Uncertanity Handling in Knowledge Based System

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Abstract
The traditional goal in the field Artificial Intelligence (AI) is to develop computer based system that can exhibit intelligence. The true applications of AI are precisely the Knowledge Based Systems (KBS). These systems possess the knowledge at an expert level in a specific domain such as medicine, law, engineering, etc. One of the most important intelligent activity of human beings is decision making. The term uncertainty refers to " imprecise or insufficient knowledge". The most challenging part is making decisions based on this uncertain data. This brings out a special domain namely, uncertainty handling in KBS in the field of AI . In this paper we consider various methods of handling Uncertanity in Knowledge Based systems .The paper also presents a comparative study of Evidence Point mechanisms with Bayesian Theorem ,Dempster Shafer model and Fuzzy Logic.

Keywords
KBS,Uncertanity, Evidence point mechanisams

1. Introduction

AI is a branch of computer science that can create intelligent systems,Systems that learn new concepts and tasks, systems that can reason and draw useful conclusions about the world around us.
AI is generally associated with Computer Science, but it has many important links with other fields such as Mathematics, Psychology, Cognition, Biology and Philosophy, among many others.[16] Considered methods of reasoning under conditions of certain, complete, unchanging and consistent facts. It was implicitly assumed that a sufficient amount of reliable knowledge (facts, rules, and the like) was available with which to deduce confident conclusions. But strict classical logic formalisms do not provided realistic representations of the world in which we live. On the contrary, intelligent beings are continuously required to make decisions under a veil of uncertainty.
Uncertainty can arise from a variety of sources. For one thing, the information we have available may be incomplete or highly volatile. Important facts and details which have a bearing on the problems at hand may be missing or may change rapidly. In addition, may of the 'facts' available may be impressive, vague or fuzzy. Indeed some of the available information may be contradictory or even unbelievable. However, despite these shortcomings, we humans miraculously deal with uncertainties on a daily basis and arrive at reasonable solutions. If it were otherwise, we would not be able to cope with the continually changing situations of our world.

Sources of Uncertainty

1. Data: missing data, unreliable, ambiguous, imprecise representation, inconsistent, subjective, derived from defaults, etc.
2. Expert knowledge: inconsistency between different experts.
3. Plausibility: "best guess" of expert.
4. Knowledge Representation: restricted model of the real system, limited expressiveness of the representation mechanism.
5. Unsound Reasoning Methods.

Medicine is a field in which such help is critically needed. Our increasing expectations of the highest quality health care and rapid growth of ever more detailed medical knowledge leaves the physician without adequate time to devote to each case and struggles to keep up with the newest developments in his field.
Continued training and recertification procedures encourage the physician to keep more of the relevant information constantly in mind, but fundamental limitations of human memory and recall coupled with the growth of knowledge assure that most of what is known cannot be known by most individuals. Here is the opportunity for new computer tools to: help organize, store, and retrieve appropriate medical knowledge needed by the practitioner in dealing with each difficult case, and to suggest appropriate diagnostic, prognostic and therapeutic decisions and decision making techniques.
In most developing countries insufficiency of medical specialists has increased the mortality of patients suffering from various diseases. The insufficiency of medical specialists will not be overcome within a short period of time. The institutions of higher learning could however, take an immediate action to produce as many doctors as possible. However, while waiting for students to become doctors and doctors to become specialists many may suffer. Current practice for medical treatment required patients to consult specialists for further diagnosis and treatment.
Relying on the knowledge of human experts to build expert computer programs is actually helpful for several additional reasons: First, the decisions and recommendations of a

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program can be explained to its users and evaluators in terms which are familiar to the experts. Second, because we hope to duplicate the expertise of human specialists, we can measure the extent to which our goal is achieved by a direct comparison of the program's behavior to that of the experts. Finally, within the collaborative group of computer scientists and physicians engaged Artificial Intelligence in Medicine (AIM) research, basing the logic of the programs on human modules supports each of the three somewhat desperate goals that the researchers may hold.

Computer technology could be used to reduce the rate of mortality and reduce the waiting time to see the specialist. Computer program or software developed by emulating human intelligence could be used to assist the doctors in making decisions without consulting the specialist directly. The software was not meant to replace the specialist or doctor, yet it was developed to assist general practitioners and specialists in diagnosing and predicting patients' condition from certain rules or 'experience'. Patients with high-risk factors or symptoms or predicted to be highly affected with certain diseases or illness, could be short listed to see the specialist for further treatment. Employing the technology, especially Artificial Intelligence (AI) techniques in medical applications, could reduce the cost, time, human expertise and medical error.

