A CASE BASED APPROACH (PROTOTYPE 5.0)†

11.1. Introduction

Although, for more than 30 years the rule-based reasoning (RBR) has been the predominant technology for KBS / ES projects in different domains, but, however, this approach is critisized for: (i) It is sometimes difficult to translate the knowledge of a domain into rules; (ii) Managing thousands of rules for a practical system design seems very difficult since (a) the system would be very complex and time consuming to develop, (b) they are difficult to maintain once developed [1], (c) it is very difficult to add/subtract rules as well as to pinpoint the effects of a rule within such a complex system as complex debugging procedures are required; (iii) The time required, with this volume of rules, to reach a conclusion seems untolerably high; (iv) It is very hard to find out the contradictory rules for the system. Although, however, some improved techniques, e.g., object-oriented technology, have been proposed for knowledge representation and management to ease the debugging process of knowledge but knowledge acquisition, the primary task of KBS / ES development, still remains to be a complicated task.

Case based reasoning (CBR), a graceful alternative of rule based approach, is gaining swift momentum as a relatively new technology. CBR is a problem-solving paradigm using past experiences to guide problem-solving [2]. In CBR, cases similar to the current problem are retrieved from the case memory, the best match is selected from those retrieved, and if an adaptation is necessary then the best match will be adapted to fit the current problem based on the differences between the previous and current cases. The issue of knowledge acquisition needs to be revisited here. Where do we start knowledge acquisition? As argued by di Piazza and Helsabeck [3], the extraction of cases seems to be the most effective way to begin knowledge acquisition for any KBS / ES project because the case description is the easiest way for the experts to express him(her) self. Obviously, the previous cases must be available to the experts. It is usual in medical domain that the doctors observe cases, diagnose and advice what is their daily fare. So, case-based reasoning might be a good choice. Moreover, CBR does not require an explicit domain model and so knowledge elicitation would be performed by gathering case histories [4]. From case histories rule generation might be possible describing the system.

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† This is based on the publication [Proc. of the Nat. conf. on Medical Informatics, Institute of Public Enterprise, Hyderabad, India, 6-7 April, 1999, 99 - 107] of the author.

Two problems can be encountered when one relying exclusively on case-based reasoning [5] : (i) it is difficult to start from the very begining with an empty case library; and (ii) after some time the case library can become huge and contains much redundancy. Therefore, it is better to combine the case-based reasoning with some other paradigm to compensate for these marginal insufficiencies. As a potential compensating candidate, the rule-based reasoning component can play useful role with the help of system knowledge and heuristics. This essentially means that the rule-based part can offer a solution as and when requested. The following highlights the circumstances when one has to request for rule-based approach:

- No old solution can be found for a current situation in the case library. For this event, the rule-based reasoning part can be activated. But, however, such RBR generated solution should be checked more carefully.

- There might be some situations which are almost same but not identical. Such cases cause a high level of redundancy of the case library. Replacement of such a class of very similar cases by a set of rules can partially solve this problem.

- The rule-based reasoning part can also assist in solving some specific situations.

11.2. **Neonatal Resuscitation Management : A case study**

CBR has already been applied in different domains such as Engineering, Medicine, Design, Law, Business planning [6-11]. But, however, to our knowlegde, CBR has not been applied to the problem domain of neonatal resuscitation management. This work suggests a case-based approach with rule-based augmentation for developing a knowledge based system for neonatal resuscitation management. From academic point of view, CBR's application to this domain might be a novel concept, but before applying it to this domain one has to answer: is it a workable and valid solution?

The goals of neonatal resuscitation are to prevent the morbidity and mortality associated with hypoxic-ischemic tissue (brain, heart, kidney) injury and to re-establish adequate spontaneous respiration and cardiac output [12].

In general, APGAR- scheme [12] is used for resuscitation management which is shown in table 11.1.

