Uncertainty Management in a Distributed Knowledge Based System

Naseem A. Khan
AT&T Bell Laboratories
Summit, New Jersey 07901

Ramesh Jain
Dept of Electrical Engineering and Computer Science
University of Michigan, Ann Arbor, MI 4B109

Abstract

In many situations, a knowledge source may not give definite hypothesis; it can only express its belief and disbelief in multiple hypotheses, We present a scheme of uncertainty management in such a system. Disbelief is given a considerable importance in our approach Various experts influence one another and show co-operative behavior by mutually changing their confidence factor values. The final decision about the feasibility of a certain hypothesis is based on the mean value and the consistency of the confidence factor values of the experts.

1. Introduction

In several applications, a knowledge based system (KBS) may use many knowledge sources which may have different representations When the knowledge base is small, a single inference engine may work satisfactorily. However, if multiple knowledge sources are used in an expert system, the above architecture may be inappropriate. It may be necessary to associate a separate engine with each chunk of knowledge This leads to the idea of a distributed control mechanism in which each chunk of knowledge associated with its inference engine represents a Knowledge Source (KS). A KBS using distributed problem solving (DPS) techniques to organize knowledge is called a distributed KBS.

In our research, the paradigm of DPS is used for object recognition [KhaB4, KhJ84]. The claim of our work is that the paradigm of DPS is well suited to object recognition using multiple KSs. Various KSs communicate with each other in a team-like fashion. KSs mutually influence each other in the process of disambiguation of their results. A final decision based on the mean value of their Confidence Factor Values (CFVs) and the degree of organization in the CFVs is made.

In the process of uncertainty management we also give disbelief a considerable importance. In works like MYCIN [Sho76] a certainty factor is computed by subtracting disbelief value from belief value for a hypothesis and is used in later calculations. This implies that it emphasizes the net difference between supporting and opposing bodies of evidence. This net difference may mislead by hiding much necessary information. We believe that an opposing evidence for an alternative reinforces supporting evidence for other alternatives and vice versa.

This paper addresses the following problems briefly; (i) modifying the belief value or the disbelief value of an individual expert for an alternative based on the disbelief values or belief values, respectively, of the same expert for other alternatives in the process of *competition* between hypotheses, (ii) computing the CFV of each expert for each alternative based on the modified belief value and the modified disbelief value of the alternative, (iii) updating the CFV of an expert for an alternative based on the CFVs of other experts for the same alternative, a process called *cooperation* and (IV) combining the CFVs of all the experts to give a final value for each alternative and deciding the best alternative based on the associated CFY The details of our approach are given in [KhJ85]

2. Previous Work

Past research in the field of belief revision has yielded various approaches for modifying and combining belief values [DoL8O] AI systems, especially expert systems, adopt numerical methods for reasoning about uncertainty Most of the approaches developed to combine and propagate certainty measures are based on subjective Bayesian techniques [DHN76 SBF79]. Since a plethora of statistical data is required in Bayes' theorem, subjective probabilities are used instead of these data in expert systems This leads to inconsistencies and inaccuracies [Sho76, SBF79 ShB75]. Shafer fSha76] distinguishes between *aleatory probability* or *theory of chance* and *epistemic probability* or *theory of belief.* Shorthffe [Sho76I used belief functions for combining certainty measures [GLF81] applied Dempster's rule for combining disparate bodies of evidence, [BarBI] describes methods of numerical computation of evidence

3. Competition

In a complex environment a KS may not give a reliable information. *In* such a situation one may use several KSs, each of which brings a different perspective to the problem None of the KSs is perfect Thus we must combine relevant informations from all KSs Each expert determines (1)the degree of belief and (11) the degree of disbelief for each alternative. Since the possible alternatives stored in the KB are finite, the absence of an alternative strengthens the evidence for the presence of other alternatives. Similarly, the presence of an alternative strengthens the evidence for the absence of other alternatives. The match between the input and KB model leads to belief and disbelief values between 0 and 1. In order to determine the modified degree of belief for an alternative, an expert uses two pieces of evidence: (i) the degree of belief and (n) the degrees of disbelief of other alternatives

[Sha76] suggests the use of Bernoulli's rule of combination for combining two bodies of supporting evidence. If E_1 and E_2 are the belief values of two pieces of supporting evidence, then the combined-belief value E_c is given by the function

$$E_c = E_1 + E_2(1 - E_1) \tag{1}$$

However, this function cannot be used as it is because if either E_1 or E_2 is 1, the combined value is always 1 regardless of the other value, and the result is commutative. Thus if a KS is *confident,* the other is ignored. Another problem underlying the use of the expression (1) is that each piece of supporting evidence is given the same degree of reliance. This problem can be solved by assigning a relative weight w(< 1) to the second source Then

$$E_c = E_1 + w \cdot E_2(1-E_1) \quad (2)$$

Since in most applications, the disbelief of other alternatives plays a role which is less significant than the belief value of an alternative itself, the modified form (2) of Bernoulli's rule of combination can be applied to update the belief value We believe that it is always safe to be conservative (rather than to overestimate) while relying on a secondary piece of evidence in the process of increasing the value of the evidence for the presence or absence of an alternative Therefore we choose the minimum of disbelief values of all the other alternatives in (2) for E_2 giving us a modified belief value (MBV) We determine a MDV of each alternative in a similar fashion,