2. Knowledge-Based Systems (KBS)

General purpose problem solvers which used a limited number of laws or axioms were too weak to be effective in solving problems of any complexity. This led to the design of what is now known as Knowledge-Based Systems, systems that depend on a rich base of knowledge to perform difficult tasks.

KBS is a computer system that is programmed to imitate human problem-solving by means of artificial intelligence and reference to a database of knowledge on a particular subject.

Knowledge-based systems are systems based on the methods and techniques of Artificial Intelligence. Their core components are the knowledge base and the inference mechanisms.

In general, knowledge elicited by a knowledge engineer in a knowledge-based system is often characterized by uncertainties, as the facts are beliefs and rules are the situation-action behavior of a human expert. When the knowledge engineer is unable to establish the truth of a proposition, he may have to resort to collecting evidences from multiple sources.

Handling of uncertainty is inextricably bound up with the development of knowledge-based systems. Knowledge-based systems (KBS) are complex software systems that aim to replicate human abilities of problem solving and decision making in uncertain environment. KBS have capability of capturing human knowledge from a variety of knowledge sources such as books, manuals and human experts. The knowledge often takes the form of facts (or valid propositions) and rules. In order to measure the degree of truth of these facts and rules, we must rely on the available evidence, which can be in support of or against them.

Evidence Point

If we have full (100%) positive evidence, without any (0%) negative evidence against a proposition P, then we call it as a true proposition. If it is the other way round we call it as a false proposition. A proposition is uncertain if it does not belong to either of these two categories. In essence, to each proposition P, we associate an ordered pair (α, β) call it as an evidence point (EP) of P, denoted by

$$EP(P) = (\alpha, \beta) \in [0, 1] \times [0, 1]$$

The quantity α represents the positive evidence in support of, and β represents the negative evidence, disagreeing with the same proposition P at the same time. The notion of an evidence space [0, 1] × [0, 1] is shown in Figure 01, as the collection of these evidence points. It is firmly assumed that the sources of information are highly reliable. With this concept the algebra of evidence points for pooling of evidence points comprising of logical connectives $\neg$, $\vee$, $\wedge$.

<u>Evidence: The very idea</u>

These days the main reason for not applying knowledge-based systems (KBS) in a business environment is the massive effort needed to build such a system, based on the available evidence. Knowledge acquisition is not a major problem to any frontline industry. The main difficulty lies in managing the uncertainty associated with the organizational development process. This uncertainty is mainly due to the available evidence (for and against) in the respective contexts. Let us consider the following situation:

Dr Sam has recently got his Ph.D. from an Institute and applies for job in a research establishment. He was supposed to produce three letters of reference supporting his candidature (preferably from three professors). He goes to three professors and procures these as the following:

1. X is the research supervisor of Dr Sam, enumerates some (say 70%) positive and some (say 30%) negative aspects about Sam gives an Evidence Point (EP) ass (0.7, 0.3).
2. Y taught one graduate course to Dr Sam as part of his research-training program. Dr Sam got a 'C' grade in the course. The EP given by Y is (0.5, 0.0).
3. Z attended Dr Sam's research seminar and Dr Sam had some discussion with Z. on the basis of this information Z gives the EP (0.6, 0.0).

With these available EPs given by X, Y and Z the knowledge engineer has to derive EP for the truth of the statement viz., Dr Sam is suitable for the research establishment.
The pooled evidence point can thus be realized (obtained) in several possible ways, such as:

1. By considering, the minimum value among the positive evidences and maximum value among the negative evidences, which gives (0.5, 0.3), or
2. By considering, individually the arithmetic mean of the positive and negative evidences, which gives (0.6, 0.1)

We represent the evidence as a point in an evidence space as shown in Figure 1. We refer the axes viz. $\beta = 0$ and $\alpha = 0$ as the Line of Confirmation and the Line of Negation, respectively. The line $\alpha + \beta = 1$ is called the Line of Demarcation. The diagonal $\alpha = \beta$ is called as the Line of Contradiction. Extreme points like (1, 1), (0, 0) represents respectively that of total contradiction and no information about the proposition. For a perfectly true proposition, we can thus associate an evidence point (1, 0) and (1, 0) that of for a perfectly false proposition.
Since these positive and negative evidences are supposed to be gathered from two independent sources of evidence, thereby their sum need not always be equal to 1. Consider another situation: If a political columnist A declares that there will be change of government in several Asian countries within the next six months, we have then some positive evidence for the proposition, P: There will be a change of government in several Asian countries within the next six months.