Table 11.1. **APGAR scheme**[12]

SIGN	0	1	2
Heart rate/minute	Absent	Below 100	Over 100
Respiratory effort	Absent	Slow, irregular	Good, crying
Muscle tone of limbs	Flaccid	Some flexion	Active motion
Reflex stimulation(catheter in the nose)	No response	Grimace	Cries,coughs or sneezes
Colour	Blue or pale	Body pink,extremities blue	Pink

11.3. CBR's Validity

Before applying case based reasoning to this problem domain, we must have to clarify CBR's validity in this research. In the line of Farngou et al. [11], we would like to explore this issue of validity from two perspectives (i) AI prespective, and (ii) Domain perspective.

11.3.1. AI perspective

One of the important application areas of AI is expert system (ES) / knowledge based system (KBS). To solve problems KBS / ES use knowledge in the form of human experience. Obviously, the success/failure of the development and use of KBS / ES should certainly depend on the understanding of the mechanisms human experience use in solving problems. This essentially demands the understanding of the human cognitive processes. About 37 years back, Newell and Simon [13] proposed rule based approach as a model of human cognition. The rules take the form: IF < condition > THEN < action >. Using this 'condition-action' pair scheme, a good number of attempts has been made to develop KBS/ES in different domains starting from MYCIN. There are reports of relative success/failure of these attempts. Concentrating on medical domain one might observe that a very few attempts find their applications in actual medical floor. Why ? One of the reasons might be the cognitive approach in the form of rule-based reasoning. Do experts think in the form of rules and solve problems from memory ? [14].

An altenative cognitive approach presented by Riesbeck and Schank [15] is 'case based' thinking. They view that human experiences are stored in the human brain in the form of previous cases, rather than a set of rules. According to them, the basic justification for the use of CBR is that human thinking does not use logic or reasoning from first principle. In addition, CBR is not constrained to a model and so, it allows the addition/subtraction of new cases or experience, medical practitioners acquire during case handling, without the need of complex debugging what is required in rule-based reasoning.

11.3.2. **Domain Perspective**

In medical domain doctors are supposed to observe, diagnose and advise depending on signs and symptoms. The correctness of diagnosis should certainly depend on the proper manifestation of signs and symptoms. In this regard there are a good number of uncertainties involved in the domain[16]. Any software tool, in particular, a computer based consultation systems / ES-developed to aid doctors in their decision making needs to take into account the inexact nature of information expecting to lead to rational decisions.

A number of methods have been proposed to deal with different aspects of inexact information management with their varying degrees of success. In essence [17], 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.

In expert systems, the common approaches in dealing with inexactness 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 models has yet been universally adopted by theoreticians or by practitioners. Most of the attempts have been made to manage different forms of inexactness using rule-based approach.

From the perspective explored above, it may be stated that there is no unique model for managing all types of knowledge - exact and inexact nature. Successful doctors are said to have better 'clinical eye'. The sharpness of the clinical eye should certainly depend on the experience and as experience enters into a discussion suggests the applicability of CBR approach. It is unlikely that the doctors use rule book for diagnosis of a new case. Rather, he or she are more likely to use their experiences and judgement. Moreover, case descriptions can incorporate the uncertainties of different forms.

We have tried to explore both the AI and domain perspective of applying the CBR approach to the problem domain. Convincingly, CBR approach might be a viable approach to the problem domain. This is highlighted as follows:

- No unique model is available for managing all types of knowledge of exact and inexact nature for the problem domain. CBR does not demand an explicit model, so knowledge elicitation can be achieved by acquiring cases [4].

- Doctors use heuristics and personal judgement during a consultation session in the presence of so many uncertainties, and so it is unlikely that knowledge can be as structured as in the form of production rules. This suggests that problem domain might be suited to CBR techniques.

- Updation of knowledge base is easier in CBR approach as doctors gain from their experiences. But for the rule/model-basaed approach the knowledge updating process would require complex debugging process.

- Less experienced users of a KBS/ES who lack in-depth domain knowledge, may find CBR more user-friendly since they would have the ability to retrieve cases, whether or not the user has input all the necessary problem situation data [18].

