CHAPTER 9

FUZZY CONCEPTS AND PAEDIATRICS [1]

9.1. Introduction

Much of human knowledge is imprecise and vague. In medical domain in general, and in paediatric domain in particular, doctors frequently have to take decisions based on vague and imprecise knowledge which can be called inexact knowledge which comes from our linguistic articulations. A convenient framework for dealing with such vague, linguistic articulated knowledge is fuzzy logic and fuzzy set theory. This **chapter** presents ideas on a research direction incorporating an outline of some fuzzy concepts in paediatrics in order to design a powerful expert system which needs to take into account such fuzzy concepts.

To understand the meaning of the term "**fuzzy**", we may take a simple of the weight of a baby. The weight of a baby expressed by different vague linguistic articulations such as **good**, **bad**, **satisfactory** etc., instead of exact numeric measurements. Such linguistic articulations like **good**, **bad** or **satisfactory** are fuzzy terms (values) for the variable weight. These terms have shades of meaning. For example, the weight of many babies may be described as **satisfactory** but their exact measurements may differ markedly. Terms like **good**, **satisfactory** etc., do not assume a simple unique value but a range of values. The boundaries of such linguistic articulations are not sharp but fuzzy which essentially means that the decision path from **satisfactory** to not **satisfactory** is a gradual progression which has no sharp boundary. Moreover, if the weight of a baby is decreased by some gramms only, he / she can retain the value **satisfactory**.

Our real-life reasoning systems often use some inexact knowledge of fuzzy form leading to some rational decisions. However, as the knowledge itself is inexact, the derived decisions can not be exact but approximate, having a good rationality.

In about 30 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 engineering applications. In Japan alone, more than

[1] This is based on the publication [Proc. xxx Annual Conv. of CSI; 9 -12 Nov 1995, 258-267, Hyderabad] of the author.

2000 patents have been issued [1]. This approach has been used in a commercially notable expert system REVEAL from ICL [2,3] which is essentially a decision support system. A number of commercial / research knowledge based shells have also incorporated fuzzy reasoning; for example, FRIL [4]; LEONARDO [5]; CUBICALC [6]; TILSHELL [7]; SYSTEM Z-II [8]; SYSTEM Z-IIe [9]. Its applicability and usefulness are increasing interestingly in diverse fields [10-13]. In medical domain, fuzzy logic has previously been successfully used in a number of knowledge based systems [14-20]. For paediatric problem domain Ong and Qiu-He [21] report on interesting application. Here, the investigators have applied fuzzy logic for the diagnosis of convulsions in children. Using only symptoms (without CSF test) of twenty five patients to make diagnosis, their system achieved an accuracy of 92% compared to 67.7% on the average by normal [22]. However, in our opinion, the potential of fuzzy logic has not been exploited at length to cover different aspects of the paediatric domain. This motivated us to explore such possibility of use of this logic in paediatric problem domain, in particular, for 'neonates'.

In the next section, we discuss the basics of fuzzy logic and fuzzy set theory. Section 9.3 presents fuzzy concepts in neonates problem domain. In section 9.4, a fuzzy knowledge based consultation system (version 2.0) has been presented using **Appendix A**. In the last section, we draw our conclusion.

9.2. Basics of Fuzzy Logic and Fuzzy Set Theory

The concept of fuzzy set and fuzzy logic were introduced by Zadeh [23]. Zadeh was working in the field of control engineering. His intention in introducing this fuzzy set theory was to deal with problems involving knowledge expressed in vague, linguistic terms. Classically, a set is defined by its members. An object may be either a member or a non-member : the characteristic of traditional (**crisp**) set. The connected logical proposition may also be true or false. This concept of crisp set may be extended to fuzzy set with the introduction of the idea of partial truth. Any object may be a member of a set 'to some degree'; and a logical proposition may hold true 'to some degree'. Often, we communicate with other people by making qualitative statements, some of which are vague because we simply do not have the precise datum at our disposal e.g. a person is **tall** (we have no exact numerical value at that moment) or because the datum is not measurable in any scale e.g. a **beautiful** girl (for **beautiful**, no metric exists). Here, **tall** and **beautiful** are fuzzy sets. So, fuzzy concepts are one of the important channels by which we mediate and exchange information, ideas and understanding between ourselves. Fuzzy set theory offers a precise mathematical form to describe such fuzzy terms such as **tall**, **small**, **rather tall**, **very tall**, etc. in the form of fuzzy sets of a linguistic variable. To represent the shades of meaning of such linguistic terms, the concept of grades of membership (μ) or the concept of possibility values of membership has been introduced. We write $\mu(x)$ to

