Journal of International Information Management

Volume 3
Issue 3 *Special Edition*

Article 9

1994

A neural network driven fuzzy system approach to decision making

Mirza B. Murtaza
Prairie View A & M University

Vipul K. Gupta
University of Houston

A neural network driven fuzzy system approach to decision making

Mirza B. Murtaza
Prairie View A&M University

Vipul K. Gupta
University of Houston

ABSTRACT

It is necessary to model and manage uncertainties efficiently and effectively in solving decision-making problems. Fuzzy reasoning and logic offers a natural means of handling uncertainty. This paper discusses the development of an architecture that utilizes the advantages of fuzzy logic and neural networks that can be used in decision-making.

The present paper outlines the reasons that motivate development of models that integrate fuzzy logic and neural networks. This discussion is followed by a brief overview of fuzzy logic and its concepts that are essential in understanding the application presented in the paper. The paper then describes the classification procedure used by the model, which is followed by its application to the decision making problem in construction modularization.

INTRODUCTION

In solving decision-making problems, it is essential to model and manage uncertainties efficiently and effectively. There can be several causes of uncertainty in a decision-making situation, such as problem complexity, ill-posed questions, imprecision in computations, ambiguity in data/knowledge representation, problems in input interpretations, and noise of several types (Keller & Tahani, 1992). In the past, rule-based expert systems have been used for handling uncertainty in such problems. Generally, the expert systems are based on classical logic and developers need to add special methods for handling uncertainty. Some of the methods used for handling uncertainty in expert systems include heuristic approaches, probability theory, possibility theory, and fuzzy theory.

Fuzzy reasoning and logic offers a more natural means of handling uncertainty. All propositions can be modeled by possibility distributions over appropriate domains. Since fuzzy reasoning realizes the flexible reasoning similar to human logical reasoning, a considerable amount of research work has been performed in this (Takagi & Hayashi, 1991). Still there are some problems related to fuzzy reasoning to be solved, such as finding an easy to implement mechanism for determining a membership function, and lack of learning functions. Because of such reasons, suggestions have been made for synergy of neural networks and fuzzy logic.

The theories of neural networks and fuzzy logic offer complementary ways of modeling brain activity. Neural network, on one end, models the lower level processes of human reasoning, i.e., the physiology of the brain. On the other end, fuzzy logic provides a method of modeling higher level processes, i.e., psychological modeling of the mind (Rocha & Yager, 1992).

Although considerable research effort has been put in the area of pattern recognition, it still offers challenges to designers and engineers who try to mimic human abilities of recognition and classification of complex situations (Pedrycz, 1991). A decision-making problem also falls in this category since it can easily be converted to a pattern recognition problem with a little effort (Burke, 1991). The physical features of a pattern recognition problem correspond to attributes of a decision making problem. The classes of a pattern recognition problem are equivalent to the alternatives of a decision situation. In this paper, on the lines suggested by Pedrycz (1991), a decision-making methodology is developed that uses fuzzy logic and neural network approaches.

FUZZY LOGIC AND CLASSIFICATION

In general, the human mind is not capable of handling a huge mass of numerical information. Instead, its excellence at classification and categorization tasks results from its capability of processing a mixture of symbolic and numeric information (Pedrycz, 1991). For the development of a decision-making methodology, there is also a need of interpretation of results of the classifier, and thus a need for user-friendly interface.

There are two major tools that are applicable to the design of a classification procedure - traditional artificial intelligence techniques (symbolic computation) and numerical computation. In pattern recognition, symbolic computations generally do not handle any numerical information. When numerical information is available, it is converted to symbolic form. Numerical computation methods that are generally used in science and engineering applications are complementary to artificial intelligence techniques. Although they are efficient and effective, they do not use any interpretation mechanisms for numeric data.

Because of the use of such characteristics as gradual membership, fuzzy sets form links between symbolic and numerical computation. In essence, a fuzzy set represents a collection of objects which is a general symbolic concept. And the grades of membership within the fuzzy set that specify the relationship of objects are numerical in nature. When specifying the degree of membership in a class, there is no requirement that it is to be denoted by a single number. Thus, it offers an ability to describe class membership in a linguistic format.

As an example, use of four terms such as high belongingness to the class, moderate belongingness, low belongingness, and no belongingness may be more appropriate in a situation. The first term is represented by a triangular membership function (.8, 1, 1). The second linguistic term specified as (.5, .7, .9) refers to class membership of moderate belongingness, the third term specified by (.2, .4, .6) describes low belongingness. These terms indicate that it is difficult to classify these patterns in the class. The last term (0, .1, .2) indicates that the pattern does not belong to the class. Compared to probability-based pattern classification, this fuzzy logic based method does not impose any strict restrictions. In probability-based classification, sum of probabilities stating class membership must be equal to one. Fuzzy logic is free of this kind of constraints and, thus, can handle unclear and ambiguous classification situations.