- Developing rule/model-based system is really more complex and time consuming compared to CBR approach. 800% cost saving is reported using CBR approach [19].

With the above justifications of applying CBR to this domain, we should not underestimate the role of RBR (rule-based reasoning). Because CBR may be augmented by RBR compensating the marginal insufficiencies in the former as discussed in the introduction. So, in this work an attempt has been made to develop a case-based system with rule-based augmentation.

11.4. **The System**

A case-based screening system requires a retrieval mechanism that can retrieve similar cases, a selection mechanism that can select the best match and an adaptation mechanism to fit the new situation. The present system consists of : an input interface, a case memory, and a decision maker. The decision maker has itself three components: the matching/selection module, adaptation module, and the rule based reasoner module. The schematic view of the system is shown in fig. 11.1. The system is implemented using Level5(Object), a tool kit from Information Builders Inc, USA under PC-based window environment.

For the consultation system, consultation starts with the input interface accepting the new case(s). Using the input interface it provides multi-selection-based input screen (see figs.11.2 & 11.3) for the description of the new case. The new case 'feature-values' may consists of crisp values as well as non-crisp values in terms of linguistic articulations. The input interface then passes the case to the matching/selection module. If the exact matching is not found then the control is passed to the adaptation module. After adaptation if exact matching is not found, the control is passed to the rule-based reasoner part of the system.

