CHAPTER 7

Uncertainty Management in Peadiatric Problems†

7.1. Introduction

In certain circumstances, either we have no knowledge about an object or we have some incomplete, vague and imprecise knowledge about an object [1-3]. A system to aid in human decision making needs to take into account the inexact nature of information expecting to lead to rational decisions. For a medical domain, different forms of inexactness may come to the floor. The clinical expression of an illness involves the multi-dimension interactions of the abnormalities of various self-regulated physiological mechanisms with the patient's environment. This is further influenced by the patients and physicians' variability in expression and understanding of the problem. Uncertainty remains prevalent throughout the practice of medicine, and causes anxiety in patients and physicians [4]. Variation in physicians' practice styles and organization characteristics (sites of medical care) has been linked to uncertainty [5]. Numerous patient and physician factors could affect the clinical decisions and result in medical uncertainty. Lacking any unique theory to manage all the forms as a whole, different approach have been proposed with their own zone of applicability.

In section 7.2, the sources and nature of inexactness have been discussed the medical domain. Section 7.3 deals with the tools for managing those inexactness in information. Some common approaches of dealing with inexactness in expert systems have been discussed in brief. In section 7.4, a suitability analysis has been provided in context to the present problem domain. In the last section, our discussions have been provided.

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7.2. Sources and nature of inexact Information

Understanding logical and physical sources of inexactness is necessary. In table 7.1, the possible physical sources and their nature and explanation have been presented. From the table 7.1, one can observe that there are not just one or two sources of inexactness, but seven major areas, which between them break down into almost, twenty sub-areas. It also indicates the varied nature of inexactness. Combining all these possible physical sources, one can identify the following possible logical sources of inexactness of information:

- Lack of adequate data,
- Inconsistency of data,
- Inherent human fuzzy concepts,
- Matching of similar rather that identical situations,
- Differing (expert) opinions,
- Ignorance,
- Imprecision in measurements,
- Lack of available theory to describe a particular situation.

In our system, five types of inexactness have been classified as follows:

- Uncertain information
- Fuzzy information
- Simultaneous occurrence of uncertainty and fuzziness
- Uncertain-fuzzy
- Non-monotonic nature

Table 7.1. Sources and nature of inexactness.

SOURCES and	NATURE	EXPLANATION
Problem domain	a) Lack of precise numeric aspiration levels; to some or all controlling physiological b) Lack of appropriate or available well defined algorithms.	In a medical diagnostic system, it is very difficult to assign precise aspiration levels parameters. Moreover, human body does not follow a strict algorithmic approach for its running. To manage the situation, the doctors are, sometimes, forced to rely on heuristics.
Child	a) Lack of adequate data; b) Inconsistency of data; c) Subjective reply; d) Reply in fuzzy terms e) Fumbling answer; f) No information.	Sometimes, a child may not be able to supply any verbal relevant information where language development is not adequate. The other natures of inexactness are also frequently received by a doctor during a consultation session.
Parents / Guardians	a) Lack of adequate data b) Inconsistency of data; c) Subjective reply; d) Reply in fuzzy terms; e) Fumbling answer indicating lack of confidence; f) Ignorance.	Parents / guardians sometimes fail to supply complete history of the child, may be, due to their illiteracy. The other forms of reply are also frequently as received by a doctor during a consultation session.
Doctors	Matching of similar rather than identical situations: model in equivalence.	Sometimes doctors are supposed to apply heuristic knowledge gained in a number of years of practice. Any particular heuristic may not work with similar situation.
Laboratory tests / technicians	Imprecision in measurement during clinical/ pathological/radiological tests: instrumental/ technician's error; impurity with the chemicals /glass wares used.	It is reported, sometimes, that the findings from the clinical view of a doctor may not match the findings from laboratory reports. Doctors, then advice to repeat the test for confirmation.
Symptoms	a) Most of the symptoms are valid for more than one adverse situation; b) Information hiding.	A particular symptom may be reflected from two or more adverse situations. A secondary symptom may be more prominent than a primary symptom in a situation: information hiding.
Non-availability	Laboratory results not available.	Laboratory investigations may not be possible either due to financial constraints or there may not be any laboratory in the nearby area.

At the starting of a typical consultation session, a doctor has to interrogate the child, where possible, or the parents / guardians of the child on different issues. She / he may examine the child with his / her medical / clinical view and so on. She / he may face the above forms of inexactness of information which may be the result of the combined conspiracy of the above discussed sources and other unidentified sources. Here, proper management of inexact information is necessary which plays a pivotal role in rational decision making.