represent the membership of some object to the set X. Membership of an object will vary from full membership to non-membership :

- $\mu = 0$ for no membership;
- $\mu = 1$ for full membership;
- $0 < \mu < 1$ for partial membership.

Any fuzzy term may be described by a continuous mathematical function or discretely by a set of pairs of values {numeric values of linguistic variable, corresponding grade of membership}.

For example, '**tall**' may be described by a sigmoid as shown in fig. 9.1.

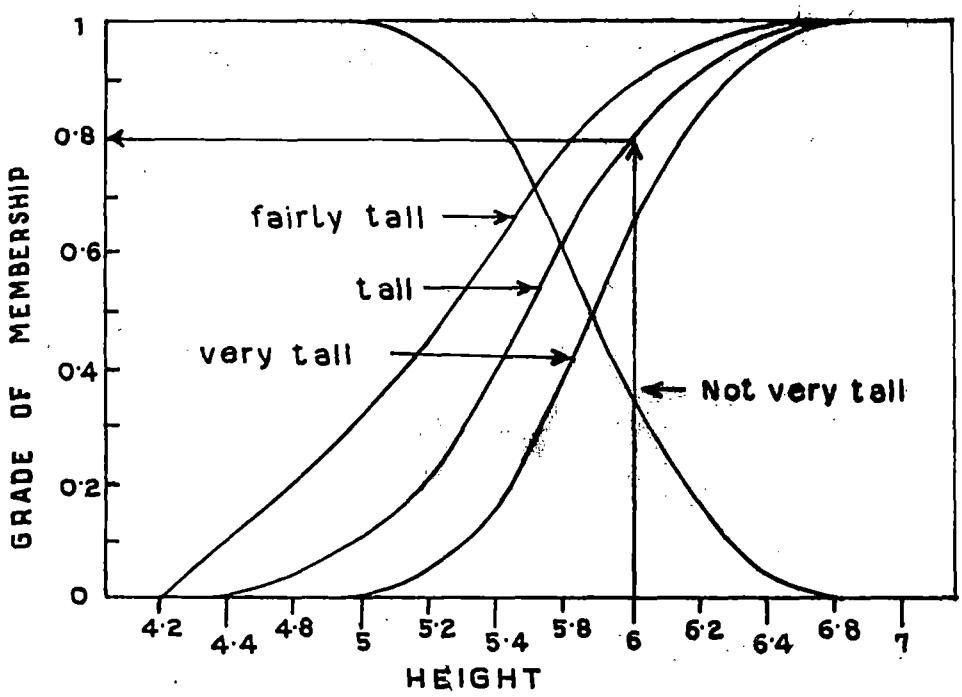

Fig. 9.1 Fuzzy term tall with modifiers

The fuzzy term '**tall**' can also be described by the following fuzzy set :

Height	Grade of membership
4'0"	0.00
4'2"	0.00
4'4"	0.01
4'8"	0.04
5'0"	0.10
5'2"	0.20
5'4"	0.38
5'8"	0.62
6'0"	0.80
6'2"	0.92
6'4"	0.98
6'8"	1.00
7'0"	1.00

Note that these membership values are not probability values which are the measure of randomness. So, the sum total of membership values should not be 1.

Every element of the fuzzy set will have its corresponding membership value in this range (fig.9.1). Having the numerical representation of these linguistic terms, one has to define the set theoretic operations of union, intersection and complementation along with their logical counterparts of conjunction, disjunction and complementation which are as follows :

- Union (logical OR) - the membership of an element in the union of two fuzzy sets is the larger of the memberships in these sets.