TRUTH EVALUATION IN FUZZY LOGIC

In fuzzy logic, the truth values of propositions are considered as fuzzy sets that are defined over a unit interval, namely, 0 and 1. The truth evaluation procedure can be used for matching two fuzzy statements (Pedrycz, 1991). Given two statements, X is A and X is B, where X is a variable that has two associated linguistic values. The process of truth evaluation can be applied for matching these statements; this process results in determination of a fuzzy truth value t: [0,1] Æ [0,1], that implies the following:

(X is A) is t = X is B (a)

The fuzzy sets A and B, with continuous membership functions, are defined in the same space since they are the values for the same variable. The value t is computed as follows:

$$t(v) = \sup_{x:A(x) = V} B(x) \qquad \text{(b)}$$

If the space x has a finite set of values, then supermum in (b) can be replaced by max B(x) (Kosko, 1992).

Let B(x) be an interval-valued quantity distributed over c. The truth value is calculated as follows:

t (v) = 1 if v Œ [v_1 , v_2]
0 otherwise (c)

where,

v_1 = inf A(x)
x Œc
v_2 = sup A(x)
xŒc

The membership function of B can be determined given A and t. The truth value t is like a functional modifier imposed on A:

B = t (A) (d)

or B(x) = t (A(x)) for the entire universe of discourse.

CLASSIFIER STRUCTURE

Suppose there are several features (or decision factors/ attributes) on which the classification of patterns is based. And each feature is described by a finite set of linguistic labels (or values). The classification procedure (Pedrycz, 1991) can be summarized below:

STEP 1. For a particular feature, the labels can be denoted by $A_1, A_2, \ldots, A_N$. The values of the feature are compared with labels. In other words, the fuzzy truth value t_j, is to be determined in the following relationship:

(X is A_j) is t_j _ X is A, where j = 1, 2, . . ., N.

Using (c), the truth values can be determined.

The purpose of this step is to convert values in a physical feature space (labels) to a logical space, and thus the values of various features (attributes) can easily be handled. In fact, there is no restriction on the data format used for classification (decision making); in addition to being labels, they can be numerical values or even numerical intervals.

STEP 2. The fuzzy truth values of feature are then converted into truth values for pattern class membership. One of the most efficient methods for handling this conversion would be a neural network like back propagation or counter propagation. The purpose of this step is to translate the truth values logical space into the class membership logical space. After the application of neural network, output values will be fuzzy sets $k1_1$, $k1_2$, $k1_3$, $k2_1$, $k2_2$, $k2_3$, . . ., kp_1, kp_2, kp_3.

STEP 3. Like feature descriptors, a set of linguistic descriptors of each class membership are also specified, such as, strong or borderline membership. Using the procedure given in (c), the truth values received from the neural network can modify these fuzzy sets. That is, an induced fuzzy set B modified by t results from set A. Let the fuzzy sets of class membership be K_1, K_2, . . ., K_p: [0,1] Æ [0,1]. For a particular class, e.g., class 1, the fuzzy sets denoting the strength of class membership are calculated as $k1_1$ (K_1(v)), $k1_2$ (K_2(v)), $k1_3$ (K_3(v)), v Œ [0,1]. Now these values for a set are ranked and the most preferred is picked. In the same manner, values for other classes are also ranked, and thus a complete view of all classes is obtained.

EXAMPLE APPLICATION

The above described procedure can be illustrated by a decision-making example. The problem used here is construction modularization decision-making, which is discussed in detail in literature (Murtaza, Fisher, & Skibniewski, 1993; Murtaza, 1993; Murtaza & Gupta, 1993). Construction modularization is a technique of developing parts of an industrial plant or commercial building away from the project site, transporting the parts (or modules) to the site and assembling them. The technique has been increasingly utilized in industrial and commercial construction in recent years.

There are several attributes involved in construction modularization decision-making which are divided into five categories, namely, plant location, environmental and organizational, plant characteristics, labor, and project risks. The number of attributes is about forty and each attribute can take three possible values. There are also three possible classes (decision alternatives): extensive modularization, partial modularization, and conventional (that is, no modularization).