4. Cooperative Competition

When the opinions of various experts about the same alternative change each other and each expert consequently modifies its own opinion about that alternative, the process is regarded as cooperation.

4.1. Confidence Factor Value

The experts modify the belief and disbelief values of the alternative in the process of competition The Confidence Factor Value (CFV) of an expert for an alternative is found as follows

CFV = MBV - MDV

4.2. Cooperation

During the process of cooperation, the CFVs of an alternative obtained by the experts influence each other

Values of the CFVs were modified using the following two mechanisms of cooperation

1 Mean-Highest: In this case, the highest CPV for the alternative among the experts is found and each expert increases its CFV to the mean of the highest CFV and its own CFV The motivation behind the scheme is that even if a single expert succeeds to a high extent for an alternative, it helps all the other experts in the disambiguation process. Suppose that before updating AI=0.5 A2=0.9 A3=0.1. After updating AI = .7 A2=0.9 A3=0.5

This method of updating has the drawback that all the CFVs are increased because of only one value, the highest. This is a very optimistic approach.

2: Increment towards a High Value and Decrement towards a Low Value: In this method the change takes place towards both the high value and the low value. An expert changes the CFV towards the next higher CFV and towards the next lower CFV obtained by other experts For the above example, the updated values will be

AI=0.5 + (0.9-0.5)/2 - (0 5-0.I)/2 = 05
A2=0.9 (0.9-0.5)/2=0.7
A3=0.1 + (0.5-0.1)/2=0.3

This method of updating CFVs involves a kind of averaging process and is better than the above method because the change in the CFV is influenced by both higher and lower values However, the new value is the same as taking the average of adjacents except for values at the extreme positions. In other words, its own value does not contribute in determining its new value, unless it is either the lowest or the highest value. When only two experts are participating, each of them gets the same updated CFV, which is equal to the mean of the two experts' CFVs Also, even if the difference between the CFV of an expert and that of the higher or lower adjacent expert is very high, the change in the CFV occurs in the same way, i e the change is equal to the mean of the CFVs of the two experts This may not be a very practical approach but it leads to the following approach.

4.3. Influence and Ego-Altruistic Cooperation

The drawbacks of the method 2 can be eliminated by changing the CFV of an expert by a degree depending upon the difference between the CFV of the expert and those of the higher and lower adjacent experts The experts with extreme values change only in one direction This process of confidence smoothing has a very important feature that the change in the CFV for an alternative obtained by the expert is both positive and negative, depending on the values of the higher adjacent and lower adjacent experts

4.3.1. Notion of Influence

Suppose there are N equally important experts in the decision making process The N experts can be placed on a straight line with respect to their CFVs In the example below, AI, A2, and A3 are the CFVs and AI > A2> A3 Only adjacent nodes influence each other AI is influenced by A2, A2 is influenced by AI and A3 and A3 is influenced by A2 Since A2 is lower than AI AI gets *negative influence* from A2. Also, since A2 is greater than A3, A2 gets *positive influence* from AI and *negative influence* from A3 A3 gets *positive influence* from A2.

The influence between nodes is a function of the distanced between them [The distance is the difference between the CFVs of the experts] The influence increases with the increase of the distance up to a point, and then decreases with the increase of the distance The magnitude of the influence(I) between two nodes is given by the following function

$$I = d/2 \quad \text{when } d =< 0.5$$
$$= (1-d)/2 \quad \text{when } d > 0.5$$

Total influence(1) at a node is the sum of the positive influence(I_p) and negative influence(I_n) at that node.

$$I = I_p - I_n$$

Thus, updated value of the node =Value of the node + Total influence

In this approach, the experts are generous to accept influence when their CFVs are closer to each other; otherwise, the experts are egoistic by not changing much when their CFVs differ by a high degree. When the difference in CFVs is more, each individual expert tends to rely more on its own confidence factor. This sort of cooperation introduced here is called *ego- altruistic co-operation.*

5. Decision Making

All the hypotheses with their CFVs corresponding to each expert are still competing for their selection. This section describes the decision making procedure Our problem may be considered very similar to the problem of multicriteria decision making. We may assume that the CFVs of experts are same as the costs according to different criteria and the decision should be made considering all these costs. It can be shown iKhJ85], however, that none of the existing approaches can be applied here.

