological responses to painful stimuli) during anaesthesia. A number of rules are used to examine different possibilities, highlighting the capabilities of the theory of evidence framework.

2. Deficiencies in fuzzy logic for FDD

A fuzzy logic knowledge base can take many forms. Common fuzzy models include the linguistic and relational forms. The linguistic (or Mamdani) model uses rules such as

If x Is A Then D

where A is an n-dimensional fuzzy relation and D is (usually) a one-dimensional fuzzy set. x is a crisp n-dimensional vector of observed data. A relational model can be viewed as a collection rules, each with the form

If x Is A Then D Through R

where R is an element of the relation matrix and limits the effect of the antecedent part on the diagnosis.

In an FDD application, D would represent the diagnosis that any fault existed, or a particular type of fault existed. It is convenient (or standard) therefore, to define D on the domain of 'fault existence'

$$y \in [0, 1]$$

where $y = 1$ corresponds to the fault existing, and $y = 0$ corresponds to the fault not existing. The question then arises as to what $y \in [0, 1]$ means. The obvious answer is that the fault partially exists but this is not particularly satisfactory because existence is basically a crisp concept. In fact, this is obvious if the defuzzification process is examined. There are a number of possibilities for this process. A reasonable design choice is to base defuzzification on the centre of gravity method, so that

$$y_0 = \frac{\int y\mu_C(y)\,\mathrm{d}y}{\int \mu_C(y)\,\mathrm{d}y}$$

where y_0 is the defuzzified conclusion giving the degree of fault existence, $\mu_C(\cdot)$ is the membership function of C, which is the conclusion of the diagnostic rule

$$\mu_C(y) = \min(\mu_D(y), \mu_A(x))$$

The use of the centre of gravity for defuzzification prevents $y_0 = 1$ unless D is a singleton at $y = 1$. That is, the diagnosis essentially has no fuzziness (it is crisp), only a membership degree. If D is indeed a normalised (unit height) singleton, then this membership is given by

$$y_0 = \mu_C(y) = \mu_A(x)$$

That is, the concluded fault existence is the degree to which the observed data matches the fuzzy relation A. From an FDD perspective there are two potential problems with this.

- There is no probabilistic or other consistent frame of reference that can be used to interpret y_0.
- No information regarding the reliability of the diagnosis is conveyed.

The first point is partly a result of the fact that fuzzy operators representing linguistic AND and OR, for instance, can be chosen quite arbitrarily. For example, fuzzy operators used for AND range from t-norms (such as the minimum membership of the operands) to the arithmetic mean. Valid results for 0.4 AND 0.6 range between 0 and 0.5. This kind of variability obviously does not help in interpreting inferred conclusions. Work has been done on determining the linguistic appropriateness of various fuzzy operators [3] but is perhaps not so applicable when a probabilistic interpretation is required.

A related problem is found in the construction of diagnostic rules. Human experts often provide such rules in linguistic form. However, expressions such as 'high AND not low' may dramatically affect the degree of fulfilment of an antecedent expression, depending on the definition of the fuzzy operator used for AND, and also the definition of the fuzzy set expressing the concept of 'not low'. In fact, the incorporation of seemingly redundant information is a major dilemma in designing fuzzy rules.

The second point concerns the lack of information regarding the reliability of a conclusion. For example, in a fuzzy inference statement

If t Is high AND x Is LONG Then y

where y is the degree of fulfilment of the antecedent expression, an unknown x effectively results in the rule

If t Is high Then y

and still $y \in [0, 1]$. In the extreme case, if no information is available then what should the conclusion be?

Of course, the issues described will not be perceived to be problems in all the FDD applications. However, there are domains, notably in medicine, where diagnosis is routinely performed in the absence of useful information. Even in classical FDD, there is the problem of obtaining additional data that will aid in the diagnosis after a fault has been detected.

3. Fuzzy measure theory

Evidence theory, also known as Dempster–Shafer theory [2] can be seen as a generalisation of possibility theory (as used in fuzzy set theory) and also statistical probability theory. It is concerned with bodies of evidence, which are assignments of weights to crisp events such as fault occurrence.

