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Fuzzy Inference Systems: Types & Applications

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Abstract

Fuzzy Inference Systems (FIS) have gained significant attention due to their ability to handle uncertain & imprecise data. FIS provide an alternative to traditional rule-based systems by using fuzzy sets, which allow for more flexibility in decision-making. This paper presents a review of the different types of FIS, including Mamdani, Sugeno, & Tsukamoto FIS, & their respective applications. Mamdani FIS is widely used in engineering applications, while Sugeno FIS is suitable for decision-making & prediction applications. Tsukamoto FIS is used for modelling non-linear systems. Additionally, the paper discusses the challenges & limitations of FIS & provides suggestions for future research directions. Overall, this review paper provides valuable insights into the types & applications of FIS & highlights the potential benefits & challenges associated with their use.

Keywords: logic, mathematical logic, fuzzy, fuzzy Interference, fuzzy logic, Application

Introduction

In 1965, L. Zadeh saw a need for a more flexible alternative to the binary truth/falsity assumptions of Boolean logic, & thus he founded the subject now known as fuzzy logic (or fuzzy systems). However, fuzzy logic allows for varying degrees of veracity, which can be used to determine how well an object fits within a fuzzy set.

Variables in human language have counterparts in fuzzy sets. For this reason, many fields find fuzzy approaches attractive for encoding a priori (expert) knowledge.

The nomenclature (confusing to outsiders) & occasionally exaggerated claims in the subject of fuzzy logic contribute to the field's reputation for controversy. There are two distinct meanings of the word "fuzzy logic" (Zadeh 1996). Fuzzy logic, in a narrow sense, is a formalism for "approximate" reasoning & an extension of multi valued logic. Fuzzy logic, in a broader sense, also refers to fuzzy set theory, which is concerned with sets with fuzzy (unsharp) borders. Fuzzy sets can be used to "fuzzify" any mathematical subject (Le., graph theory, pattern recognition, topology, etc.) by substituting the concept of a crisp set with a fuzzy set. However, such fuzzification's practical utility remains application-dependent.

Fuzzy inference systems are collections of fuzzy rules that relate inputs to outputs. Such a (fuzzy) representation of a mapping has two benefits. In the first place, it facilitates the accurate representation & use of a priori information (human expertise) of the system. The second benefit is the flexibility of this representation. The downside is that people's perceptions & experiences can make the formulation of fuzzy rules & fuzzy sets (i.e., their membership functions) arbitrary. Therefore, it is difficult to build a fuzzy system without first determining the scope of its use. This is often done by rigorous experimental verification of a prototype fuzzy system (either hardware or software).

Input & output variables (such sensor & actuator signals) in engineering applications are often quantified using precise numerical values. Fuzzification, the process of generating a fuzzy representation of a crisp input value, & defuzzification, the process of transforming a fuzzy output value into its crisp equivalent, are two additional processes needed in a practical system that combines crisp input/output signals with fuzzy a priori knowledge.

The typical layout of a fuzzy inference system is depicted in Fig.1, below, wherein experts provide the necessary fuzzification & defuzzification techniques, as well as the specification of the input & output fuzzy sets & the fuzzy rules themselves. Given enough rules, a set of fuzzy rules can accurately reflect any input-to-output mapping. Approximating real-valued functions (nonlinear in input variables) is a common control application. Fuzzy nonlinear control describes this method. Despite the fuzziness of the vocabulary employed to characterise this mapping, the structure in Fig. 1 effectively implements a crisp input-output mapping (i.e. a function). Therefore, it could be instructive to draw parallels between this (fuzzy) representation & other approximating functions (for regression) in neural networks & statistics.

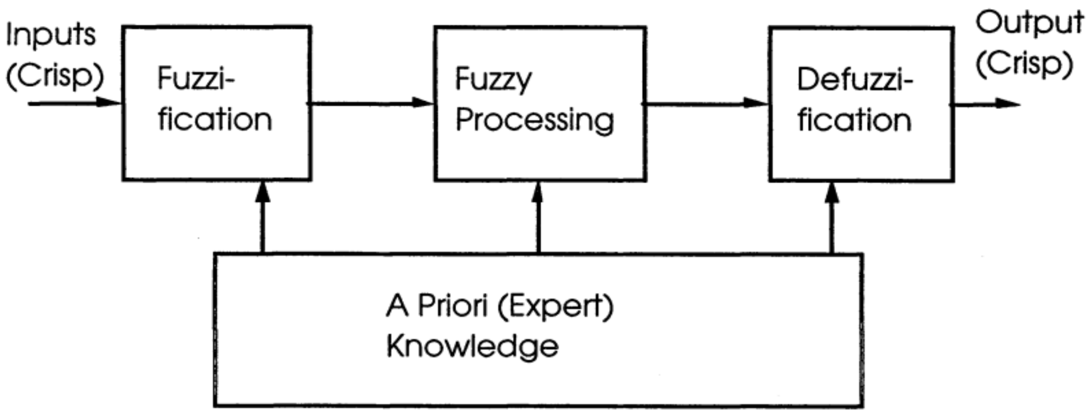

Fig1 block diagram for FIS (13)

Sometimes, fuzzy inference systems are presented as a novel method for modelling input-output relationships. Many writers, however, have demonstrated a close relationship between neural network/statistical approaches & fuzzy inference systems (Brown & Harris, 1994). The primary goal of this work is to clarify this relationship so that the benefits & drawbacks of fuzzy systems can be grasped with greater clarity. Each fuzzy rule, as will be demonstrated below, is equivalent to a local (or kernel) model in a 'non-fuzzy' statistical or neural network parameterization.