7.3. Tools for managing Inexact Information

A number of methods have been proposed to deal with different aspects of inexact information management with their varying degrees of success. In essence [6], they can take one of the seven forms such as non-numerical techniques, categorical techniques, probabilistic modelling, ad-hoc techniques, Bayesian inference, fuzzy logic, and Dempster-Shafer theory of evidence.

The common approaches in dealing with inexactness in expert systems are: Bayesian probability approach, DS-theory of evidence, Stanford CF-calculus, and Fuzzy set theoretic approach. In addition, inexact reasoning has itself non-monotonic aspect. It may be noted here that none of the methods except CF-calculus has been developed with a reference to AI and expert systems and neither has yet been universally adopted by theoreticians or practitioners.

- Bayesian probability theory [7]

  The Bayesian approach is based on formal probability theory and has shown up in several areas of AI research, including expert systems and pattern recognition problems. However, this particular approach can deal only with uncertainty.

  This approach has been used in a number expert systems. One such notable expert system is PROSPECTOR developed [8] as a consultation system for mineral exploration. We may cite here at least one PROSPECTOR - like system which has been developed based on this theorem where the above assumptions are implied [9].

- **Dempster/Shafer theory of evidence** [10-12]

  Dempster-Shafer theory has been considered as a prominent candidate to handle inexactness in expert systems.

- **Stanford certainty factor model** [13]

  In a production system, different certainty factors are attached to every premises. These certainty factors are combined to get the overall certainty of the inference.

- **Fuzzy set theory** [14]

  This approach has been used in a commercially notable expert system REVEAL from ICL [15] which is essentially a decision support system. A number of commercial knowledge based shells have also incorporated fuzzy reasoning [16-20]. As a matter of fact, fuzzy logic has previously been used successfully in a number of knowledge based systems and the trend is good enough [21-23]. In 1937 the quantum philosopher Max Black had published a paper which defined the key concepts of a vague set [24]. The concept of fuzzy set and fuzzy logic were introduced by Zadeh [14]. His intention of introducing this fuzzy set theory was to deal with problems involving knowledge expressed in vague, linguistic terms.

- **Non-monotonic reasoning**

  Most of the available knowledge-based consultation systems / expert systems and different ES-shells use monotonic reasoning as their inference strategies which essentially assume that axioms do not change and conclusions drawn from them remain true. In contrast to monotonic reasoning, nonmonotonic reasoning (NMR) proceeds with its reasoning as if the assumptions are true with their possible inexactness in the information. With its reasoning it reaches a conclusion. If one finds the conclusion absured, it is demanding at this stage to change an assumption and / or to change the associated (un)certainty values. NMR may be considered as an important feature of human problem solving and commonsense reasoning.

The information supplied by the parents/guardians or by the child himself/herself is subjective sometimes. To deal with this subjective reply, a kind of inexactness, NMR will be useful. NMR is also important and advantageous in connection with modifiability.

7.4. Suitability analysis

Let us now investigate the suitability of the above method(s) of handling inexactness in information which seem(s) to be most sympathetic to the problem domain at our hand.

7.4.1. Bayesian probability theory

This approach works with two major assumptions: (1) All the statistical data on the relationships of the evidence with the various hypothesis are known in advance of processing starts; (2) All relationships between evidence and hypothesis are independent. Despite the commercial success of PROSPECTOR, the wide applicability of this approach is restricted and sometimes infeasible in some problem domain [2]. These assumptions are the bottlenecks of using this technique for a problem domain of diagnostic nature of child growth and development. In a medical diagnostic problem domain, it is very difficult for the domain experts to collect or estimate all prior conditional and joint probabilities. This seems to contradict the reasons of using an expert systems framework when and / or where the complete logic may not be known in advance.

For the medical domain, the assumption of independence of relationships between evidence and hypothesis cannot really be justified. The last problem arises in connection with modifiability, a desirable feature of an ES, of knowledge base. The knowledge base may have to be changed or updated due to different reasons. Particularly, when complete and sound knowledge may not be available in advance, a fact for the present domain, existing system should easily and quickly incorporate the required changes. In this situation, there is the need to rebuild all probability relationships which seems to be a cumbersome task. Considering all these factors, we find hardly any good reason to use this technique for the present problem domain at our hand.