Given a domain X of possible events, a basic assignment m is a mapping

$$m : P(X) \to [0, 1]$$

where $P(X)$ is the power set (set of all subsets) of the domain. For any element $A \in P(X)$, the basic assignment $m(A)$ gives the amount of evidence that supports that event and no other. Basic assignments are required to follow the axioms:

$$m(\Phi) = 0$$

$$\sum_{A \in P(X)} m(A) = 1$$

The first of these states that evidence cannot exist that supports no element of the domain. This axiom can always be fulfilled if the domain is chosen carefully. The second constraint ensures normalisation of evidence. The pairs of basic assignments and the elements over which they are defined constitute a *body of evidence*. For a singleton event A, the body of evidence $\beta(A)$ can be defined by $m(A)$, $m(A^*)$ and $m(A \cup A^*)$.

A body of evidence can also be completely specified by two *fuzzy measures*, belief and plausibility, which are given by

$$\mathrm{Bel}(A) = \sum_{B \subseteq A} m(B)$$

$$\mathrm{Pl}(A) = \sum_{B \cap A \neq \Phi} m(B)$$

respectively. The set B is defined on the same domain as A. A fuzzy measure g is a mapping

$$g : P(X) \to [0, 1]$$

and is also required to follow certain axioms [12] including

$$g(\Phi) = 0; \qquad g(X) = 1$$

$$g(A) \le g(B) \forall A \subseteq B, \quad A, B \in P(X)$$

Belief can be interpreted as the total evidence directly supporting the event A. In the case of a singleton element

$$\mathrm{Bel}(A) = m(A)$$

Plausibility is the amount of evidence not contradicting the same conclusion, that is

$$\mathrm{Pl}(A) = 1 - \mathrm{Bel}(A^*)$$

In the case of a singleton element

$$\mathrm{Pl}(A) = m(A) + m(A \cup A^*)$$

In addition to this evidential interpretation, plausibility and belief may also be regarded as the upper and lower probabilities of an event [13]

$$\mathrm{Pl}(A) \ge p(A) \ge \mathrm{Bel}(A)$$

With complete information, the three measures converge. However, if information that is required for making a diagnosis is unreliable or missing then the difference between belief and plausibility increases. In the extreme case of perfect ignorance belief becomes zero and plausibility one.

3.1. Incomplete information

This concept can be embodied using completeness factors, which are also fuzzy measures defined as mappings from $P(X)$. The completeness of a diagnosis D for given symptoms A will be written as $\mathrm{Com}(D|A)$. The belief and plausibility of D for given bodies of evidence $\mathrm{Bel}(A)$ and $\mathrm{Pl}(A)$ may be calculated by

$$\mathrm{Bel}(D) = \mathrm{Bel}(A)\,\mathrm{Com}(D|A)$$

$$\mathrm{Pl}(D) = 1 - (1 - \mathrm{Pl}(A))\,\mathrm{Com}(D|A)$$

These equations assume that the completeness of D^* for given A^* is the same as that of D for given A. It will be seen