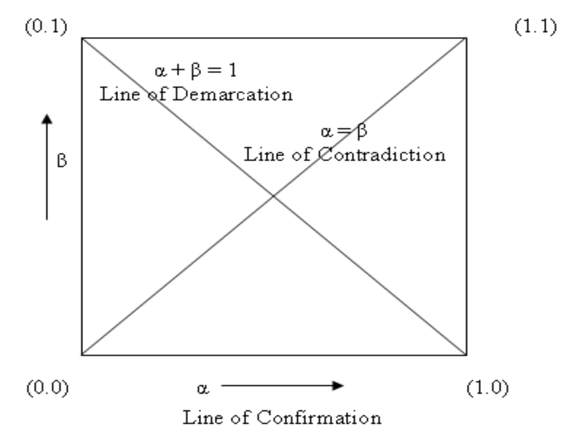

Fig. 01 Evidence Space

Let another political columnist contradict the above proposition, and then we can say that, we have some negative evidence for the same proposition (P). In between if someone asks me, whether there will be a change of government in several Asian countries with in the next six months, my answer (among several possible answers) will be as follows:
Initially, I got the evidence about the P to be (1,0) due to person A and later it got changed to (0,1) due to person B. As a result my decision about P became uncertain, which results:
There (*may be*) a change in government in several Asian countries within the next six months. The possible EP for this uncertain proposition could be ((1+0)(/2, (0+1)/2)=(0.5, 0.5).
Thus, in order to resolve a conflicting situation, my response will be an uncertain proposition, because of the availability of both positive and negative evidences for the same proposition at the same time. As a result this will not convey either the truth or falsity of the original proposition. Then how do we go for the degree of truth-value of such an uncertain proposition, based on its available evidence?
Thus, in reality, to resolve the conflicting situations, one has to resort on the *indicators of evidence* such as, IT MAY BE TRUE, IT MAY BE FALSE, IT IS MORE OR LESS TRUE (Rollinger 1983).
Rollinger found some transformation matrices for various evidence indicators. Dominance nature of the positive evidence over the negative evidence, or vice-versa in the resultant evidence point, helps us in resolving conflicting situations. Suppose we associate "n" evidence pairs (α_i, β_i) to "n" propositions P_i, i = 1,2,…,n. Then how do we go for determining the EPs for the compound propositions, arising from logical operations such as ¬, ᵛ, ∧**?** This motivated us to consider evidence point algebra as follows:
We consider the location of any EP (α, β) in evidence space at three different levels viz., $(\alpha + \beta < 1)$ or $(\alpha + \beta = 1)$ or $(\alpha + \beta > 1)$. We observe that the status of the EPs with $\alpha + \beta < 1$ are points that lack of evidence, the status of the EPs with $(\alpha + \beta = 1)$ looks similar to the probability measure of events in the realm of probability theory. The status of the EPs with $(\alpha + \beta > 1)$ are points of excess evidence.

Algebra of Evidence Points

We introduce three logical operations viz., negation ¬ , conjunction ᵛ and disjunction ∧ while considering the EPs as defined:

Let EP (P) = (α, β) then,

EP (P) = $(1 - \beta, 1 - \alpha)$ if $\alpha + \beta > 1$
= $(1 - \alpha, 1 - c)$ otherwise.

Let the EP (P) = (α, β) then,

(3.1) EP ($\neg$P) = (1 - β, 1 - α) if α + β = 1
= (1 - α, 1 - β) otherwise

Let the EP (P) = (α_1, β_2) and EP (Q) = (α_2, β_2)
then

(3.2) EP (P $\vee$ Q) = (Max (α_1, α_2), Max (β_1, β_2)) if $\alpha_i + \beta_i > 1$, i = 1, 2
= (Max (α_1, α_2), Min (β_1, β_2))
otherwise.

