

Fuzzy Logic Expert System-A Prescriptive Approach

Wahid palash¹, Md. Fuzlul Karim², Sumaiya Sultana Rika³, Md. Faruque Islam⁴

¹(IICT, Bangladesh University of Engineering Technology, Bangladesh)

²(EEE, American International University- Bangladesh, Bangladesh)

³(CSE, Ahsanullah university of science and technology, Bangladesh)

⁴(EEE, American International University- Bangladesh, Bangladesh)

ABSTRACT: A membership value of a fuzzy set has been defined as the degree to which an element belongs to this fuzzy set. It is possible to give other interpretations to the membership degree like a certainty factor, a degree of truth, a degree of satisfaction and a degree of possibility. In 1978 Zadeh extended the fuzzy set theory to a possibility theory where the membership values are considered as degrees of possibility. Zadeh justifies the possibility theory by the fact that the imprecision that is intrinsic in natural languages is, in the main, possibility rather than probabilistic in nature. In contrast to the statistical perspective of the information which is involved in the coding, the transmission and the reception of the data, the theory of possibility focuses on the meaning of the information. One of the reasons the scientific community took an interest in the fuzzy logic theory is the financial success of fuzzy control in home appliances in the Japanese industry. In 1990, the consumer products market using fuzzy controllers was estimated to 2 billion dollars. Interestingly enough L. A. Zadeh is a major contributor of the modern control theory. The control theory is a very precise and strict approach in order to model systems or phenomena.

Keywords -Linguistic variable, Fuzzy set, Control Theory, System, and operator.

I. INTRODUCTION

One central concept in the possibility theory is the possibility distribution which is the counterpart of the probability distribution in the probability theory. A possibility distribution is a fuzzy set called fuzzy restriction, which acts as an elastic constraint, whose membership function determines the compatibility or the possibility with the concept of the fuzzy set. Given a possibility distribution it is possible to compute the possibility of another fuzzy set defined on the same universe [1]. Consider for instance the possibility distribution 'young' of a linguistic variable 'age' defined on the universe U and the fuzzy set 'around 35' also defined on U. By knowing that 'Mary is young' it is then possible to calculate the possibility that 'Mary is around 35'. Note that the possibility represents a degree of feasibility whereas the probability is related to a degree of likelihood implying that what is possible might not be probable and, conversely, what is improbable might not be impossible. The possibility theory opens the door to the fuzzy reasoning which can represent and manipulate the natural language. Almost all human related problems are so complex and so vague that only approximate linguistic expression can be used. The fuzzy approximate reasoning is based on different fuzzy inference patterns which deal with different implication interpretations and also determine the way the uncertainties are propagated. The fuzzy inference can then compute or deduct elastic constraints (fuzzy sets) determined by membership functions via the possibility concept. The idea of fuzzy logic was first advanced by Dr. Lotfi Zadeh of the University of California at Berkeley in the 1960s [2]. Dr. Zadeh was working on the problem of computer understanding of natural language. Natural language (like most other activities in life and indeed the universe) is not easily translated into the absolute terms of 0 and 1. (Whether everything is ultimately describable in binary terms is a philosophical question worth pursuing, but in practice much data we might want to feed a computer is in some state in between and so, frequently, are the results of computing.) Fuzzy logic includes 0 and 1 as extreme cases of truth (or "the state of matters" or "fact") but also includes the various states of truth in between so that, for example, the result of a comparison between two things could be not "tall" or "short" but ".38 of tallness."

II. FUZZY CONTROL THEORY

As all the aspects of the model have to be specified, modeling a complicated system is an extensive operation. For example, an application could be used to predict the path of a hurricane but if it has to be developed from scratch, the hurricane will be gone before the application is ready to use. In the control theory, the number of processes to be implemented grows exponentially relatively to the number of variables defining the system. For this reason some systems cannot be modeled even by high speed computers. A solution to this problematic is to roughly define systems with the help of the fuzzy logic theory. The fuzzy control is based on the approximate reasoning which offers a more realistic framework for human reasoning than the two-valued logic. The main advantages of fuzzy control over the classical control theory is its ability of implementing human expert knowledge, its methods for modeling non-linear systems and a shorter time to market development.