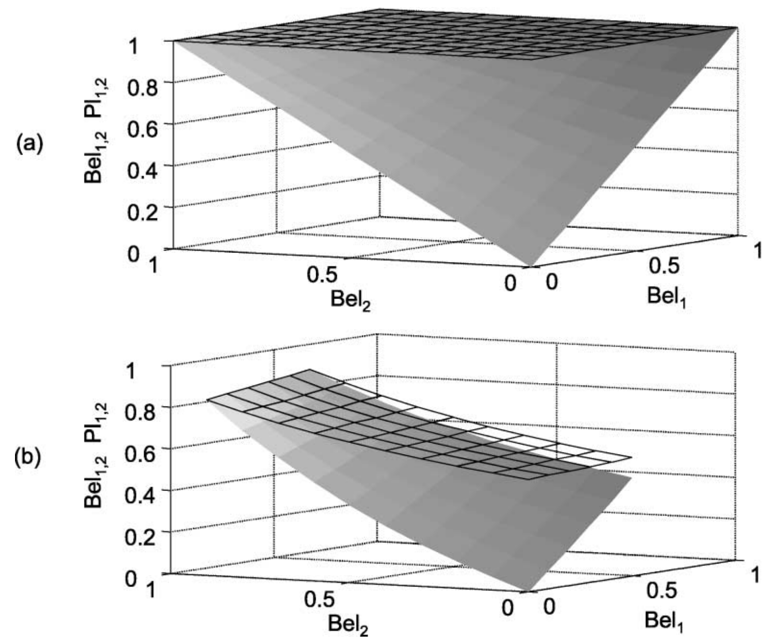

Fig. 1. Combination of evidence using Dempster's rule.

that the state of total ignorance about D, or perfect irrelevance or unreliability of A when diagnosing D corresponds to $\mathrm{Com}(D|A) = 0$, or $\mathrm{Com}(D|\emptyset) = 0$. Where all relevant information is available $\mathrm{Com}(D|A) = 1$ and basic assignments for the diagnosis are the same as for the symptoms. This interpretation of completeness allows evidential inference using an If…Then structure, as in

If A Then D Through $\mathrm{Com}(D|A)$

$$\beta(A) \Rightarrow_{\mathrm{Com}(D|A)} \beta(D|A)$$

where $\Rightarrow$ is an implication (inference) operator defined from one body of evidence to another, through relevant completeness. The diagnosis $\beta(D|A)$ will be known as a conditional diagnosis. This form of inference has obvious parallels with the relational and linguistic forms of fuzzy models. The difference is that antecedent and consequent parts are bodies of evidence, not fuzzy sets.

In the case of non-interactive sources of evidence it is apparent that weighting the individual symptoms is equivalent to weighting the rule. That is, given a weight w_A for a symptom A and a weight w_B for a symptom B the overall belief is given by

$$\mathrm{Bel}(D) = (w_A \mathrm{Bel}(A))(w_B \mathrm{Bel}(B)) = \mathrm{Bel}(A)\ \mathrm{Bel}(B)\ w_A w_B$$

In the context of completeness, the interpretation of this result could be that symptoms A and B are not totally relevant, and their combined degree of irrelevance can be treated as contributing to a completeness of less than either individually. That is

$$\mathrm{Com}(D|A, B) = w_A\ w_B$$

Of course, it is still necessary to find a means to compute the appropriate belief and plausibility for the given event.

4. Evidential inference

The general model of evidential inference proposed in this paper has its analogue in the relational fuzzy model. D is a diagnosis to be made and X represents the set of all relevant symptoms. Then the linguistic rules are given by

If A_j Then D Through $\mathrm{Com}(D|A_j)$

where $A_j \in P(X)$ and there are $j = 2n - 1$ rules with n being the number of elements in X (that is, j indexes all combinations of individual symptoms). The completeness factors $\mathrm{Com}(D|A_j)$ are assigned by human experts, or some other method.

The bodies of evidence for symptoms within the antecedent expressions A_j are effectively conjunctively combined. Linguistically, '*symptom*$_1$ AND *symptom*$_2$ AND…' must be present to make the diagnosis using that particular rule. In evidence theory, the appropriate conjunction operator is clearly indicated by the relationship between the sources of evidence. In practice, two relationships are commonly encountered — independence and non-interactivity.

Sources of evidence may be considered independent when they provide bodies of evidence for the same event or symptom but do not require the presence of another source. For example, two thermometers measuring the temperature of a patient are independent. Evidence so provided can be combined using Dempster's rule

$$m_{1,2}(A) = \frac{1}{1-K} \sum_{B \cap C = A} m_1(B)\, m_2(C)$$

$$K = \sum_{B \cap C = \Phi} m_1(B)\, m_2(C)$$

where A, B and C are sets of events defined on the same domain and the subscripts 1 and 2 denote the two sources of evidence. The effect of Dempster's rule in combining evidence for two cases is shown in Fig. 1. Part (a) shows the belief (surface) and plausibility (mesh) output for a range of beliefs from sources 1 and 2, with $\mathrm{Pl}_1 = \mathrm{Pl}_2 = 1$. Part (b) shows the same with $\mathrm{Pl}_1 = 0.6$ and $\mathrm{Pl}_2 = 0.9$.