A pictorial description of attribute values is given, thus for each attribute value three linguistic labels are used, such as strong, borderline, or lack of belongingness. Given the value of an attribute, it can be determined with what strength the value belongs to each label using equation (c). One of the important labor-related decision attributes is labor availability at the proposed project site. The three values used are low, medium, and high. If the labor availability is somewhere between low and medium, it will result in the following inputs: strong belongingness to low, borderline belongingness to medium, and no belongingness to high label. The advantage of using fuzzy logic at this stage is that the rules exist that can handle somewhat different linguistic values also, such as very low (which is equal to the square of low) and somewhat low (which is equal to the square root of low).

Once the labels for attribute values are determined, they can be provided to a neural network for processing. Any efficient classification or clustering neural network can be used for this purpose. In this example, self-organization feature map is used because of its shorter training times and easier implementability.

The linguistic description of class membership is designed on the basis of three categories, namely, supporting class membership, borderline class membership, and excludes class membership. The membership functions are described by fuzzy truth values defined between 0 and 1. All of these functions are triangular in the example and are given as (0.6, 1, 1), (0.3, 0.5, 0.7), and (0,0,0.4), respectively.

For neural network implementation purposes the unit interval in which fuzzy truth values are defined is discretized. Thus there are six elements uniformly distributed between 0 and 1, that is, 0, 0.2, 0.4, 0.6, 0.8, 1.0. Therefore, in the neural network 18 output nodes are needed to represent each class and also 18 input nodes to represent each attribute. Example cases are presented to the neural network several times and weights are updated using the following equation (Kohonen, 1989):

$$w^{t+1} = w^t + a\,(x - w^t) \tag{e}$$

where w^t is weight vector at previous step, x is input vector, and a is learning rate. The output values of the network are fuzzy values that modify fuzzy sets of class membership using equation (c). This provides the strength of class membership, thus classes are ranked in each category, i.e., in supporting class membership, in borderline class membership, and in excluding membership. Since self-organizing feature map is an unsupervised learning method, it was determined only after training which output node represents what class. This determination was based on the actual decisions made in example cases by the experts.

CONCLUSIONS

The objective of this paper is to illustrate the use of a neural network driven fuzzy system in decision making. All the information about the problem attributes is preprocessed, since the inputs can be in linguistic terms, numerical values, or as a numerical interval. The truth values of these inputs are then obtained. A neural network performs the optimal mapping between the logical space of these values and the logical space of class membership. Finally, fuzzy logic is used to determine strength of class membership from these values.

The procedure discussed here utilizes the strengths of two powerful techniques—fuzzy logic and neural networks. It offers a new way of developing various new models for decision making. New capabilities can be added to the architecture at preprocessing and post-processing levels to create robust and novel applications. For example, different reasoning paradigms, such as Boolean logic, production rules can be included in the above architecture to preprocess the initial inputs. The learning paradigm, self-organizing feature map, can also be replaced by other neural network paradigms, such as back propagation, counter propagation, or neocognitron to accommodate the different problem applications.

REFERENCES

Burke, L. I. (1991). Introduction to artificial neural systems for pattern recognition. *Computers and Operations Research, 18*, 211-220.

Keller, J. M. & Tahani, H. (1992). Implementation of conjunctive and disjunctive fuzzy logic rules with neural networks. *International Journal of Approximate Reasoning, 6*, 221-240.

Kohonen, T. (1989). *Self-organization and associative memory.* New York, NY: Springer-Verlag.

Kosko, B. (1992). *Neural networks and fuzzy systems: A dynamical systems approach to machine intelligence*. Englewood Cliffs, NJ: Prentice-Hall.

Murtaza, M. B. (1993). *A decision support model integrating neural networks and an expert system for construction modularization.* Unpublished Ph.D. dissertation, Dept. of Industrial Engineering, University of Houston.

Murtaza, M. B., Fisher, D. J., & Skibniewski, M.J. (1993). A knowledge-based approach to construction modularization decision making. *Journal of Construction Engineering and Management, 119*, 115-130.

Murtaza, M. B., Gupta, V. K., & Fisher, D. J. (1993). A comparison of decision making performances of single and multi-layered neural networks. In C. H. Dagli (Ed.), *Intelligent Engineering Systems through Artificial Neural Networks*, Vol. 3, ASME Press.

Takagi, H. & Hayashi, I. (1991). NN-driven fuzzy reasoning. *International Journal of Approximate Reasoning, 5*, 191-212.

Pedrycz, W. (1991). Fuzzy logic in development of fundamentals of pattern recognition. *International Journal of Approximate Reasoning, 5*, 251-264.

Rocha, A. F. & Yager, R. R. (1992). Neural nets and fuzzy logic. In *Hybrid Architectures for Intelligent Systems*, A. Kandel and G. Langholz (Eds.). CRC Press.