GENERATION OF FUZZY "IF...AND...THEN..." RULES

Les M. Sztandera
Philadelphia College of Textiles and Science
Philadelphia, PA 19144, USA

Abstract: This paper describes a method which automatically generates membership functions and "IF...AND...THEN..." rules for a fuzzy system. The method consists of the following four steps: Step 1 divides the input and output spaces into several fuzzy subsets and assigns linguistic terms to them; Step 2 generates fuzzy rules using the lingustic terms assigned in Step 1; Step 3 counts the conflicting fuzzy rules and those with the highest number of counts remain in the system; others are deleted; Step 4 determines a mapping based on the remaining rules.

I. INTRODUCTION

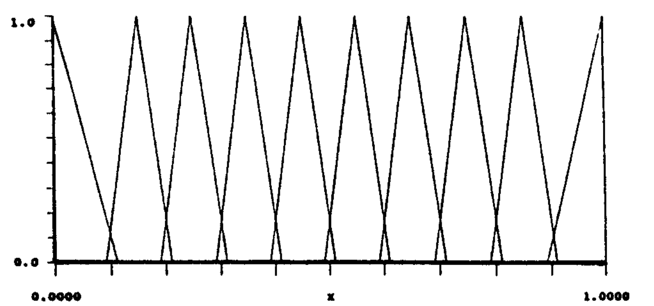
For most real world control and pattern recognition problems the information concerning the design comes either from an experienced human controller or from sensor measurements. Suppose, the environment facing the human controller is so complicated that no mathematical model exists for it. The task here is to design a fuzzy rule generation system to replace the human controller. Generating fuzzy sets from data using either fuzzy or neural techniques has been proceeding on several fronts. A neural network architecture that learns from fuzzy "IF...AND...THEN..." rules [1] was recently designed. In [2] Fuzzy CID3 algorithm, which generates fuzzy subsets from numerical data and executes ranking among those subsets to distinguish between categories, was proposed. In [3] modeling and formulating of fuzzy knowledge bases using neural networks was investigated. These methods show a way of using neural network technology as a "tool" within the framework of a fuzzy set theory. A hyper-box fuzzy set representation and background rules were the basis for another fuzzy model [4]. Also, a fuzzy approach for generating "IF...AND...THEN..." rules from numerical data where ingeration of human experts is possible [5, 6] exists.

This paper proposes an idea to reduce the number of rules by relying upon the most frequently encountered associations.

II. PROCEDURE

Suppose the data set under investigation consists of the three dimensional data where the first two coordinates form the input, and the third one is the output. The goal is to design a classifier capable of predicting the output given new two dimensional inputs. So, we have two input variables and one output variable. We have to know to ranges for both input and output.

Our task is to generate a set of fuzzy rules from the training input-output pairs and use these fuzzy rules to model the system. We proceed in the following manner. First, we divide the input and output spaces into several fuzzy subsets and assign linguistic terms to them. Let's assume that the domains of input variables: *one* and *two* are divided into ten regions and are assigned the following linguistic terms: very very low, very low, low, low-medium, medium, medium-high, high, very high, very very high, and extremely high. The domain of output variable, *out*, is divided into two regions with linguistic terms low and high assigned to them. Next, we assign to each region a fuzzy membership function. Different shapes of membership functions are possible, but we use triangular shapes with height 1 at the center of the region, and 10% overlap between neighboring sets. The next step is to generate fuzzy rules using the lingustic terms assigned in the previous step.

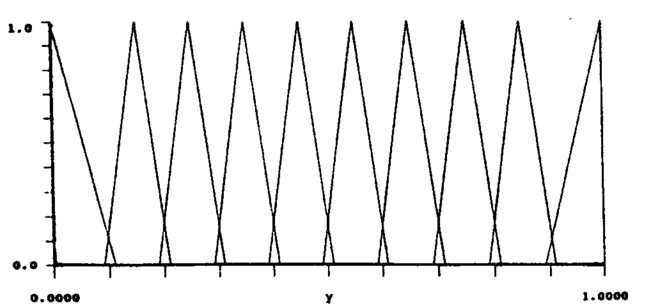


Sample Rules:

IF x is very very high AND y is extremely high THEN z is high

IF x is very very low AND y is extremely high THEN z is high

IF x is medium AND y is medium-high THEN z is high



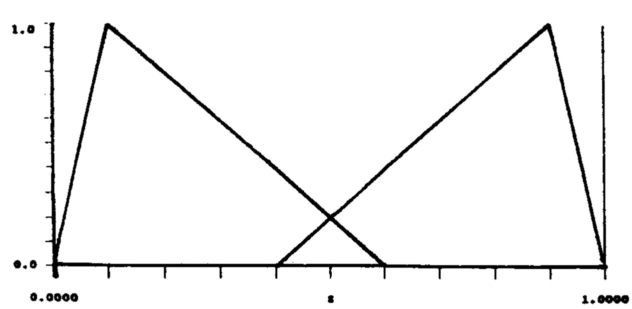


Fig. 1. Sample membership functions along with "IF... AND...THEN..." rules.

Since the antecedents are different components of a single input vector, the rules are in the form of "IF... AND...THEN...", where the "IF... AND..." part is generated from the input data, and the "THEN" part is generated from the output data. As the data may be conflicting, and so far we have generated one rule for each data pair, the following heuristics is employed. The conflicting fuzzy rules are counted and those with the highest number of counts remain in the system; others are deleted. Figure 1 shows the membership functions used along with sample rules. In the last step fuzzy inference engine is executed and a mapping based on the remaining rules is determined. Product-min or max-min inferences may be used. Defuzzification is based on the center of gravity method which is sensitive to all the remaining rules.

III. CONCLUSIONS

In this paper, we developed a general method to generate membership functions and "IF...AND...THEN..." rules from numerical data. The main features and advantages of the generation method are: i) it is a simple and straightforward quick-pass build-up procedure; hence, no time-consuming iterative training is required; ii) there is a lot of freedom in choosing the membership functions; this provides us with a lot of flexibility to design systems according to different requirements. We believe that the system designed by using our method can perform successfully for cases where numerical data is provided.

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