In the case that sources provide evidence about different symptoms, for example temperature and blood pressure, they are said to be non-interactive. Assuming that non-interactive sources are also independent it can be shown that

$$\mathrm{Bel}(A \times B) = \mathrm{Bel}(A)\mathrm{Bel}(B)$$

$$\mathrm{Pl}(A \times B) = \mathrm{Pl}(A)\mathrm{Pl}(B)$$

where A and B are events on different domains for which bodies of evidence are provided, and $\times$ represents the Cartesian product (that, is A and B both occur). This result is analogous to that for independent probabilities.

So far, a method for calculating bodies of evidence for antecedent linguistic expressions has been presented. Completeness factors can be used to infer conditional diagnoses $\beta(D|A_j)$ that must be combined in some manner to arrive at an overall diagnosis $\beta(D)$. Essentially, the conditional belief and plausibility measures can be treated as estimates of the actual belief and plausibility. Their value as unbiased estimators will, however, depend on the statistical properties of the information on which they are based, and the process by which the completeness factors were determined. This depth of information will be assumed to be unavailable, as will usually be the case in applications for which evidence theory is chosen in preference to probability theory. Two general approaches are discussed for the determination of $\beta(D)$:

- Dempster's rule of combination;
- limiting functions based on belief and plausibility.

The use of Dempster's rule of combination for estimating the overall conclusion essentially treats each conditional conclusion as a separate, independent source of evidence. Given that these conditional conclusions have been derived on the basis of the same theory and using the same evidence, the assumption of independence (and therefore, Dempster's rule) seems somewhat inappropriate. However, it may also be argued that the degree of independence between conditional conclusions is analogous to that between human experts. Fundamentally, the difference between experts is the emphasis that they put on different aspects of the available evidence. This differentiation is realised by the use of completeness factors. The use of Dempster's rule has the additional property that conditional conclusions resulting from perfect ignorance are automatically ignored. That is, any pair $\mathrm{Bel}(D|A) = 0$, $\mathrm{Pl}(D|A) = 1$ has no effect on the combined evidence. Variations of Dempster's rule accounting for the reliability of sources (perhaps on the basis of the completeness of the evidence they exploit) can also be used. However, note that evidential disjunction operators such as that given by Oblow [14]

$$m_{1,2}(A) = \sum_{B \cup C = A} m_1(B)\, m_2(C)$$

are not suitable because they tend to focus on differences between bodies of evidence. That is, evidential disjunction assumes that either of the two bodies of evidence is correct. Dempster's rule, by contrast, assumes that both bodies of evidence are correct.

For example, given two fundamentally contradictory bodies of evidence with $\mathrm{Bel}_1(A) = 0.8$, $\mathrm{Pl}_1(A) = 0.9$, $\mathrm{Bel}_2(A) = 0.1$ and $\mathrm{Pl}_2(A) = 0.2$, combination using Dempster's rule gives $\mathrm{Bel}_{1,2}(A) = 0.49$, $\mathrm{Pl}_{1,2}(A) = 0.03$. That is, given that both sources are correct, then the overall belief and plausibility are a compromise between them. The actual meaning required is that one of the two sources is guaranteed correct (which is an exclusive OR). This may be attained to a certain extent by averaging the basic assignments, however, this in itself is a heuristic combination.

A more satisfactory solution is to use limiting rules of combination. For example, we may choose to use the maximum belief, and minimum plausibility corresponding to that belief

$$\mathrm{Bel}(D) = \max_{A \in P(X)} \mathrm{Bel}(D|A)$$

and then the minimum plausibility corresponding to that belief

$$\mathrm{Pl}(D) = \min_{A \in P(X), \mathrm{Bel}(D|A_j) = \mathrm{Bel}(D)} \mathrm{Pl}(D|A_j)$$

The interpretation of this approach is that we use the combination of symptoms that provides the most evidence for a given diagnosis, and then is the most complete of all competing, remaining diagnoses. This can be considered a disjunctive (linguistic OR) combination of the bodies of evidence.

