UFME7K-15-M Intelligent and Adaptive Systems

Fuzzy Logic (continued)

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Intelligent Adaptive Systems Lecture 3

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"So far as the laws of mathematics refer to reality, they are not certain. And so far as they are certain, they do not refer to reality."

`Albert Einstein`

"As complexity rises, precise statements lose meaning and meaningful statements lose precision."

`Lotfi Zadeh`

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- Practical was the Simulink Tank demo (sltank)
- Now we look at Fuzzy Inference Systems in a bit more detail

Why Fuzzy Systems?

"our contention is that the conventional quantitative techniques of system analysis are intrinsically unsuitable for dealing with humanistic systems or, for that matter, any system whose complexity is comparable to that of humanistic systems."

The basis for this contention rests on what might be called the **principle of incompatibility**

"the essence of this principle is that as the complexity of a system increases, our ability to make precise and yet significant statements about its behavior diminishes until a threshold is reached beyond which a precision and significance (or relevance) become almost mutually exclusive characteristics."

Zadeh(1973)

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- it is the *imprecision of the goal* that makes it possible for humans to park a car without making any measurements or numerical computations.
- humans possess a remarkable innate ability to exploit the tolerance for imprecision to achieve tractability, robustness and low solution cost,
- whereas traditional control techniques fail to do so when they employ crisp rather than fuzzy algorithms to arrive at a solution.

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- Defuzzification

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- If (level is okay) then (valve is no_change)
- If (level is okay) and (rate is negative), then (valve is close_slow)

An example of fuzzy implication:

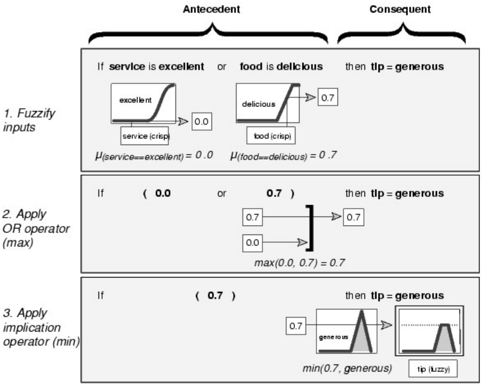

Figure 1: Fuzzy Implication

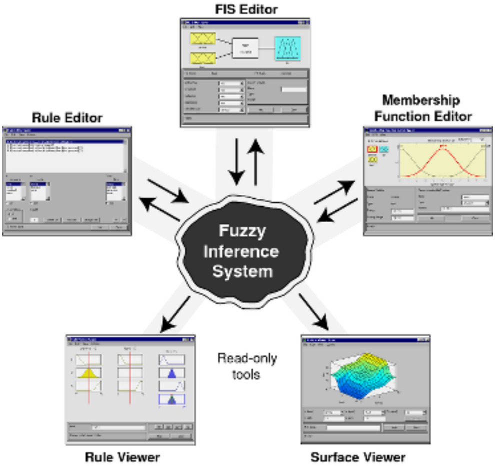

Figure 2: Fuzzy Inference System

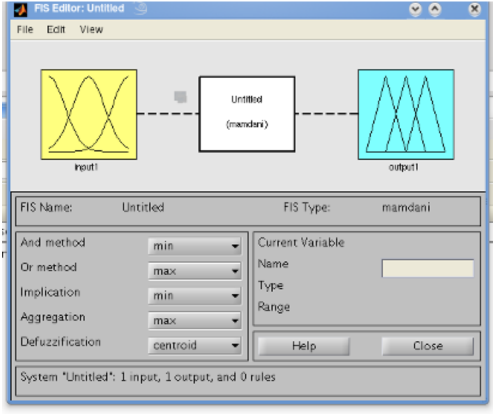

Figure 3: Fuzzy Inference System Editor

Linguistic Variables

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  - for example, the Level variable could take the values Low, OK and High