(3.3) EP (P $\wedge$ Q) = (Min (α_1, α_2), Min (β_1, β_2)) if $\alpha_i + \beta_i > 1$, i = 1, 2
= (Min(α_1, α_2), Max (β_1, β_2))
otherwise.

These operations require two segmented statements depending on the total evidence, denoted by m (P) = α + β. Let T and F respectively indicate a true and false proposition respectively. Then we may write: EP (T) = (1, 0) and EP (F) = (0, 1). Then for any arbitrary proposition P with EP (P) = (α β) it is easy to verify that:

(3.4) EP (P $\vee$ T) = EP (T), EP (P $\wedge$ T) = EP (P), and
EP (P $\vee$ F) = EP (P); EP (P $\wedge$ F) = EP (F)

(3.5) EP (T $\vee$ F) = EP (T), EP (T $\wedge$ F) = EP (F) and
EP ($\neg$T) = EP (F); EP ($\neg$F) = EP (T)

These relations resemble the conjunction and disjunction with true (T) and false (F) including the De Morgan's laws in mathematical logic.

We say EP (P) = (α β) as evidently valid or invalid based on α + β>1 or otherwise. It is realized that the De Morgan's laws are valid only if both the evidence points for P and Q are evidentially invalid. The similarity of the last two equations with standard results in two-valued logic is obvious and this way the algebra of evidence vectors preserves certain laws that are in-vogue in predicate logic (or two-valued logic).

Aspects of Decision Making

After sufficient amount of evidence has been acquired, how is the decision inferred, in case of sum of the evidences exceed one? Let EP (P) = (α, β) with α + β >1, then it can also be said that it has an excess evidence otherwise it is called lack of evidence. In either of these cases, to make a decision, P is normalized as

EP(P_0) = {α/(α + β), β/(α + β)} = {α_0, β_0} with $\alpha_0 + \beta_0 = 1$.

This is a sure point on the line of demarcation α + β = 1 as shown in Fig 02. A process is adopted to get the maximum attainable positive evidence as following: Using simple geometric principles, it can be realized that

EP(P_1) = {(1 + α - β)/2, (1 – α + β)/2} if α > β
= {1 – α + β}/2, (1 + α - β)/2} if α < β

Let α > β, (even if α < β, one can easily argue) then by considering the convex combination of the points P_0 and P_1 (as shown in Fig 02) an EP of any general point P_i is shown as
EP (P_i) = (α_i, β_i) = q{ α_i/ ($\alpha_i + \beta_i$), β_i/($\alpha_i + \beta_i$)} + (1 - q) {(1 + α_i - β_i)/2, (1 - α_i + β_i)/2} where 0<q<1.

At this junction it can also be observed that

a_i = the success factor of q{ α_i/($\alpha_i + \beta_i$), β_i/($\alpha_i + \beta_i$)} + (1 - q) {(1 + α_i - β_i)/2, (1 - α_i + β_i)/2 > α_i/ ($\alpha_i + \beta_i$)
b_i = the failure factor of q{ α_i/ ($\alpha_i + \beta_i$), β_i/($\alpha_i + \beta_i$)} + (1 - q) {(1 + α_i - β_i)/2, (1 - α_i + β_i)/2 < β_i/(α_i+β_i)

It can also be witnessed that

Max {α_i - α_1} = (α_1 - β_1)/2($\alpha_1 + \beta_1$) {$\alpha_1 + \beta_1$ - 1} and
Min {β_i - β_1} = ((β_1 - α_1)/2($\alpha_1 + \beta_1$) {$\alpha_1 + \beta_1$ - 1}

This observation is very much helpful especially while we apply this idea to some real world situations. Foe example, suppose that the calculated EP of a software project "Proj" is provided, based on several customer/ software requirement specifications. Then using these results, it is possible to look at the maximizing success factor, and minimizing the failure factors of "Proj", possibly by the same amount. This improved success factor will give the improved reliability of that software project which in turn will help in identifying the respective parameters, that influence the software project's reliability.