A variation on this approach is to use the maximum belief and the minimum plausibility greater than or equal to that belief

$$\mathrm{Bel}(D) = \max_{A \in P(X)} \mathrm{Bel}(D|A)$$

$$\mathrm{Pl}(D) = \min_{A \in P(X), \mathrm{Pl}(D|A) \rangle \mathrm{Bel}(D)} \mathrm{Pl}(D|A)$$

In this case, the combination of symptoms is used to provide the most evidence for a diagnosis, and then the most evidence against that diagnosis while still ensuring that the plausibility is greater than the belief. Of course the opposite approach could also be taken — use the minimum plausibility and maximum belief less than this plausibility. However, this tends to assume that all symptoms are available and reliable.

Table 1
Bodies of evidence (belief, plausibility) for symptoms and diagnosis of inadequate analgesia

Case	iHR_1	iHR_2	iSys	dPV	niPV	IA	Rule
1	1, 1	1, 1	1, 1	1, 1	1, 1	1, 1	7
2	0.8, 1	0.8, 0.9	0.7, 0.8	0.7, 0.9	1, 1	0.54, 0.90	5
3	0.8, 1	0.8, 0.9	0.7, 0.8	0.3, 0.5	1, 1	0.54, 0.82	4
4	0.8, 1	0.8, 0.9	0.7, 0.8	0.3, 0.5	0.4, 0.6	0.23, 0.59	5
5	0.8, 1	0.8, 0.9	0.7, 0.8	0.3, 0.9	0.5, 1	0.27, 0.82	4
6	0.8, 1	0.8, 0.9	0, 1	0.7, 0.9	1, 1	0.54, 0.90	5
7	0.8, 1	0.8, 0.9	0, 1	0.3, 0.5	1, 1	0.29, 1.0	1
8	0.8, 1	0, 1	0.7, 0.8	0.7, 0.9	1, 1	0.45, 0.92	5
9	0.1, 0.3	0.8, 0.9	0.7, 0.8	0.7, 0.9	1, 1	0.34, 0.80	6
10	0.5, 0.5	0.5, 0.5	0.5, 0.5	0.5, 0.5	0.5, 0.5	0.2, 0.4	5

The evidential inference mechanism is now fully defined. If the deficiencies of fuzzy logic for FDD are addressed, it can be seen that using evidence based reasoning:

- The use of elements from $P(X)$ for creating antecedent expressions specifies whether a symptom should be included. If a symptom is not necessary, then this is accounted for by the assignment of zero completeness.
- Reliability information is conveyed by the difference between the plausibility and belief, which may be considered the upper and lower probabilities of a diagnosis.
- Operators for antecedent expressions are fully specified depending on the relationship between sources of evidence.

5. Diagnosis of inadequate analgesia

As a comprehensive example showing the use of the evidence-based framework, consider the diagnosis of inadequate analgesia (IA) for patients undergoing anaesthesia. IA results in involuntary physiological responses to painful stimuli. The list of symptoms includes increases in heart rate (iHR) and systolic blood pressure (iSys), and a decrease in pulse volume (iPV).

Estimates of the heart rate can be provided by at least two sources — the electrocardiogram, and the pulse oximeter. Strictly speaking, the pulse oximeter measures blood pressure impulses in the peripheral vessels, not the rate at which the heart beats. However the pulse rate can be considered an independent measure of the heart rate and an increase in pulse rate is therefore an additional symptom (iHR). The changes in pulse volume in particular can be masked to some degree by the use of vaso-constricting drugs, and so pulse volume cannot be required as a symptom for the diagnosis of IA. However, an increase in pulse volume would be a strong contra-indicator and this prompts the use of another symptom — non-increasing pulse volume (niPV). Regarding blood pressure measurements, the changes associated with IA may not be detected if non-invasive blood pressure (NIBP) measurements are being taken, via an inflatable cuff. This is because the changes in blood pressure associated with IA occur on a relatively short time scale. The usual NIBP sampling period of 2–5 min is far too infrequent to detect these changes.