  μ(A OR B) = max(μ(A), μ(B)) e.g.,
  μ(tall OR small) = max{μ(tall), μ(small)}

- Intersection (logical AND) - the membership of an element in the intersection of two fuzzy sets is the smaller of the memberships in these sets.

  μ(A AND B) = min(μ(A), μ(B)) e.g.,
  μ(tall AND small) = min{μ(tall), μ(small)}

- Complement (logical NOT) - the degree of truth of the membership to the complement of the set is defined as (1 - membership).

$$\mu(\text{NOT A}) = 1 - \mu(A) \text{ e.g.,}$$
$$\mu(\text{NOT tall}) = \{1 - \mu(\text{tall})\}$$

Example :

In fig. 9.1, we may consider two fuzzy sets : **fairly tall** and **not very tall**. The height 5′4″ has a grade of membership of 0.62 in the first set, and 0.86 in the second. Thus, the grade of membership in the combined set **fairly tall** AND **not very tall** is min (0.62, 0.86) = 0.62.

The grade of membership in the combined set **fairly tall** OR **not very tall** is max (0.62, 0.86) = 0.86. And, the grade of membership in the set **NOT very tall** = 1 - μ (**very tall**) = 1 - 0.14 = 0.86.

Fuzzy numbers, like ordinary numbers, can be used in different arithmetic operations like addition, multiplication etc. that give another fuzzy number as the result [8] as shown in fig. 9.2.

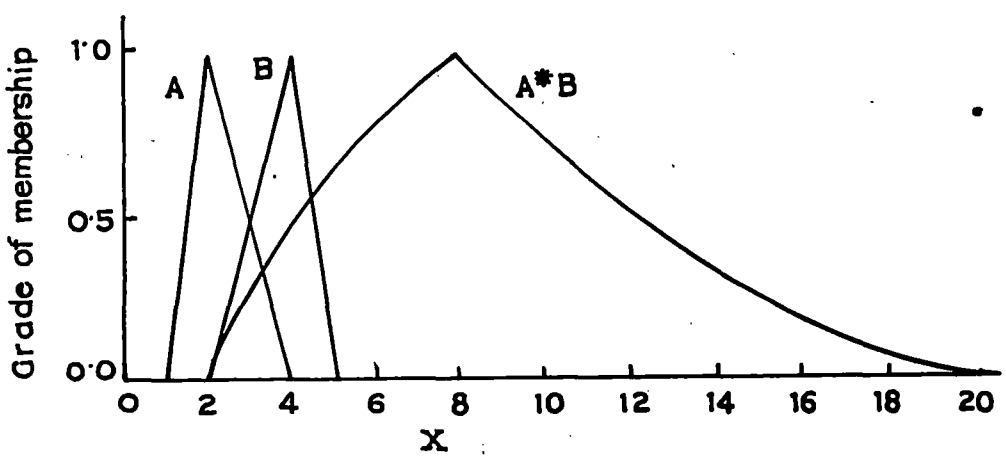

Fig. 9.2 Multiplication of two fuzzy numbers

Moreover, some fuzzy modifiers or 'hedges' such as **very**, **around**, **rather**, **quite**, **fairly**, **extremely** are common in our real-life knowledge-transfer. One can obtain the possibility distribution of a fuzzy concept like **very tall** or **fairly tall** by applying arithmetic operations on the fuzzy set of the basic fuzzy term **tall**. Power factors are a simple and convenient way for the required arithmetic operations since the grade of membership of a fuzzy set falls in the interval [0,1]. For example, we can calculate the possibility values of each height in the fuzzy set representing the fuzzy concept **very tall** by taking the square of the corresponding possibility values in the fuzzy set of **tall** (fig.9.1). Similarly, we can tackle the situation for **fairly tall** by using the square root operation on fuzzy set **tall** (fig.9.1). If one wants to generate fairly tall but not very tall, the following procedure may be followed. First we generate the set **fairly tall** by taking the square root of **tall**; then the set **very tall** by squaring **tall**; then the set **not very tall** by negating the set **very tall**. Finally, we take the intersection of these two sets (representing **but** by the **and** operation) producing the final set.