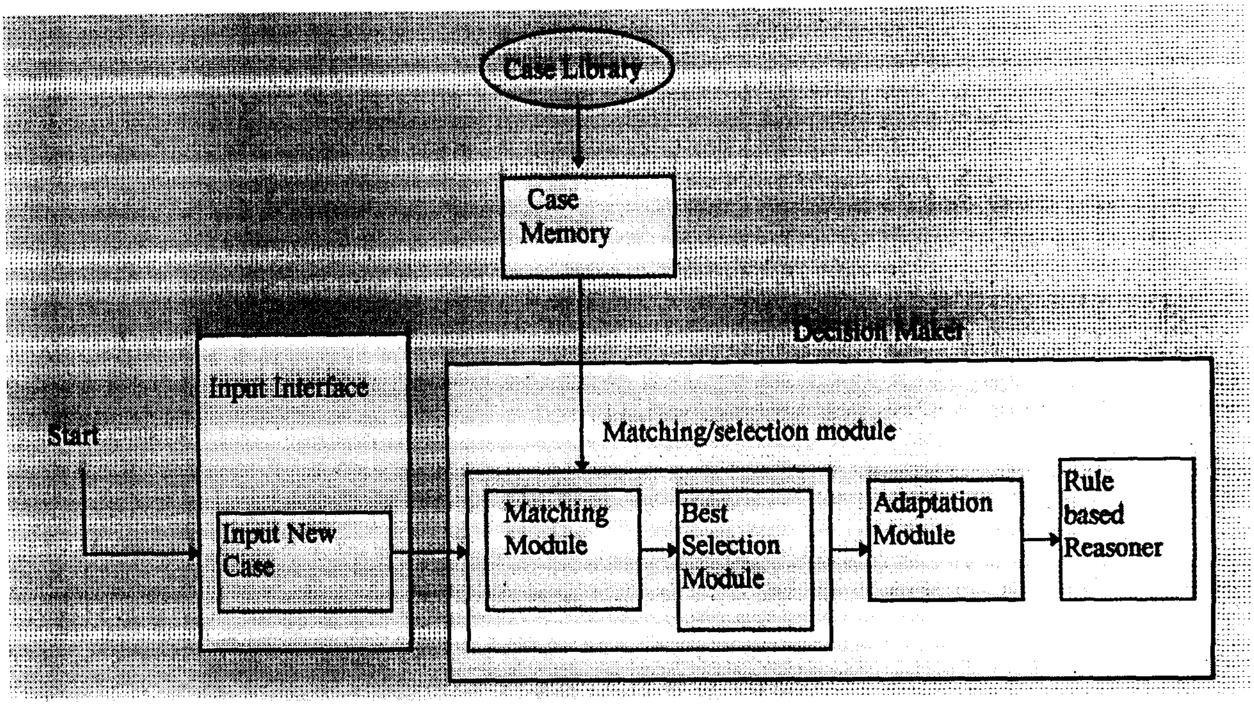

Fig.11.1. Schematic view of the system

From the domain experts, case descriptions have been collected. Although most screening cases are useful in CBR, storage of all cases (in thousands) can lead to overly large case memory [10]. Moreover, the time for screening would be undesirably high. The case memory is therefore intended to contain a representative set rather than a complete set of cases which keeps the memory size relatively small. The case memory is currently populated with 25 cases. As representative examples, we site here two cases of interest.

<u>Case 1</u> : Level II resuscitation

- Respiration : None
- Heart rate : Less than 100/minute
- Colour : Whole body pink feet blue
- Muscle tone of limbs : Flexion at three joins rest flaccid
- Reflex : First touch sneeze

<u>Case 2</u> : Level III resuscitation

- Respiration : Rate normal character rythmic
- Heart rate : 100/minute
- Colour : Whole body pink feet blue
- Muscle tone of limbs : Flexion at four joins rest flaccid
- Reflex : First grimace then sneeze