In the control theory systems are characterized by input and output variables as well as a set of rules. These rules define the behavior of the system [3]. The output variables are then calculated by inference based on the input variables and the given rules. An inference is the construct 'A implies B, B implies C then A implies C'. When a premise 'X implies Y' holds then Y is true if X is true and, conversely, X is false if Y is false. This is called a syllogism and a famous example is:

Implication: All men are mortal

Premise: Socrates is a man

Conclusion: Socrates is mortal

In the control theory the premises are defined by rules in the form 'If X is F Then Y is G' where X (resp. Y) is an input (resp. output) variable and F (resp. G) is a condition on X (resp. Y). Zadeh introduced in 1973 the compositional rule of inference which extends the inference mechanism in order to take the fuzziness into account. In 1993, Fullér and Zimmermann demonstrated the stability property of the conclusion using the compositional rule of inference which states that a conclusion depends continuously on the premise when the t-norm defining the composition and the membership function of the premise are continuous. This property guarantees that small changes in the membership function of the premise, eventually due to errors can imply only a small deviation in the conclusion.

The fuzzy rules can then be expressed in the natural language by the use of linguistic variables. Zadeh's fuzzy inference example where the conditions are expressed by the means of words is:

Implication: If a tomato is red then it is ripe

Premise: This tomato is very red

Conclusion: This tomato is very ripe

These words allow the fuzzy rules to integrate the semantics of the human knowledge and can be represented as fuzzy sets. The evaluation process of the fuzzy inference also differs from the classical control theory in the sense that all the rules involving a given output variable are computed simultaneously and their results are then merged in order to derive the value of the output variable. This is a major advantage over the classical control theory as it implies a compensation mechanism between the involved rules. As a result, a much smaller set of rules is required to model a system as the intermediate values of the input variables are dynamically interpolated from the existing rules. It also implies an inherent fault tolerance; consider that a rule has been erroneously implemented or that a hardware defect returns wrong results, the value of the output variable can be compensated by other rules defining this variable.

Many concrete applications using fuzzy control can be found. The most famous one is the opening in 1988 of a subway system in Sendai city (Japan) using the fuzzy control to accelerate and brake the trains more smoothly than a human driver. Compared to conventional control, this new approach achieved significant improvements in the fields of safety, riding comfort, accuracy of stop gap, running time and energy consumption. Other concrete applications can be found in domestic appliances like washing machines and vacuum cleaners, in visual systems like camera auto focus and photocopiers, in embedded car systems like anti-lock braking systems, transmission systems, cruise control and air conditioning, etc.

III. FUZZY EXPERT SYSTEM

Expert systems are a successful example from the broad field of artificial intelligence. Expert systems are knowledge-based systems which can derive decision or conclusion based on an extensive knowledge on a particular domain. More precisely, "an expert system is a program that can provide expertise for solving problems in a defined application area in the way the expert's do". This knowledge is represented in a set of 'If-Then' rules. By applying inferences on the specified rules, expert systems are able to derive optimal decisions. A major problematic, however, is to convert the experts' knowledge into a set of 'If-Then' rules which are exact given that the human representation of the knowledge cannot be sharply determined. This drawback can be

overcome by introducing the fuzziness. This is done by allowing the definition of fuzzy rules, i.e. rules with words determined by a membership function, and by applying the previously defined fuzzy inference [4]. Just like in the fuzzy control, the fuzzy inference allows a dynamic compensation between the different fuzzy rules which results in the definition of a smaller set of rules. Fuzzy expert systems are usually involved when processes cannot be described by exact algorithms or when these processes are difficult to model with conventional mathematical models. Although the rules definition and the inference mechanism of fuzzy expert systems are similar to those in fuzzy controls, fuzzy expert systems do not come under the category of fuzzy control. Fuzzy control applications (often called fuzzy controllers) work in a closed loop schema where the output variables, which are derived from the input variables, directly act on the considered object. The rules are then executed in cycles in order to maintain a system. In the case of fuzzy expert systems and, more generally, for fuzzy diagnosis, fuzzy data analysis and fuzzy classification systems, the output information of a fuzzy system is dedicated to a human user or a monitoring device and hasn't any impact on the object itself.