Possibly much human reasoning is based on the concepts of implications which states that :

IF antecedent THEN consequent.

For example,

IF is A THEN Y is B.

If **antecedent** is true, **consequent** will also be true. This is **modus ponens** inference. However, there are other ways of reasoning from implications such as **modus tollens** and **hypothetical syllogism**. **Modus tollens** is based on the reasoning from data about Y to a conclusion about X. In **hypothetical syllogism**, an implication relating X to Y is combined with an implication relating Y to Z to yield an implication relating X to Z. Researchers in fuzzy logic have explored fuzzy versions of all of these, but only modus ponens has seen applications in expert systems. The present author, obviously, will continue discussion using **modus ponens** approach.

Often human knowledge is expressed in such a way that antecedent and / or consequent may contain fuzzy and / or crisp values. The following table may be considered valid :

Antecedent	Consequent
crisp	crisp
crisp	fuzzy
fuzzy	fuzzy

Note here that for 'fuzzy A' degree of truthness of B should not be greater than that of A. Fuzzy logic allows both the antecedent and consequent to be fuzzy propositions. These fuzzy propositions comprise statements involving linguistic variables, which will have shades of meaning or varying degrees of truth. An antecedent of any rule may be a simple clause (or atomic propositions) or may be a combination of number of clauses connected via the fuzzy logical operators AND, OR, NOT AND and NOT OR. For examples :

Example 1.

IF

Rhythms (sleep and meals) of a baby is satisfactory
THEN
Growth of the baby should be good.

Example 2.

IF

Production volume is high

AND

Flexibility is high
THEN
Variety is high [10].

Recently, however, some reserchers [21] have suggested an extension to the basic conjunctions of AND and OR by incorporating the ADD and REL conjunctions for the linkage of premises in conventional rules.

Now, we have a fact 'Rhythms of a baby is highly satisfactory' which matches with the rule as stated in above example 1. We have to find out the corresponding conclusion which will be reflected from the consequent section of the rule. The fuzzy concepts satisfactory and good can be modeled by a fuzzy relation R, represented by a matrix. Let F_1 and F_2 be the fuzzy sets representing the concepts satisfactory and good, respectively. One can obtain the fuzzy relation R [24] by performing some fuzzy operations on F_1 and F_2 , expressed as vectors. Different approaches have been proposed to compute the fuzzy relation R. One may use the Cartesian product $F_1 \times F_2$ to get the mapping or relation $R\,(F_1 \longrightarrow F_2)$.

The fuzzy concept highly satisfactory can be represented by a fuzzy set F, which we may obtain by applying an arithmatic operation (a square operation in this case) on F_1 . The fuzzy set C representing the effect or conclusion after the application of the said fact can be deduced by applying a fuzzy operator called composition operator (denoted by $\mathbf{O}$) on F and R i.e.,

$$C = F \;\mathbf{O}\; R$$

A number of forms for composition operator has been suggested to compute C. Most of the developers of expert systems prefer the **max-min** composition rule of Zadeh [25]. Obviously, the vector C will indicate very good and the conclusion growth of the baby should be very good will be drawn.

9.3. Fuzzy Concepts in 'NEONATES' Problem Domain

In developing any computer based expert system, one has to acquire knowledge from domain experts to be stored in knowledge base(s). Inferencing procedure works on these knowledge base(s) using some basic facts as input. The knowledge base(s) used by a typical computer-based expert system often comprises vague, linguistic rules as articulated by domain experts, i.e., Paediatricians in the field of paediatrics. Moreover, the basic facts on which the reasoning process starts may also often comprise such vague, linguistic articulations. In designing an expert system with fuzzy uncertainty / inexactness for a problem domain, one has to identity, first, the linguistic variables for the domain. Next, one has to define the term set of fuzzy sets which adequately covers the spaces of the domain. The members of a term set are linguistic terms characterising the corresponding linguistic variable. Once such fuzzy variables and term sets are defined, the knowledge representation using rules will become easy. For example, for the present problem domain (for a neonate), some main linguistic variables and the corresponding term sets may be identified as :