The set of symptoms, iHR, iSys, dPV and niPV, are utilised to examine the use of evidence-based reasoning for the diagnosis of IA, where the following rules (where the conjunctive operator $\diamond$ represents independent, non-interactive evidence), with non-zero completeness are considered

$$\beta(\text{iHR})\diamond\beta(\text{niPV}) \Rightarrow_{\text{Com1}} \beta(\text{IA}|\text{iHR}, \text{niPV})$$

$$\beta(\text{iSys})\diamond\beta(\text{niPV}) \Rightarrow_{\text{Com2}} \beta(\text{IA}|\text{iSys}, \text{niPV})$$

$$\beta(\text{dPV}) \Rightarrow_{\text{Com3}} \beta(\text{IA}|\text{dPV})$$

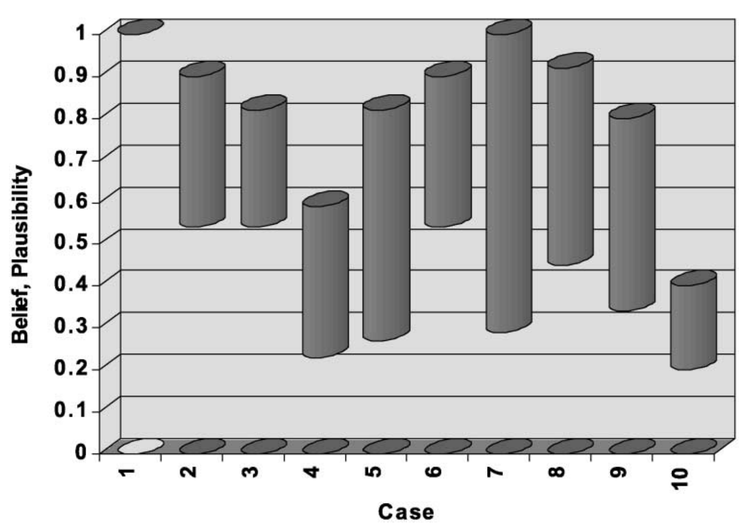

Fig. 2. The bars show the range between plausibility and belief for each of the cases.

$$\beta(\text{iHR})\diamond\beta(\text{iSys})\diamond\beta(\text{niPV}) \Rightarrow_{\text{Com4}} \beta(\text{IA}|\text{iHR, iSys, niPV})$$

$$\beta(\text{iHR})\diamond\beta(\text{dPV}) \Rightarrow_{\text{Com5}} \beta(\text{IA}|\text{iHR, dPV})$$

$$\beta(\text{iSys})\diamond\beta(\text{dPV}) \Rightarrow_{\text{Com6}} \beta(\text{IA}|\text{iSys, dPV})$$

$$\beta(\text{iHR})\diamond\beta(\text{iSys})\diamond\beta(\text{dPV}) \Rightarrow_{\text{Com7}} \beta(\text{IA}|\text{iHR, iSys, dPV})$$

The completeness factors Com$i$ given above (where i identifies the rule) can be assigned in accordance with the axioms on fuzzy measures

$$\text{Com1} = 0.3; \quad \text{Com2} = 0.2; \quad \text{Com3} = 0.1;$$

$$\text{Com4} = 0.8; \quad \text{Com5} = 0.8; \quad \text{Com6} = 0.7;$$

$$\text{Com7} = 1$$

The disjunctive combination rule used takes the maximum plausibility corresponding to the inference rule giving the highest belief. The rule is not conservative but is justified when the list of symptoms includes terms relating contra indicators (such as niPV in the inadequate analgesia example and in medicine diagnosis problems generally). Table 1 shows the diagnostic output for a number of antecedent conditions, 10 cases are examined. Two independant sources of heart rate are considered with the bodies of evidence for each being shown in Table 1. Dempster's rule is used to combine this evidence to provide the body of evidence for the symptom, iHR. Fig. 2 shows the range between plausibility and belief in the bodies of evidence for the diagnosis of IA.