Additionally, the specification of these fuzzy rules (by experts) is comparable to the design of a parametric model in the statistical method. Comparable to statistical parameter estimation is the practise of empirically tweaking fuzzy rules & membership functions.

Types of fuzzy interference system

Fuzzy Inference Systems (FIS) are a type of artificial intelligence that can be used to model complex systems with uncertain & imprecise inputs. FIS can be used in a variety of applications, including control systems, decision support systems, & pattern recognition. There are three main types of Fuzzy Inference Systems: Mamdani, Sugeno, & Tsukamoto.

Mamdani Fuzzy Inference System:

The Mamdani FIS is the most well-known type of Fuzzy Inference System. It was introduced by Ebrahim Mamdani in 1975 & has since been widely used in a variety of applications. The Mamdani FIS consists of four main components: fuzzification, rule evaluation, aggregation, & defuzzification.

During the fuzzification stage, input variables are mapped onto fuzzy sets. The rule evaluation stage combines the fuzzy sets using a set of if-then rules to generate a fuzzy output set. The aggregation stage combines the fuzzy output sets from each rule into a single fuzzy output set. Finally, the defuzzification stage converts the fuzzy output set into a crisp output value. (3,4)

Sugeno Fuzzy Inference System:

The Sugeno FIS is another popular type of Fuzzy Inference System. It was introduced by T. Sugeno in 1985 & is also known as a fuzzy logic controller (FLC). The Sugeno FIS differs from the Mamdani FIS in that it generates a crisp output value rather than a fuzzy output set.

The Sugeno FIS consists of three main components: fuzzification, rule evaluation, & defuzzification. During the fuzzification stage, input variables are mapped onto fuzzy sets. The rule evaluation stage combines the fuzzy sets using a set of if-then rules to generate a set of linear equations. The defuzzification stage solves the set of linear equations to generate a crisp output value. (5,6)

Tsukamoto Fuzzy Inference System:

The Tsukamoto FIS is a less common type of Fuzzy Inference System that was introduced by Y. Tsukamoto in 1979. The Tsukamoto FIS is similar to the Mamdani FIS in that it generates a fuzzy output set. However, it differs in that it uses a different method for rule evaluation that is based on a non-monotonic inference method. The Tsukamoto FIS consists of four main components: fuzzification, rule evaluation, aggregation, & defuzzification. During the fuzzification stage, input variables are mapped onto fuzzy sets. The rule evaluation stage combines the fuzzy sets using a set of if-then rules to generate a fuzzy output set. The aggregation stage combines the fuzzy output sets from each rule into a single fuzzy output set. Finally, the defuzzification stage converts the fuzzy output set into a crisp output value. (7,8)

Applications

Fuzzy Inference Systems (FIS) have a wide range of applications in the modern world, ranging from control systems to data mining, decision-making, pattern recognition, & more. Here are some applications of FIS in various fields:

Control systems: FIS are used extensively in control systems due to their ability to handle uncertain & nonlinear systems. They have been applied in various industries such as automotive, aerospace, robotics, & process control. For example, FIS has been used in controlling temperature, humidity, & airflow in greenhouses to improve plant growth & reduce energy consumption. [9]

Data mining: FIS are used in data mining to identify patterns & trends in large datasets. FIS can be used to classify data, cluster data, & make predictions based on historical data. FIS has been applied in various domains, such as finance, healthcare, & social media. For example, FIS has been used to predict patient outcomes based on clinical data & to identify stock market trends based on historical stock prices. [10]

Decision-making: FIS are used in decision-making processes due to their ability to handle uncertainty & imprecise data. FIS can be used to model decision-making processes, prioritize decision criteria, & recommend actions based on uncertain information. FIS has been applied in various domains, such as finance, marketing, & environmental management. For example, FIS has been used to predict the environmental impact of development projects based on ecological data & to recommend marketing strategies based on customer data. [11]

Pattern recognition: FIS are used in pattern recognition to identify patterns in complex data such as images, speech, & text. FIS can be used to classify data, extract features, & recognize patterns based on uncertain information. FIS has been applied in various domains, such as biometrics, speech recognition, & handwriting recognition. For example, FIS has been used to recognize faces in images & to transcribe speech into text. [12]

Conclusion

In conclusion, Fuzzy Inference Systems (FIS) have become an important tool in modern engineering & scientific applications due to their ability to handle uncertain & imprecise data. FIS can be used for control systems, data mining, decision-making, pattern recognition, & many other fields. The three main types of FIS are Mamdani, Sugeno, & Tsukamoto, each with its own strengths & weaknesses. FIS has been successfully applied in various industries, such as automotive, aerospace, healthcare, & finance. As technology continues to evolve & the amount of data generated increases, FIS is likely to become even more essential in many fields. Therefore, understanding the principles & applications of FIS is essential for researchers, engineers, & scientists who are seeking to solve complex problems in the modern world.

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