Earl Cox has implemented different fuzzy expert systems which have been successfully applied to the following domains: transportation, managed health care, financial services, insurance risk assessment, database information mining, company stability analysis, multi-resource and multi-project management, fraud detection, acquisition suitability studies, new product marketing and sales analysis. By comparing fuzzy expert systems with conventional expert systems Cox stated that "generally, the final models were less complex, smaller, and easier to build, implement, maintain, and extend than similar systems built using conventional symbolic expert systems".

IV. FUZZY CLASSIFICATION WITH DEFINITION

The fuzzy classification is a natural extension of the traditional classification, the same way that the fuzzy sets extend the classical sets. In a sharp classification, each object is assigned to exactly one class, meaning that the membership degree of the object is 1 in this class and 0 in all the others. The belonging of the objects in the classes is therefore mutually exclusive. In contrast, a fuzzy classification allows the objects to belong to several classes at the same time; furthermore, each object has membership degrees which express to what extent this object belongs to the different classes [5].

Definition Let O be an object characterized by a t -dimensional feature vector x_O of a universe of discourse U . Often U is the space R^t . Let $C_1; C_n$ be a set of classes which is given a priori or has to be discovered. A fuzzy classification calculates a membership vector $M = [m_1; \dots; m_n]$ for the object O . The vector element $m_i \in [0; 1]$ is the degree of membership of O in the class C_i .

In many real applications, a dichotomous assignment of an object in one class is often not possible as no unique conclusion can be derived from the object features and/or the object features cannot be exactly observed. This is particularly true for problems related to the human evaluation, intuition, perception and decision making where the problem structure is not dichotomous. The definition of the classes can be determined by using the knowledge of experts of the domain or can be automatically found by the use of data mining techniques like cluster analysis.

The fuzzy classification approach can be used for instance for diagnosis and for decision making support. In the case of a diagnosis system for ill persons, the classification procedure can derive the illness based on the symptoms of the patient or find a suitable therapy considering the illness of the patient. In a decision making process, the classification (also called segmentation depending on the context) is used to derive management decisions based on several characteristics of the objects. A major issue in this field is the complexity of the data, i.e. the abundance of information. This complexity is a source of uncertainty due to the limited capability of human beings to observe and handle large amounts of data simultaneously. As in the management field a large number of objects described by many features is usually considered, the classification approach, by grouping similar objects into classes, results in a complexity reduction which enables a better situation analysis. Furthermore, the fuzzy classification, in contrast to the classical one, by allowing objects to belong to several classes at the same time, reduces the complexity of the data and also provides much more precise information about the classified elements.

V. DATABASES & FUZZINESS

In practice, information systems are often based on very large data collections, mostly stored in relational databases. Due to an information overload, it is becoming increasingly difficult to analyze these collections and to generate business decisions. To address this issue, a toolkit for classification, analysis and decision support named FCQL (fuzzy Classification Query Language) has been developed. This toolkit is a combination of relational databases and fuzzy logic. Unlike statistical data mining techniques such as cluster or regression analysis, fuzzy logic enables the use of non-numerical values and introduces the notion of linguistic variables. Using linguistic variables and terms hides the complexity of the domain and enables a more intuitive and human-oriented querying process [6].

The proposed FCQL toolkit reduces the complexity of business data and extracts valuable hidden information through a fuzzy classification. The main advantage of a fuzzy classification compared to a classical one is that an element is not limited to a single class but can be assigned to several classes. Furthermore, each element has one or more membership degrees which illustrate to what extent this element belongs to the classes it has been assigned to. The notion of membership gives a much better description of the classified elements and also helps to reveal their potentials as well as their possible weaknesses.