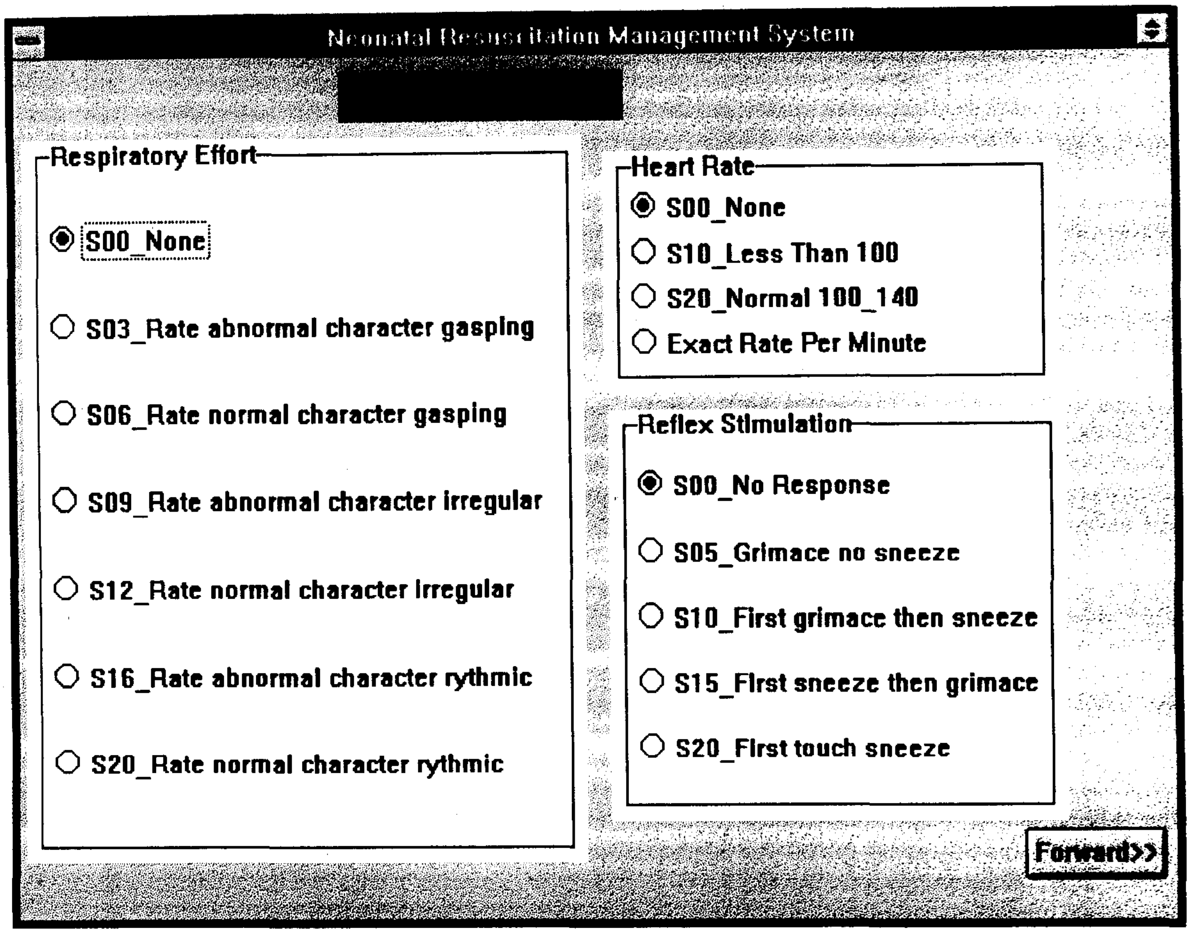

Fig.11.2. New case input

A case is a 'conceptualized piece of knowledge representing an experience that teaches a lesson fundamental to achieving the goals of the reasoner' [20]. It is important that cases are represented in a form that effectively imparts knowledge, to the user to reason with, so that a particular task can be performed [11]. In this application, the user needs to access a case (or cases) that suggests the resuscitation level of a neonate for taking further actions. There are a few issues that need addressing before a proper representation can be devised. Who will be the proposed user, Neonatalogists, general paediatricians, general medial practitioners having M.B.B.S degree or medical students undergoing training ? For its common acceptance the system should provide advice to all of its intended users (experts or novices). Therefore, the lessons presented within each case should be understandable and integrated regardless of the levels of intended users. And so system vocabulary has been selected according to the levels of intended users. The cases are grouped according to the goals, i.e., level I, II, or III. This grouping is useful for the debugging process. Every case is weighted at per the 'feature-values'. We assume that the weight of all features are equal.