5.1. Decision Making Based on the Mean Value and the Degree of Organization

Suppose there are three experts, expl, exp2 and exp3, and three alternatives, a, b, c. The CFV for each alternative obtained by the experts are as follows

alternatives

expl	a1	b1	c1
exp2	a2	b2	c2
exp3	a3	b3	c3

When the mean of the CFVs is taken for an alternative, there is a loss of information, and it is impossible to guess how much an expert is contributing Intuitively if the disparity between the CFVs of the experts is very high, it is very hard to believe results of any of the experts. As a result, the credibility of the CFV should go down for the alternative It is therefore suggested that the final CFV for an alternative depends on the two factors: (1) The mean value of the CFVs of all the experts for an alternative, and (2) The degree of organization (the uniformity of results) in CFVs of the experts for an alternative

The degree of organization in the CFVs of the experts can be found by using the concept of entropy. Since the CFVs of experts for an alternative cannot be considered probability values but could be considered as fuzzy numbers, fuzzy entropy can easily be applied to finding the degree of organization among the various experts. If $\mu_{a_1}, \mu_{a_2}, \ldots, \mu_{a_n}$ are the membership values of the members in a fuzzy subset and if we specify

$$p_{a_i} = \frac{\mu_{a_i}}{\sum_{i=1}^{n} \mu_{a_i}} ,$$

then, the fuzzy entropy is

$$H(p_{a_1}, p_{a_2}, \ldots, p_{a_n}) = \sum_{i=1}^{n} p_{a_i} \cdot \ln p_{a_i}$$

We found that the final CFV of the experts for an alternative is a linear combination of the mean-value of the CFVs of the experts and the degree of organization in the CFVs, which is represented as follows:

FINAL CFV = α . MEAN-VALUE + β . DEGREE OF ORGANIZATION

α and β are the co-efficients associated with the 'mean value' of the CFVs and the degree of organization' in the CFVs respectively.

6. Conclusion

We proposed a scheme of handling uncertainty in a distributed environment in which there are many KSs. each with a different expertise of problem solving This can be decomposed into 3 steps: (l) dealing with competing hypotheses (2) co-operation and (3) decision-making. We discussed our approach to these steps

REFERENCES

[BarB1] Barnett. J.A.. Computational Methods for a Mathematical Theory of Evidence, *Proc IJCAJ- 7,* Vancouver. British Columbia, Canada 868-875. 1981.

[Dav82] Davis. R.. Expert Systems Where are We? And Where Do We Go from Here? *Al Magazine* 3(2) 3-22. 1982. Also. A.I. Memo No. 665. Al Lab. MIT, June, 1982

[DeT72] DeLuca, A, and Termini, S., A Definition of a Non-Probabilistic Entropy in the Setting of Fuzzv Set Theory, *Information and Control* 20. 301-312. 1972

[DHN76] Duda. R., Hart, E . and Nilsson. N , Subjective Bayesian Methods for Rule-Based Inference Systems, *Technical Note* 124. Al Center, SRI International, Menlo Park, CA, 1976

[DoL80[Doyle. J. and London, P., A Selected Descriptor-Indexed Bibliography to the Literature on Belief Revision, SIGART *Newsletter,* No, 71, April, 1980

[GLFBIJ Garvey, T, Lawrence, J , and Fischler, M., A Inference Technique for Integrating Knowledge from Disparate Sources, *Proc IJCAI-7,* Vancouver, British Columbia, Canada 319-325, 1981.

[KhaB4] Khan, N A , *Ph D Dissertation,* Wayne State University, Detroit, Michigan, January 1984

[KhJ84] Khan, N. A. and Jain, R., Matching an Imprecise Object Description with Models in a Knowledge Base, *Proc. Seventh International Conference on Pattern Recognition,* Montreal Canada, August. 1984.

[KhJ85] Khan, N.A. and Jain, R., "Uncertainty management in distributed knowledge based systems," Technical Memo. TM 113B6.850123.01 AT&T Bell Labs, Jan. 1985.

[Kor7B] Kornbluth, J.S.H., Ranking with multiple objectives, *Multiple Criteria Problem Solving* S. Zionts (ed), Springer-Veriag, Berlin, 197B.

[Sha76] Shafer, G., *A Mathematical Theory of Evidence,* Princeton University Press, Princeton, 1976.

[Sho76] Shortlifle, E. H., Computer-Based Medical Consultations: MYCIN, American Elsevier New York, 1976.

[SBF79] Shortliffe, E., Buchanan, B., and Feigenbaum E., Knowledge- Engineering for Medical Decision Making: A Review of Computer- Based Clinical Decision Aids, *Proc. of the IEEE* 67(9), 1207-1224, 1979.