The FCQL toolkit transforms FCQL queries into SQL (Structured Query Language) statements for sharp databases, thus allowing business managers to formulate and analyze uncap queries at a linguistic level. Being an additional layer above relational database systems the proposed fuzzy classification approach guarantees a full compatibility with legacy applications. The FCQL toolkit also provides a graphical user interface to define the fuzzy classifications, meaning that the fuzzy classes, the linguistic variables and terms as well as the membership functions can be defined using a user friendly wizard.

Another important issue, considering the size and the security concern of the data collections, is that neither modification of the underlying databases nor migration of the existing data have to be undertaken. The fuzzy classification is achieved by an extension of the relational database schema in such a way that it directly operates on the underlying databases and requires no migration of the raw data. Furthermore the SQL commands as well as the transaction and recovery mechanisms offered by the RDBMS (Relational Database Management System) are still available.

In everyday business life, many examples can be found where the fuzzy classification approach would be useful. In the customer relationship management for instance, a standard classification would sharply classify customers of a company into a certain segment depending on their buying power, age and other attributes. If the client's potential of development is taken into account, the clients often cannot be classified into only one segment anymore, i.e. customer equity. Other application domains discussed in the outlook of this thesis are the portfolio analysis, the credit worthiness, the marketing mix theory and some personalization issues.

VI. FUZZY SHAPE QUERIES

Querying and retrieving of data from a database is an important activity. Fuzzy querying allows users to formulate queries using linguistic words, hence it is more flexible than crisp querying. In addition, fuzzy queries produce naturally ranked results whereas conventional queries bring back only undifferentiated tuples. Fuzzy queries may also provide reasonable answers where crisp queries fail to find solutions. When querying the shape database, a user can formulate a query by searching the shape name and version. Frequent users may also query shapes using the shape ID, which is automatically generated by the computer. However, it is sometimes desirable to search shapes using natural-language-like shape descriptors, especially for occasional users. It is also desirable to allow users to express preferences and thus make the querying results more feasible. Using vague predicates represented by fuzzy sets to perform a query is one approach to achieve the above targets.

Query requirement analysis is based on the task the query will complete and the type of users. The aim of querying a shape database is to obtain the appropriate shape. People usually perceive a shape by commonly used regular shape names, by pictures or by shape description. For example, for a cubical shape, people will describe it as cube, cuboid, cubic, cubical, or square. Hence, the system should allow querying by shape descriptions. If the shape number of this cube in the shape database is 10 and the user knows this number, s/he may just ask "list out the 10th shape". The query system should respect the diversity of querying, therefore multiple query options should be provided [7].

The users can be classified into primary users who use the system regularly and secondary users who use the system only casually. The query system should allow primary users to input their query as quickly as possible. This is achieved by querying the database using shape ID or name. For novice or casual users, the system should provide effective guidance. The Query-By-Example method and intelligent query assistant are usually employed to guide the query process. In the shape database, the underlying shape descriptors represent the geometric characteristics of shapes along different directions based on the shape representation approach. Although they are represented by words and can be understood by professional users, it is still hard for general users to understand and formulate shape queries using these descriptors. Hence, a Graphical User Interface is utilized to help users to formulate query. Commonly used shape descriptors are displayed in the GUI and they will be translated into underlying basic shape descriptors through a translator. In addition, the support messages, such as on-line help and error messages should be provided.

The shapes are classified into two classes: fuzzy shapes and crisp shapes. The main difference between these two kinds of shapes is the data associated with the shape parameters. For a crisp shape, each parameter has only one value whereas for a fuzzy shape, each parameter has a fuzzy set value. In the case of fuzzy query on crisp shapes, each tuple will be assigned a Degree of Fulfilment (DOF) to the fuzzy condition. In the case of fuzzy query on fuzzy shapes, the similar method as fuzzy query on crisp shapes can be employed but the calculation method for DOF is different and two DOFs are needed. In the latter case, we use the possibility and necessity degrees to measure the extent to which a datum satisfies a condition.