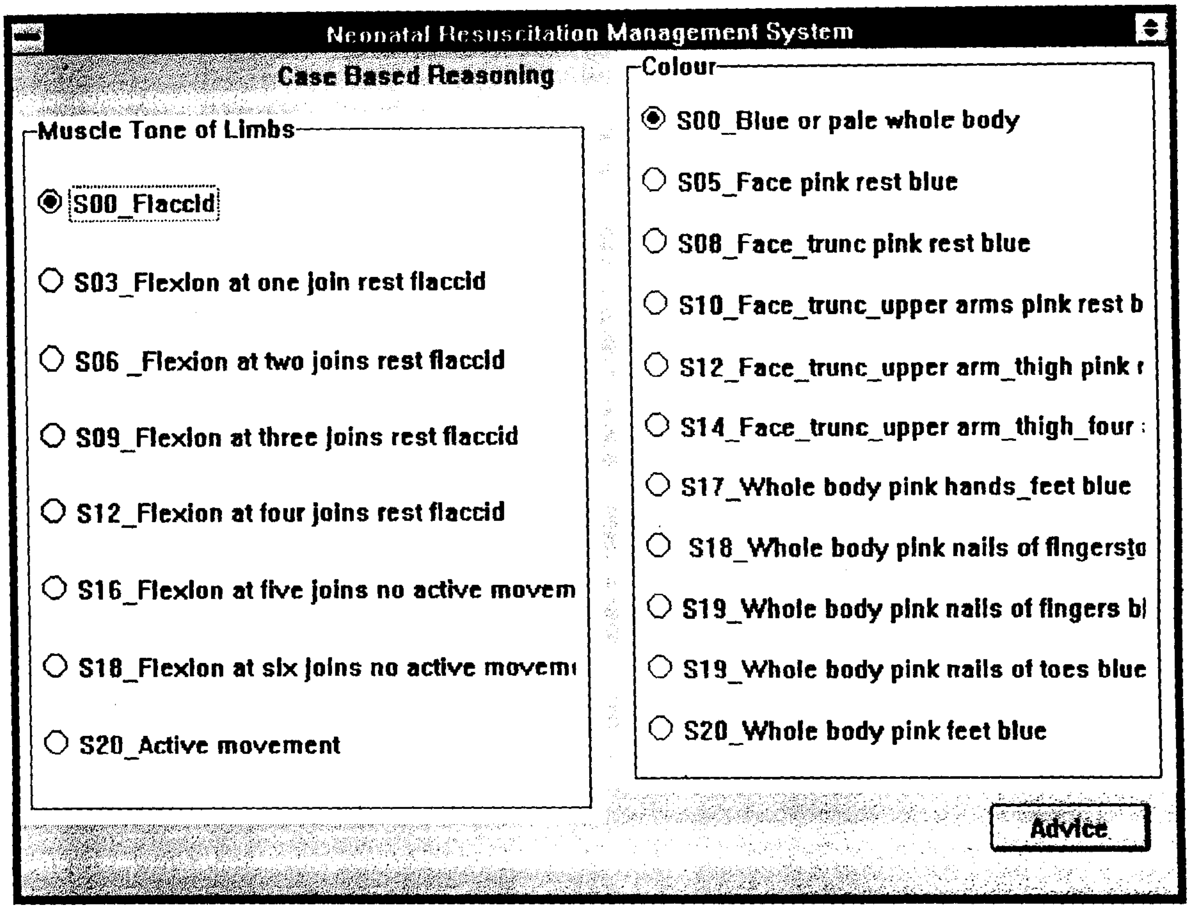

Fig. 11.3. New case input

We consider each goal as an object. Every object has its attributes - Respiration, Heart rate, Colour, Muscle tone of limbs,and Reflex. Level I object has 7 instances. Similarly, Level II and Level III have 9 instances each. We 'FIND' that instances 'WHERE' the attributes of the new case match with the old cases. The complexity of this retrieval technique is essentially linear. As the number of cases is small of the presented system, this retrieval technique might be accepted.

The overall goal of the decision maker is to advice the level of resuscitation. It consists of two parts: case retriever and rule-base reasoner. The goal of case retrieval is to find the best match between the current problem (new case) and past problem (from memory) that has a solution [15]. Upon accepting a new case, our system acts in order as follows :

Step 1

It first pursues the old cases to match the new case as 100% matching basis without any reference to the weight factors assigned to each 'feature-values'. It scans the cases at per the heighest level of weight factors assigned to the cases and the searching is stopped at the point where it gets 100% match or the number of cases are exhausted. If the scan is successful, it displays its decision; and the processing is stopped. As a matter of fact, matching on 100% basis is a rare situation; one has to take help of an adaptation scheme as described in step 2 follows.

Step 2

In this application, we adapt the input 'feature-values'. Fuzzy reasoning techniques have been emphasized by some work on intelligent systems [21,22]. We deployed here fuzzy set theoretic approach for input adaptation. The crisp 'feature-values' are fuzzified. For example, heart rate 90/minute is fuzzified as shown in fig. 11.4. It then repeats the step 1. If exact matching is not found, it proceeds to the step 3.

Step 3

In this step, the system takes the total score calculated from the weight factors assigned to each 'feature values' of the new case under consideration into account. The output decision is fuzzified as shown in fig. 1.5. Depending on the score obtained by the new case the decision is taken by the system at per fig.11.5 with the corresponding possibility value.