Case 1. In the best circumstances, the belief and plausibility for all symptoms are one. The diagnosis of IA, as expected, has full belief and plausibility. The best explanation is provided by rule 7, which is the most specific.

Case 2. More usually, the belief and plausibility of symptoms are not one. However they are still fairly high and the diagnosis is still quite positive. The best explanation is now provided by rule 5, by virtue of the high completeness of the symptoms of increasing heart rate and pulse volume.

Case 3. If the pulse volume does not fall to the degree required by dPV, but does not increase, then the belief and plausibility do not change substantially. However, the active rule changes to 4, which uses systolic pressure but does not require a fall in pulse volume.

Case 4. In a situation where pulse volume does in fact rise there will be much less evidence for niPV. The resulting diagnosis in IA changes correspondingly.

Case 5. This case differs from case 2 by a significantly lower belief in both dPV and niPV. The plausibility, however, remains high. As expected, there is more evidence confirming IA than for case 4.

Case 6. In this example the use of NIBP measurements results in the absence of blood pressure information. It can be seen that there is no change in the diagnosis because the rule in effect does not require blood pressure information.

Case 7. In this case, blood pressure information is still unavailable and pulse volume is not falling to a great degree (as for case 3). The diagnosis is now based on rule 1 and it can be seen that the lack of information results in a lower belief and increased plausibility. Note that there is less contradictory evidence than for case 4.

Case 8. The two independent sources of heart rate information are useful if one becomes unavailable. When compared to case 2, the belief in IA has fallen slightly and plausibility has increased slightly but neither to the same extent as for case 7.

Case 9. Here both heart rate sensors are providing information but there is a large degree of conflict between them. The effect on the diagnosis (when compared to case 2) is to decrease both belief and plausibility. Of interest is that the rule in effect does not use heart rate in its antecedent part.

Case 10. Finally, as an example of the difference between fuzzy logic and evidence-based reasoning, all symptoms have equal degrees of supporting and contradicting evidence. However, the likelihood of relevant symptoms being simultaneously present is less than half and this is reflected in the diagnosis.

6. Discussion and conclusions

This paper has described a method of using evidential reasoning for diagnostic inference. The framework described has a clear analogue in fuzzy relational models, including the ability to be created from linguistic If…Then rules. However, the evidential basis provides more guidance regarding the choice of combination operators. Antecedent and consequent expressions evaluate to bodies of evidence rather than fuzzy sets. This allows communication of reliability information as well as providing a statistical interpretation for diagnostic conclusions.

Of course it is still necessary to generate the bodies of evidence for individual symptoms. For example, the degree of evidence supporting an event 'too hot' can be assigned using a possibility distribution (fuzzy membership function) defined on the domain of temperature. In general

$$\text{Bel}(A) = \mu_{\text{Bel}}(x)$$

where x is a crisp measured variable, $\mu_{\text{Bel}}(\cdot)$ defines a possibility distribution on the same domain as x and A is the event to be diagnosed [15].

Possibility distributions are a valid representation because evidence is consonant. In the example above, an increase in temperature cannot provide evidence against the diagnosis of 'too hot'. The use of possibility distributions for symptoms defined on multiple dimensions may be difficult because the required distribution must be specified accurately to avoid dissonance in evidence. If it cannot, then the unreliability will be better conveyed using the combination rules previously described.

It is necessary to ensure that possibility distributions result in valid bodies of evidence. If plausibility is also to be determined using a possibility distribution

$$\mathrm{Pl}(A) = \mu_{\mathrm{Pl}}(x)$$

then the required relation is that

$$\mu_{\mathrm{Pl}}(x) \geq \mu_{\mathrm{Bel}}(x)\ \forall x$$

The distinction between possibility distributions for plausibility and belief lies in their evidential interpretation — plausibility encompasses any supporting evidence; belief accounts for directly supporting evidence.

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