- General status → {Healthy, sick};
- Birth weight → {SGA, AGA, HGA};
- Muscle tone → {flaccid, some-flexion, actively moving the extremities};
- Heart rate → {none, normal(100-140), low};
- Respiratory effort → {none, slow/irregular, good/crying};
- Reflex stimulation → {noresponse; grimace; cries, coughs or sneezes};
- Colour → {blue/pale, periphery blue and body pink, pink}.

Every member of a term set will be attached to a set of numerical values between 0 and 1 (inclusive) called possibility values or grades of membership in the term set. This fixation of numerical values, obviously, will be done by domain experts. It is, now, important to examine the 'adequacy' of a term set for the problem domain. The question of granularity of representation comes into picture in this context. If we have too few members in a term set, a system may be inadequately descriptive. If we have too many members in a term set, this may lead to unmanageable situation in two important respects. First, large amount of storage space will be required for storing fuzzy tables. Or if one desires to represent such terms using mathematical functions, the number of such functions may be unmanageably high which may lead to reduction of speed of a typical expert system. Second, the associated rules will become cumbersome.

One feasible solution of the above problem may be achieved using the concept of '**hedges**' and fuzzy logical operators AND, OR, NOT. For example, if we are talking about '**general status**' of a baby, the term set **{healthy, sick,}** may be considered as our primitive term set for the linguistic variable '**general status**'. Other fuzzy terms like **fairly healthy**, **very healthy**, **not very healthy** etc. can be derived from the members of primitive term set. Now, we are in a position to generate a fuzzy set to represent a complete phrase 'fairly healthy but not very healthy.' Fig.9.3 illustrates the required intermediate fuzzy sets to generate fairly healthy but not very healthy. This kind of analysis may be useful in assessment of a patient by a doctor. For example, a baby with respiratory distress or convulsion may be analysed in this manner for further management i.e. whether the baby needs hospitalization with or without intensive care, may be kept for observation or may be advised for domiciliary treatment.

The above concepts and ideas will certainly be useful in developing a prototype system for neonatal resuscitation management which has been considered in **chapter 11**. In the next section, we now present a fuzzy consultation system (version 2.0) for the present problem domain based on **Appendix A**.