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- Input MFs usually overlap

Viewing the Inference Process

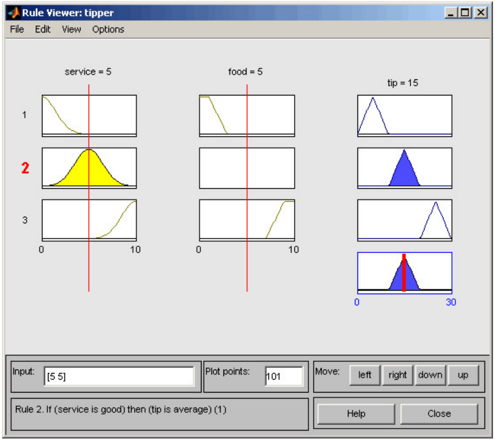

Figure 4: Fuzzy Rule Viewer

Types of FIS Used in Control

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- Sugeno (or Takagi-Sugeno)

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- output membership functions are fuzzy sets
  - After the aggregation process, there is a fuzzy set for each output variable that needs defuzzification.

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  - For a zero-order Sugeno model, the output level z is a constant (a=b =0)

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$$Output = \frac{\sum_{i=1}^{N} w_i z_i}{\sum_{i=1}^{N} w_i}$$

where N is the number of rules.

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Cart-Pole Balancing

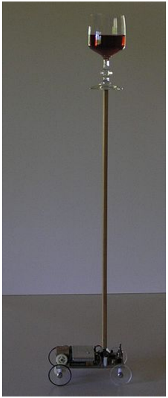

Figure 5: The Cart-Pole System (Inverted Pendulum)

- an example problem in non-linear control

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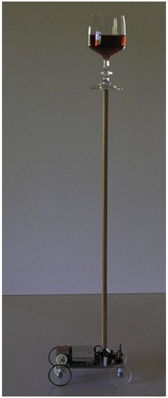

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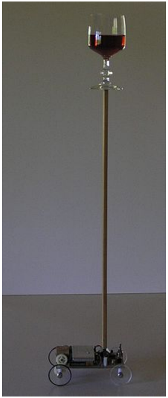

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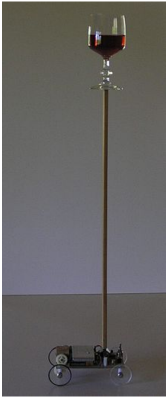

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- an example problem in non-linear control
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  - keep pole balanced
  - keep cart within bounds of track

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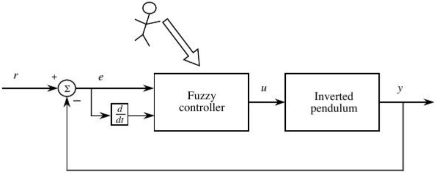
- Fuzzy controller can be used fairly intuitively

Fuzzy Controller for the Cart-pole



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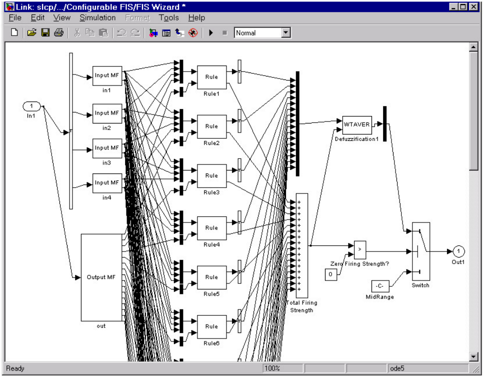

Figure 7: The Simulink Cart-Pole Simulation

A bit complicated!

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    - e.g. a rule which will change down when going downhill to enable engine-braking

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  - many others

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  - This observation underpins many of the other statements about fuzzy logic.

Some More Reading

Passino & Yurkovich, 1997, Fuzzy Control

- particularly chapter 2

Figure 8: Fuzzy Control Book

download from:

http://www2.ece.ohio-state.edu/~passino/FCbook.pdf

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Fuzzy Logic Toolbox User's Guide – MathWorks www.mathworks.com/help/pdf_doc/fuzzy/fuzzy.pdf

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