In a fuzzy database, the crisp data and the fuzzy data can be represented uniformly by fuzzy sets, and a crisp value is only a special case of a fuzzy value where the membership grade is one for a crisp element and zero for all others. Since the fuzzy shape database is mainly used for storing and retrieving initial fuzzy shapes that have fuzzy set values, hereafter we consider fuzzy queries on fuzzy data only. The possibility/necessity measures will be used to represent the upper and lower bounds of the satisfaction degree of a fuzzy datum with respect to a fuzzy condition.

The categories of fuzzy queries can be further classified into the following classes: simple query and combined query. A simple query refers to a query by a single condition. For example, the user inputs a single shape descriptor such as extremely round and a series of shapes will be retrieved from the database and will be displayed on the screen in multiple views. A combined query refers to a query composed of multiple descriptions. For example, a user inputs a combination of shape descriptions, such as extremely round and slightly bevel, and a series of shapes will be retrieved from the database and will be displayed on the screen. Shape description combination can be classified into feasible combination and infeasible combination. Feasible combination means that two descriptors on the two sides of AND operator can be used to describe the same shape at the same time. For example, the descriptors extremely cylindrical and slightly bent can exist at the same time because they describe a shape that is a slightly bent cylinder. Infeasible combination means that two descriptors on the two sides of AND operator cannot be used to describe the same shape at the same time. For example, a cylindrical shape cannot be pyramidal. The feasible combination can be passed to the inference engine for deriving the result values. The infeasible combinations will be checked out by the system according.

VII. LIMITATION OF FUZZY LOGIC

Fuzzy logic is based on same principle as classical logic, the principle of truth-functionality. Logic is truth functional if the truth value of a compound sentence depends only on the truth values of the constituent atomic sentences, not on their meaning or structure. In the two-valued logic the mentioned principle is enough for all axioms. In case of all many-valued logics, including fuzzy logic, this principle is not sufficient and as a consequence these logics are not in the Boolean frame. More precisely, fuzzy logic is a precise many-valued logic where axioms of non-contradiction and excluded middle are not satisfied. It is obvious on following example: “WHERE attribute >5 and attribute ≤ 5 ” (contradiction). In classical query it is obvious that criterion retrieves no record from database. In case of fuzzy query when the “WHERE attribute is Big and attribute is not big” criterion is used it could be expected that no record is retrieved because of non-contradiction axiom existence but min t-norm retrieves some records with $QCI \leq 0.5$. This is the consequence of not satisfied non-contradiction axiom. First way how to use the gradation in mathematics is to leave these axioms as non-adequate and accept the principle of truth functionality with all consequences. When the first way is chosen, it is possible to avoid this problem by selecting adequate t-norm or t-conform function for each query. A new t-norm T^r and a new t-conform C^r , which depend on a parameter r in $[-1, 1]$ or the correlation between the truth values of the operands are explained in. The second way is to go to the source of Boolean algebra and find the principle for gradation to be in the frame of the Boolean algebra. New approach to treating fuzziness or gradation in logic is based on the Interpolative Realizations of Boolean Algebra (IBA). The IBA ensures that the whole selection process will be in the frame of Boolean algebra and avoids theoretically possible situations when inappropriate functions are chosen.

VIII. PERFORMANCE MEASURE

The cost of query evaluation can be measured in terms of a number of different resources, including disk accesses, CPU time to execute a query and in a distributed or parallel database system, the cost of communication. In large database systems, however disk accesses which we measure as the number of transfers of blocks from disk are usually the most important cost, since disk accesses are slow compared to in memory operations. Moreover, CPU speeds have been improving much faster than have disk speeds. Thus, it is likely that the time spent in disk activity will continue to dominate the total time to execute a query. Finally estimating the CPU time is relatively hard, compared to estimating the disk access cost. Therefore, most people consider the disk access cost a reasonable measure of the cost of a query evaluation plan.