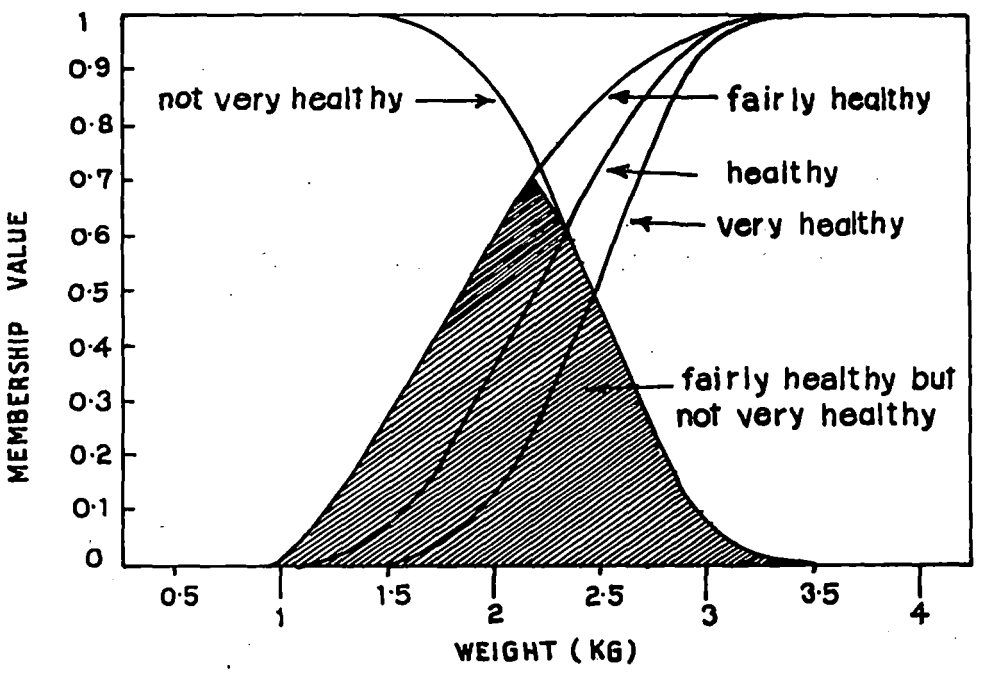

Fig. 9.3 Generating fairly healthy but not very healthy

9.4. **Prototype system (version 2.0)**

This version deals with some fuzzy concepts in terms of linguistic articulations. The architectural components of our modified system is shown in fig. 9.4. The knowledge base (KB) consists of two parts : static part and dynamic part. The static part is relatively fixed over time. The dynamic part is capable of adding new facts or facts can be removed from the KB as when required. The inference engine uses LTKB and STKB to infer new facts. It has two well-known functions : inference and control. Backward reasoning process has been used here which favours the needs of the application domain. The inference engine uses depth-first scanning but with an 'improved back tracking' using some control rules provided that sufficient domain knowledge is available. A user interacts with the system with the user interface of the system. Through this module different quaries are served by the system initiated by the inference engine. The fuzzification and defuzzification required for user supplied linguistic terms (fuzzy) and that required for fuzzy knowledge rules extracted from domain experts are governed by control section of the inference engine. The total review management is transparent to the user through this particular module. All accesses by a user to KB and review management module are through inference engine. However, logical access is presented through broken line of fig. 9.4.