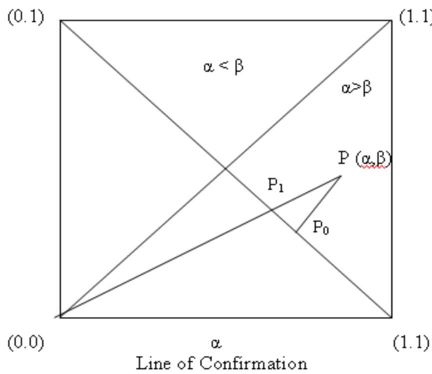

Fig.02 Decision Making Using Evidence Points

This method has been tested for its consistency both logically and mathematically. It is also observed that, the EP obtained from his process (for a particular project) gives a clue to establish the project's technical quality and reliability.

3. Uncertanity in Knowledge Base Systems (KBS)

Uncertainty in KBS can be handled in a variety of approaches. Here are some of them, with brief descriptions:

- Certainty factors
- Dempster-Shafer theory
- Bayesian network
- Fuzzy logic

Certainty Factors are used as a degree of confirmation of a piece of evidence. Mathematically, a certainty factor is the measure of belief minus the measure of disbelief. Here is an example:
If the light is green
then
OK to cross the street cf 0.9
The rule in the example says: I am 90% certain that it is safe to cross the street when the light is green.
There are certain advantages and disadvantages to certainty factors. They are easy to compute and can be used to easily propagate uncertainty through the system. However, they are created partly ad hoc. Also, the certainty factor of two rules in an inference chain is calculated as independent probabilities.

Dempster-Shafer Theory does not force belief to be assigned to ignorance or refutation of a hypothesis. For example, belief of 0.7 in falling asleep in class does not mean that the chance of not falling asleep in class is 0.3

Bayesian Networks are based on Bayes Theorem:

$$P(H|E) = \frac{P(E|H)P(H)}{P(E)}$$

Bayes Theorem gives the probability of event H given that event E has occurred. Bayesian networks have their use, but are often not practical for large systems. There is also a problem with the uncertainty of user responses.

Fuzzy logic is a superset of conventional (Boolean) logic that has been extended to handle the concept of a partial truth -- truth values between completely true and completely false. In fuzzy logic, everything is a matter of degree.
Some people think that fuzzy logic is a contradiction of terms. Fuzzy logic is a logic **OF** fuzziness, not a logic which is **ITSELF** fuzzy. Fuzzy sets and logic are used to represent uncertainty, which is crucial for the management of real systems. A fuzzy expert system is an expert system that uses a collection of fuzzy membership functions and rules to reason about data. Every rules fires to some degree.
The fuzzy inferencing process becomes much more complicated, expanding to 4 steps:

1. Fuzzification
2. Inference
3. Composition
4. Defuzzification

<u>Evidence Point Method vs Bayesian Approach</u>
In the Bayesian formalism of the theory of probability, we have three basic results that may indeed be adopted as axioms that form the corner stone of the mathematical theory of probability. If A and B are two events (or propositions), which are mutually exclusive of each other, then we have the following axioms:

1. 0 ≤ Pr (A), Pr (B) ≤ 1.
2. Pr(a sure event or proposition = 1
3. Pr (A V B) = Pr (A) + Pr (B)

If A and B are any two events, we have the obvious relation:

4. Pr (A) = Pr (A ^ B) + Pr (A ^ ¬B)
5. Pr (A) + Pr (¬A) = 1

If EP (P) = (0,0) (or (1,1)) says P is an unknowable (or highly conflicting) proposition.
If A (B) is a true (false) proposition, then EP (A) = (1,0) and EP (B) = (0,1). Using the above algebra one can observe the following interesting results:
EP (A V B) = (1,0), EP (A ^ B) = (0,1).
Conversely if we have EP (A V B) = (1,0) and EP (A ^ B) = (0,1).
Then we have either EP (A) = (1,0) and EP (B) = (0,1) or EP (A) = (0,1) and EP (B) = (1,0).
This means the compound evidence EP (A V B) is absolutely true, and the compound evidence EP (A ^ B) is absolutely false, then one of the constituent evidence pairs is for an absolutely true proposition and the other is for an absolutely false proposition. Let P and Q are two propositions, then a simple fact that max (x, y) = x+ y- min (x,y), for any two real numbers x and y establishes the fact that

6. EP (P V Q)= EP (P) + EP (Q) – EP (P ^ Q)

This is similar to the addition law of probability. Further, in the realm of probabilities we also have
Pr (A V B) ≥ Max{Pr (A), Pr (B)} and Pr (A ^ B) ≤ Min{Pr(A),