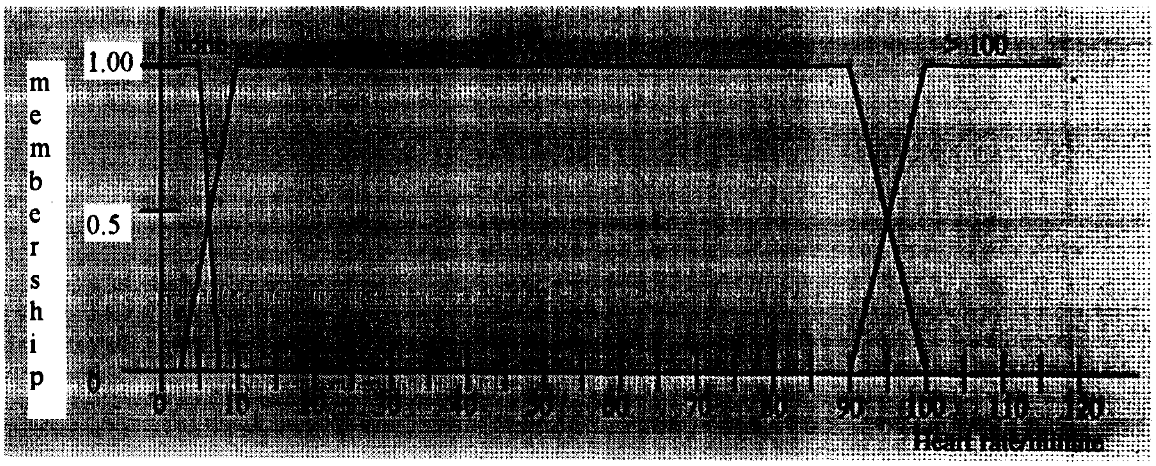

Fig.11.4. Heart rate

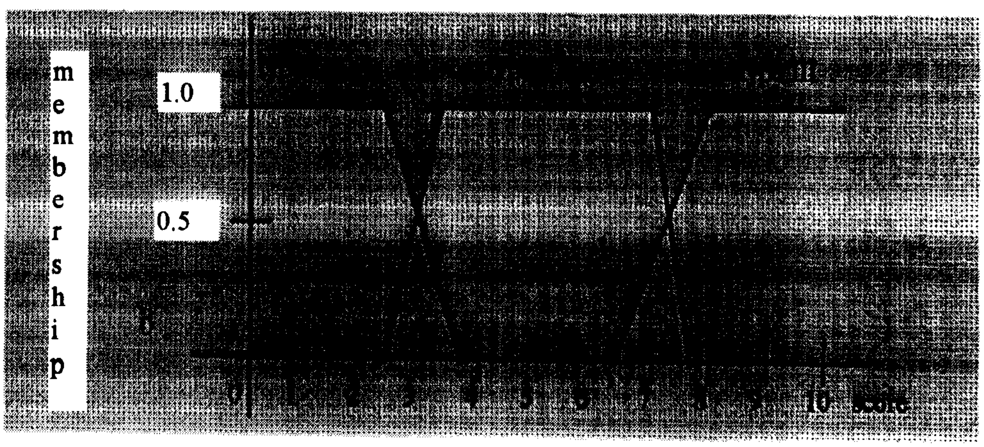

Fig. 11.5. Fuzzification of system decision

11.5. **Performance Evaluation**

Lastly, performance evaluation should be produced. As a matter of fact, it is to some extent difficult to establish the degree of performance owing to the non-availability of experimental results in the classical sense. Validating a case-based system different methods are there in the literature. Methods such as leave-one-out [18], using part of the case-library as test cases [23], and applying actual field cases from the domain. In order to validate the system more accurately, twenty-one case studies as available from a domain expert, who is not connected to this research, were analysed. The results suggested by the expert were compared with those suggested by our system. The system showed an accuracy of 85%.

11.6. **Discussions**

Starting from MYCIN, the rule based approach has long been the principal approach to use for medical diagnosis systems. The rule base paradigm suffers since it is driven neither by exemplars nor by a model (partial in most cases). For constructing intelligent systems CBR is viable alternative to rule-based systems. Current research indicates that case based approach may be better suited to medical diagnosis systems. But, however, the appeal of RBR should not be overruled. Case-based reasoning is augmented by rule-based reasoning compensating the marginal insufficiencies in the former. This chapter explores the applicability of CBR to neonatal resuscitation management with rule-based augmentation. Although, the accuracy of the current system is less than that we achieved [24] using fuzzy rule based approach (95%), nevertheless the results are encouraging. The discrepency of two results is not surprising. The accuracy of the current system would increase with the increase of cases in the memory.

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