7.4.2. Dempster/Shafer theory of evidence

The theory allows the decomposition of a set of evidence into separate, unrelated set of evidence. It allows us to use our knowledge to bound the assignment of probabilities to events without having to come up with exact probabilities when these may be unavailable; the situation where DS method may be a good candidate for applications like the integration of data from multiple radar sensors [25, 26]. It is concluded by O'Neill [1] that DS theory may be considered as a promising candidate for managing inexactness, as it includes PROSPECTOR's Bayesian belief functions and MYCIN's certainty factors as special cases. It also is based on a more mathematical foundation than either PROSPECTOR or MYCIN. However, we find to date, no notable expert system in the market using this model except some research applications [27]. The reason may be due to its involvement of so many numerical computations reducing the speed of inferencing and in the case of long inference chain the structure of the resulting belief functions would be very complex. One may expect its use where the length of inference chain is of low or moderate size. Some studies are reported to reduce the computational complexity of the method using local computation technique for computing belief functions [28-29] and using some optimizing techniques [30]. However, the ways and means of using a simplification scheme seems to depend on case specific algorithms which deserves more scrutiny and thereby restricting its general use [31]. We find no such commercially successful ES or ES-shell using this particular model. The above observations advice us, at present, not to use the technique for our present problem domain.

7.4.3. Stanford certainty factor model

This is a heuristic approach to the management of uncertainty. It is criticized as an ad-hoc technique. In particular, criticism from Adams may be considered worthwhile. Adams [32] concludes that the empirical success of MYCIN may be due to the fact that the chains of reasoning are short and the hypothesis involved are simple; this ideal situation may not be true for a complex system. Nevertheless, CF calculus finds its foundation among the expert system / expert system shell designers for its simplicity of use. The commercial success of MYCIN, EMYCIN, S.1, LEVEL5 etc. encourages people to use this technique for handling uncertainty. We do expect it useful for our problem domain to handle inexact information of uncertain nature.

7.4.4. Fuzzy set theory

In about 40 years of its existence, fuzzy set theory has been used in many areas including engineering, business, mathematics, psychology, management, semiology, medicine, image processing and pattern recognition. It may be fair to state that it has been used at length in control applications. In Japan alone, it has been reported, 2000 patents have been issued [33]. However, its applicability and usefulness are increasing interestingly in other fields as well [21-23]. In medical domain, fuzzy logic has previously been successfully used in a number of knowledge based systems [34-38]. For the paediatric problem domain, we find no such reported rigorous use. In connection with the management of inexact information in expert systems, the conventional approaches fail in four important respects [39]:

- They do not provide the means for dealing with the fuzziness of antecedents and consequents;
- They assume that the probabilities can be estimated as crisp numbers;
- They do not offer a mechanism for inference from rules in which the qualifying probabilities are fuzzy;
- The rules for composition of probabilities depend on unsupported assumptions about some conditional independence.

Fuzzy logic addresses some, but not all, of these problems. More specifically, fuzzy logic allows the antecedents and/or consequents and/or qualifying probabilities to be fuzzy. Furthermore, fuzzy logic makes it possible to estimate probabilities as fuzzy rather than crisp number.

Fuzzy set theory has done quite well as a formal mathematical system. Whether its theorems are interesting is a subjective opinion among mathematicians, but a large body of mathematical work exists. Where more work needs to be done is in establishing that fuzzy set theory actually captures something real in applicative fields and can make a pragmatic difference, for the right reasons [40].

It is tempting at this stage to use the technique as a measure of fuzzy concepts associated with the problem domain.

7.4.5. Non-monotonic reasoning

The information supplied by the parents/guardians or by the child himself/herself are subjective sometimes. To deal with this subjective reply, a kind of inexactness, NMR will be useful. NMR is also important and advantageous in connection with portability and modifiability. We expect it useful to incorporate in our system as one of the measures of inexactness in information.

7.5. Discussions

In real life situations we may have to reason with vague, insufficient, imprecise information to come to a rational decision. Any software / software tool developed for assisting peoples in their decision making needs to take into account the inexact nature of information. In this chapter, we have discussed the possible sources and nature of inexactness in information in context to the present problem domain. We have also discussed different common approaches for managing inexactness in expert systems. We have also attempted to analyse the relative suitability of those methods considering the problem domain of paediatrics. In this thesis, we have confined ourselves in considering certainty factor model and fuzzy set theoretic approach for managing inexactness.

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