Pr (B)}.
If EP (A) = (α, β), EP (B) = (γ, δ) then we have the analogous results as following:

7. m(A V B) $\geq$ Max{m(A), m(B)} and m(A ^ B) $\leq$ Min{m(A), m(B)},

One should recall here that m(A) is the measure of A = (α + β)
If A and B have both fuzzy valid, i.e., whenever $\alpha + \beta > 1$, $\gamma + \delta > 1$, then we define the conditional evidence pair as,

8. EP (P|Q) = {{Min(α, γ), Min(β, δ)}/ {($\gamma + \delta$)/2}} = {r, s} (say)

Then obviously we have e(P|Q) = {r + s}/2 and can have the result that:

9. e (Q). e (P|Q) = e (P ^ Q)

Likewise we can also introduce the "conditional evidence pair" for Q|P and arrive at the result that

10. e (P).e (Q|P) = e (P ^ Q). Hence,
11. e (P).e (Q|P) = e (Q).e (P|Q) = e (P ^ Q).

If the evidence pair EP (P) = (α, β) or the evidence pair EP (Q) = (γ, δ) is not fuzzy or either of them is fuzzy, then the relevant evidence representation pairs for P ^ Q, P V Q, have been already stated. In such cases, the conditional evidences P|Q, Q|P can be defined in ways analogous to (6). The result (9) will of course remain valid in each of these cases. Further if we interpret the conditional proposition P|Q as equivalent to the material implication P→ Q then we can observe that:

EP (P→Q) = {{$\alpha_2+\beta_2$}/($\alpha_1+\beta_1$)} EP (Q→P).

<u>Evidence-Point Method vs Dempster-Shafer Theory</u>
Dempster-Shafer Theory assumes that the answer to a particular question lies among finite set X (of propositions) called frame. The elements of this set X are mutually exclusive annd they are also exhaustive. If 'ma' is a mapping from the set of all subsets of X onto the real interval [0,1] as:

ma: $2^x \rightarrow [0,1]$ with a condition that ma(φ) = 0, m(A) = 1

where ma(A) is the weight associated with the proposition A, which measures the strength of the argument in favor of the proposition A, called a basic probability assignment (bpa). If ma(A) $\neq$ 0, A (which is a subset of the frame X) is called a focal element of X. We can define the notion of belief in a proposition A subset X, is given by the equation, Belief(A) = Bel(A) = $\sum$ m(B), over all B $\subseteq$ A.

Then we have thhe following axioms concerning belief functions: Bel(φ) = 0, Bel(X) = 1, and Bel(B_1 V B_2 V…..V B_n) $\leq \sum$ (-1) ˆ {|l| +1} Bel(Ui € Ai, where {l $\subseteq$ {1,2,…,n}, l $\neq$ φ}
The plausibility of a proposition A = Pl(A) and is given by the relation Pl(A) = 1-Bel(¬A).
Where ¬A = X|A is the negation (or complement of A with respect to frame) of A. Clearly Pl(A) is a measure of the extent to which the proposition A is believable to be true. The pair [Bel(A), Pl(A)] is a real number interval, that is, it is a subset of [0,1]. This can be seen on considering that Bel(A) = $\sum$ m(B), and Bel(¬A) = $\sum$ ma(C) with {B subset A} and {C $\subseteq$ ¬A} and

1. (B $\subseteq$ A) V {C $\subseteq$ ¬A) $\subseteq$ X

It therefore follows that, $\sum$ ma(B) + $\sum$ ma(¬B) $\leq$ ma(X) =1 that is, Bel(A) +Bel(¬A) $\leq$ 1 that is,

Bel(A) $\leq$ 1-Bel(¬A) = Pl(A).

Similarly it can verify that for any proposition A, Pl(A) + Pl(¬A) > 1. The interval [Bel(A), Pl(A)] can be regarded as providing a range for the true probability of A and Bel, Pl may be referred to as the lower and upper bounds (measures) for the probability of the proposition A.
If two belief functions Bel_1 and Bel_2 are based on independent evidences we can pool them using Dempster's rule of combination and the result is again a belief function. In symbols we can write $Bel_1 \oplus Bel_2$ as the resultant after the combination of. Thus,

2. ma(C) = {$\sum$ $ma_1(A_i)$. $ma_2(B_j)$}/{1-$\sum$ $ma_1(A_i)$.
   $ma_2(B_j)$} is valid for all subsets C of X, further
3. $\sum ma_1(A_i)\, ma_2(B_j) < 1$.

