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Study of Fuzzy Inference System (FIS), its Characteristics and Approaches for Fuzzy Inference System

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Abstract : Fuzzy Inference System (FIS) is a mathematical model that uses fuzzy logic to represent the relationships between inputs and outputs in a complex system. Fuzzy logic is a type of mathematical logic that deals with uncertainty and imprecision, and it provides a way to handle vague or ambiguous information in a more intuitive and flexible manner compared to traditional binary (true/false) logic.

Key Words : Fuzzy Logic, Fuzzy Inference System (FIS)

Introduction

In a FIS, the inputs to the system are processed through a series of fuzzy rules, which are logical statements that describe the relationship between inputs and outputs. The rules are expressed in a natural language-like format, such as "if the temperature is hot, then the air conditioning should be turned on." These rules are then applied to the input data, and the outputs are computed based on the degree to which each rule applies.

The key elements of a FIS are:

Input variables: These are the inputs to the system, such as temperature, humidity, etc.

Membership functions: These are functions that describe the degree to which an input variable belongs to a particular fuzzy set, such as hot, warm, cool, etc.

Fuzzy rules: These are the rules that describe the relationships between the inputs and outputs, such as "if the temperature is hot, then the air conditioning should be turned on."

Inference engine: This is the part of the system that processes the input data and applies the fuzzy rules to compute the outputs.

Output variables: These are the outputs of the system, such as the desired state of the air conditioning.

Characteristics of FIS:

- Read crisp value from the process
- Maps the crisp value into fuzzy value using fuzzy membership function

- Apply IF-THEN rules from fuzzy rule base and compute fuzzy output
- Convert fuzzy output into crisp by applying some defuzzification methods.

The basic process of a Fuzzy Inference System (FIS) is as follows:

Input processing: The first step in the process is to transform the input variables into fuzzy sets. This is done by assigning each input value to a particular fuzzy set, based on the degree to which it belongs to that set. The degree of membership is determined by the membership functions, which describe the shape of the fuzzy set. For example, a membership function for the fuzzy set "hot" might look like a bell curve, with the value of 1 at the highest temperature and 0 at the lowest temperature.

Rule evaluation: Once the input data has been transformed into fuzzy sets, the next step is to evaluate the fuzzy rules. Each fuzzy rule is a logical statement that describes a relationship between the input variables and the output variables. For example, a rule might state: "If the temperature is hot, then the air conditioning should be turned on." The degree to which each rule applies is determined by the degree of support, which represents the degree to which the conditions specified in the rule are satisfied by the inputs. The degree of support is calculated by evaluating the membership functions of the input variables and combining them using a method such as the minimum operator or the product operator.

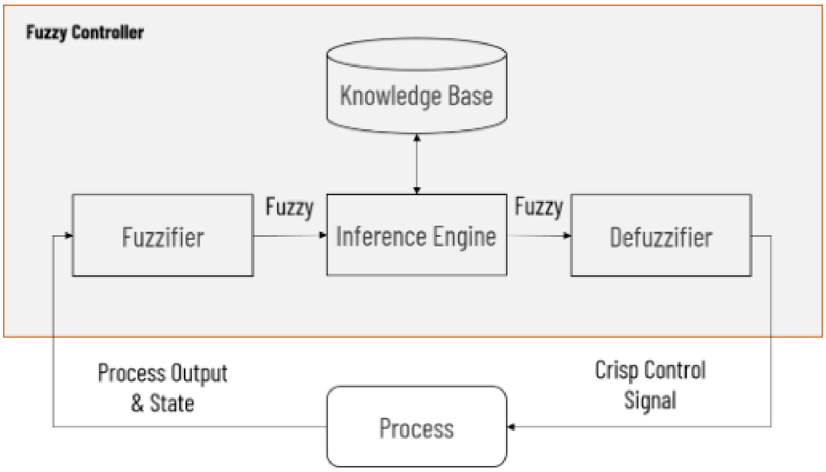
Combination of rule outputs: The outputs from the individual rules are then combined to produce a single output for the system. This is typically done using an aggregation method, such as the maximum operator, the sum operator, or the center of gravity method. The aggregation method takes the outputs of the individual rules and combines them into a single output value.

Output calculation: The final step in the process is to calculate the output value of the FIS. This is typically done using a defuzzification method, such as the center of gravity method, the mean of maximum method, or the weighted average method. The defuzzification method takes the combined outputs from the rules and transforms them into a crisp value, which represents the final output of the system.

Overall, the FIS works by transforming the input data into fuzzy sets, applying a set of rules to the input data to determine the degree to which each rule applies, and then combining the outputs of the rules to produce a final output for the system. The use of fuzzy logic provides a flexible and intuitive way to handle complex and uncertain information, making it well-suited for a wide range of applications.

Crisp input of any process (measuring temperature of air conditioner, measuring altitude, attitude, height, angle of direction for airplane etc.) is given to the fuzzifier, which applies fuzzy membership function and maps the actual readings into fuzzy value (i.e. the value between 0 to 1).

Inference engine applies fuzzy rules from knowledge base and produce the fuzzy output, which is again between 0 and 1. This output can not be used directly into any process or system. It needs to be mapped into original domain. Defuzzifier is the inverse process of fuzzification, it converts the fuzzy output into crisp output, which can be fed to the process. Crisp sets are internally converted to fuzzy sets.



Fuzzy inference system

Approaches for Fuzzy Inference System :

There are several approaches for designing Fuzzy Inference Systems (FIS), including:

Mamdani method: This is the most traditional and widely used method for designing FIS. It uses a simple set of rules that connect the input variables to the output variables. The rules are then evaluated to determine the degree to which each rule applies, and the outputs from the individual rules are combined using an aggregation method to produce a single output for the system. The Mamdani method is well-suited for applications where the relationships between the input variables and output variables are relatively simple and straightforward.

Takagi-Sugeno-Kang (TSK) method: This method is similar to the Mamdani method, but it uses a different type of rule structure. Instead of using a simple set of rules, the TSK method uses a set of linear models, where each model represents a different output variable. The TSK method is well-suited for applications where the relationships between the input variables and output variables are more complex and non-linear.

Tsukamoto method: This method is similar to the Mamdani method, but it uses a different type of aggregation method. Instead of using a traditional aggregation method, the Tsukamoto method uses the weighted average method, where the weights are determined based on the degree of support for each rule. The Tsukamoto method is well-suited for applications where the relationships between the input variables and output variables are relatively simple, but the outputs need to be defuzzified into crisp values.

Hybrid method: This method is a combination of the Mamdani method and the TSK method, and it allows the user to take advantage of the strengths of both methods. The hybrid method is well-suited for applications where the relationships between the input variables and output variables are complex and involve both linear and non-linear relationships.

Conclusion

Overall, the FIS provides a way to handle complex and uncertain information by breaking it down into smaller, more manageable pieces and then processing it through a series of simple logical rules. This makes it well-suited for applications in fields such as control systems, data analysis, and decision making, where traditional methods may not provide adequate results.

Each of these approaches has its own strengths and weaknesses, and the best approach will depend on the specific requirements of the application. The choice of approach will also depend on factors such as the complexity of the problem, the amount of data available, and the computational resources available.

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