We use the number of block transfers from disk as a measure of the actual cost. To simplify our computation of disk-access cost, we assume that all transfers of blocks have the same cost. This assumption ignores the variance arising from rotational latency and seek time. To get more precise numbers, we need to distinguish between sequential input / output, where the blocks read are contiguous on disk, and random input/output, where the blocks are noncontiguous, and an extra seek cost must be paid for each disk input/output operation. We also need to distinguish between reads and writes of blocks, since it takes more time to write a block to disk than to read a block from disk. A more accurate measure would therefore estimate

1. The number of seek operations performed
2. The number of blocks read
3. The number of blocks written

And then add up these numbers after multiplying them by the average seek time, average transfer time for reading a block, and average transfer time for writing a block, respectively. Real-life query optimizers also take CPU costs into account when computing the cost of an operation. For simplicity we ignore these details, and leave it to you to work out more precise cost estimates for various operations.

The cost estimates we give ignore the cost of writing the final result of an operation back to disk. These are taken into account separately where required. The cost of all the algorithms that we consider depend on the size of the buffer in main memory. In the best case, all data can be read into the buffers and the disk does not need to be accessed again. In the worst case, we assume that the buffer can hold only a few blocks of data approximately one block per relation. When presenting cost estimates, we generally assume the worst case.

IX. CONCLUSION

The meaning and purpose of the previous query is understandable for the user who creates and uses it. In case of reuse of the same query in e.g. different time period or by different user the meaning and purpose of query is not obviously clear at the first glance. Fuzzy query contains logical conditions defined by linguistic expressions whereby the query becomes easy understandable and applicable. The meaning of a query remains the same, only the parameters and shapes of fuzzy sets are changeable to allow the query adaptation to new situations or requirements. A disseminated number without meaning (without explanatory metadata) does not tell very much to user. A number in a WHERE clause does not. An Approach to Fuzzy Database Querying, Analysis and Realization explain the purpose of a query in many situations. As metadata are used to explain the meaning of the figures, the linguistic expressions are used to explain the meaning of a query. Fuzzy query enables also simplified and easy to use distance measurement of records around selected value. For this purposes normalized (fuzzy set is normalized if $\sum_{x \in A} A(x) = 1$) and symmetric fuzzy sets shown in figure 4 are used. The criterion "WHERE attribute is approximately 5" can be described with "about" fuzzy set. The query retrieves all records that have attribute value equal to 5 and all records that have QCI>0 and QCI value is a distance value of each selected record.

ACKNOWLEDGEMENT

We are earnestly grateful to one our group member, Md. Fuzlul Karim, EEE, American International University-Bangladesh. For providing us with his special advice and guidance for this project. Finally, we express our heartiest gratefulness to the Almighty and our parents who have courageous throughout our work of the project.

REFERENCES

- [1]. B. K. Bose, "Expert systems, fuzzy logic, and network application control", Proceeding of the IEEE, vol.81, Aug. 1996.
- [2]. L. H. Tsoukalas and R. E. Uhrig, "Fuzzy and Neural Approaches in Engineering", John Wiley, NY, 1997.
- [3]. Math Works, Fuzzy Logic Toolbox User's Guide, Jan., 1998.
- [4]. B. Jaychanda, simulation studies on "Speed Sensor less Operation of Vector Controlled Induction Motor Drives Using NeuralNetworks", Ph.D. Thesis, IIT, Madras, Chennai.
- [5]. T. Takagi and M. Sugeno, "Fuzzy identification of a system and its application to modeling", IEEE Trans. Syst. Man and Cybern., vol.15, pp.116-132, Jan./Feb. 1985.
- [6]. I. Milki, N. Nagai, S. Nishigama, and T. Yamada, "fuzzy P-I controller", IEEE IAS Annu. Meet. Conf. Rec., pp. 342-346, 1991.
- [7]. M. Nasir Uddin, Tawfik S. Radwan and M. Azizur Rahman, "Performances of Fuzzy-Logic-Based measurement", IEEE TRANSACTIONS ON INDUSTRY APPLICATIONS, VOL. 38, NO.5, SEPTEMBER/OCTOBER 2002, P1219.