In the evidence point formalism, for any evidence pair EP(P) = (α, β) the first component is a measure of Belief in the proposition P and 1-β is a measure of plausibility in the proposition. This is due to the fact that plausibility of a proposition involves the disbelief in that proposition. Thus, it can be realized that for any proposition P, we can always have a positive evidence (α) which confirms its validity, is belief, and the plausibility in such a case will be 1 minus the negative evidence (β), which negates the same proposition. Here too it is observed that the pair [Bel, Pl] forms an ordered pair, very much useful for an intelligent decision-making.

<u>Evidence Point Method vs Fuzzy Logic</u>

Any situation, which is "inexact" in nature or is incapable of being described by perfect notions or exact concept, is fuzzy. Fuzziness is a type of imprecision or inexactness stemming from the grouping of elements into classes that do not have sharply defined boundaries. Such classes abound in all situations that involve ambiguity or vagueness or ambivalence in (mathematical) models of empirical phenomena. A fuzzy set is a class that permits the possibilty of partial membership. If X = α is a class of objects and A is an ordered pair

1. $A = \{ \alpha, \mu A(\alpha) \}, \alpha \in X$.

We may refer to X as the universe or frame and $\mu A(\alpha)$ as the grade of membership of α in A. the grade $\mu A(\alpha)$ is a real number belonging to the interval [0,1] and the extreme value viz., 0 and 1 connote non-membership and full membership respectively. Comparison is possible for the (degree of) truths of inexact statements α in A and β in A. The statements like, $\alpha \in A$, $\beta \in A$, and $\alpha > \beta$, which mean that α is at least as true as β. Whenever $\alpha \in A$, $\beta \in A$, and , $\alpha < \beta$ we can conclude that α is no more true than β. Basic operations on fuzzy sets (which are subsets of a frame) can be introduced to tackle questions like: (1) Is A = B? and (2) Is A contained in B?

Compounding operations like conjunction and disjunction over fuzzy sets can also be introduced but in such matters some degree of subjectivism is unavoidable. To arrange a comparison of evidence point theory with fuzzy set theory it is desirable to opt from the following rules of operation of conjunction ^, disjunction V, and negation ¬. If X is the frame and P, Q are two subsets of X, we may then define the membership functions as:

2. $\mu\{P \vee Q\}(x) \le \mathrm{Min}\{\mu P(x), \mu Q(x)\}$, $\mu\{P \wedge Q\}(x) \ge \mathrm{Max}\{\mu P(x), \mu Q(x)\}$ and $\mu\{\neg P\}(x) = 1 - \mu P(x)$

In evidence point theory, we have already seen earlier that the compounding laws for the operations of conjunction, disjunction and negation. If evidence pairs EP(P), EP(Q) are both fuzzily valid, then

3. $ma(P \vee Q) \ge \mathrm{Max}\{ma(P), ma(Q)\}$ and $ma(P \wedge Q) \le \mathrm{Min}\{ma(P), ma(Q)\}$

Recalling the definitions of the estimate of the evidence value of an evidence pair α, β we have statements similar to the above two-statement (3) involving estimates of evidence values. We can identify the grade of membership of a fuzzy set viz., μP (x as the estimate of truth-value of the negation of the proposition. That is,

4. $\mu P(x) = 1 - e(P)$

We can then see the consistency, nay the parallelism of the relations' (2) in a fuzzy set theory with the relations

5. $e(P \vee Q) \ge \mathrm{Max}\{e(P), e(Q)\}$ and $e(P \wedge Q) \le \mathrm{Min}\{e(P), e(Q)\}$.

This can be rewritten as $e\{\neg(P \vee Q)\} \le \mathrm{Min}\ \{e(\neg P), e(\neg Q)\}$ and $e\{\neg (P \wedge Q\} \ge \mathrm{Max}\{e(\neg P), e(\neg Q)\}$

In Fuzzy Set Theory, (2) are the basic rules of definition of the operations of conjunction and disjunction. In evidence point theory, equation (4) or (5) are merely corollaries from the basic rules of operations for combining evidences. The algebra of operations in the case of evidence points is more general than that in the case of fuzzy sets.

4.REFERENCES

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