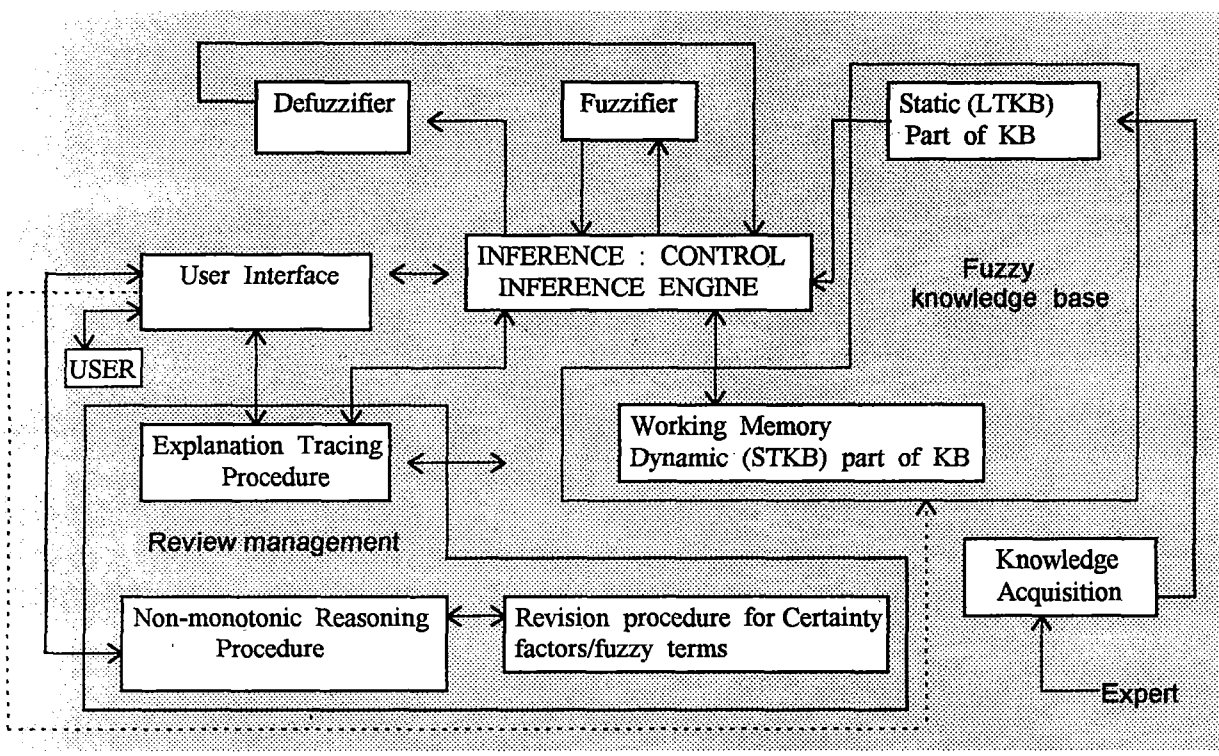

Fig. 9.4 System architecture

9.4.1. **A typical consultation session**

The following presents an excerpt from a typical consultation session with the system. The objective of this excerpt is to highlight some of the important features of the system. It is a menu-driven system.

A CONSULTATION SYSTEM FOR CHILD GROWTH AND DEVELOPMENT

MAIN MENU

Addition of records and consultation
Previous record with reference number
Printing record with reference number
Read records
Updation
Delete records
Dos
Exit

Enter Command ☐

CAUTION :
PRESENT
PROTOTYPE
NOT FOR
MEDICAL
USE

Considering the first menu, the particulars like name, age, parents' name etc about the child have to be supplied along with the values of different activities to be examined in terms of CF / fuzzy values. We get the following analysis :

Reference No.: c22/8/95basam43	Age : up to One Year
Activity	CF/Fuzzy Values On 2/8/95
Axial Muscle Tone	Good
Muscle Tone of Limbs	Very good
Spontaneous Gestures	Very good
Gripping	Good
Relation	Good
Emotional & Social Development	Almost poor
Language	Almost poor
Rhythms	Very good
EEG	Good

ABNORMAL ACTIVITIES
Emo_Social_Development
Language

Press a Key

SUMMARY

Total No. of Activities : 9

VERY GOOD : 3 GOOD : 4 ALRIGHT : 0 UNKNOWN : 0
ALMOST POOR : 2 POOR : 0 POOREST : 0

EXPERT CONCLUSION : GROWTH IS ALMOST NORMAL

Press a Key

If then compares with the previous values, if required, and then offers an advice as follows :

COMPARISON WITH PREVIOUS RECORD

Growth increasing in 80% cases.
The variation upto 10% has been neglected.

CONCLUSION :
The growth of the baby is expected to be normal

Press a Key

ADVICE

Please take care of the following activities of Basudev

Axial Muscle Tone
Emotional & Social Development
Language

Press a key

9.5. Conclusions

In this chapter, we have presented an outline of fuzzy concepts in paediatric problem domain to show the usefulness and importance of fuzzy logic and fuzzy set theory keeping in mind the importance of experience and judgement that an expert uses when examining a patient. In designing computer-based expert systems, one of the key problems to manage inexact knowledge of different kinds. One important kind is fuzziness arising from human linguistic articulations. It is argued that fuzzy concepts have to be dealt with properly to offer a rational decision. After a brief introduction to fuzzy logic and fuzzy set theory, we have identified different primary linguistic variables and corresponding term sets which will be required during the design of an expert system. Some potential problems, e.g. the problem of 'adequacy' of a term set, have also been addressed in this context. A prototype system (version 2.0) incorporating some fuzzy concepts in terms of linguistic articulations has been presented. In **chapter 11**, we are to present a fuzzy knowledge based neonatal resuscitation management system.

Finally, fuzzy logic offers a natural and convenient way of expressing inexactness of fuzzy nature. The naturalness of fuzzy logic may certainly assist us in both knowledge acquisition and inferencing procedures. Due to the naturalness of input - such as around 105^{0}F, a little, normal, the programs for inferencing are generally much smaller and faster than conventional programs using binary logic.

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