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THE COMPARATIVE ANALYSIS OF FUZZY LOGIC CONTROLLER CAN BE USED FOR CONTROLLING COMPLEX SYSTEMS

In the article possibility of application of the fuzzy logic is considered. The computational mechanism and block-schematic of fuzzy logic controller is represented. The main principles are considered and the features of management on basis of the theory of fuzzy sets are revealed. Methods can be used for designing fuzzy logic controllers is considered.

Introduction. Recently, much attention has been paid to the application of knowledge-based control techniques for flight control. It shows that techniques like neural fuzzy systems can provide appropriate tools for nonlinear identification, control of high performance aircraft, helicopters, flight control reconfiguration and advisory systems. Fuzzy systems are used as supervisory, expert systems.

Knowledge-based (expert) control tries to formalize the domain-specific knowledge, and uses reasoning mechanisms for determining the control action from the knowledge stored in the system and the available measurements. Knowledge-based control systems try to enhance the performance, reliability and robustness of current control systems by incorporating knowledge that cannot be accommodated in analytic models upon which conventional control algorithms are based. Knowledge-based systems can be used to realize the closed-loop control actions directly, i.e. replace conventional closed-loop controllers, or they can complement and extend conventional control algorithms via supervision, tuning or scheduling of local controllers [1].

A common type of knowledge-based control is rule-based control, where the control actions corresponding to particular conditions of the system are described in terms of if-then rules. Fuzzy Logic Controllers (FLCs) are rule-based systems, where fuzzy sets are used for specifying qualitative values of the controller inputs and outputs. Much of the expert's knowledge contains linguistic terms such as *small, medium, large,* etc., which can be appropriately represented by fuzzy sets. Using fuzzy logic, experts' (linguistic) knowledge of the process control can be implemented. After the rules and membership function are designed, the function of the fuzzy controller can be tested using system analysis and simulation software (e. g. MATLAB/SIMULINK)[2].

The main idea. Using fuzzy sets and fuzzy set operations, it is possible to design a fuzzy reasoning system, which can act as a controller. In Figure 1 [2], the structure of a typical fuzzy logic controller (FLC) is shown. The control strategy is stored in the form of if-then rules in the rule base.

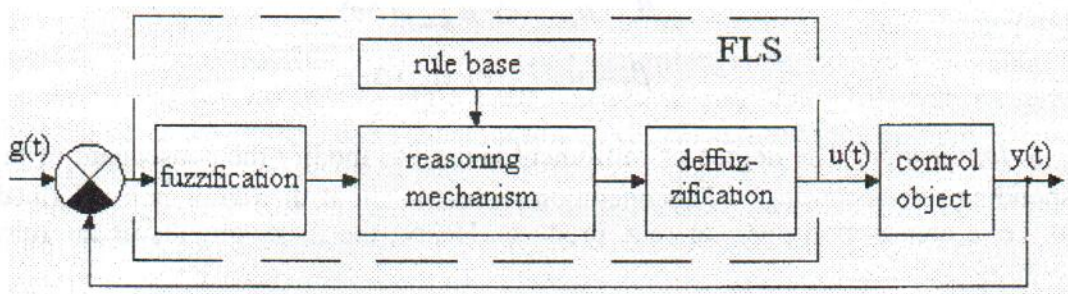

Figure 1: Block-schematic representation of fuzzy logic controller.

They represent an approximate static mapping from inputs (e.g. "errors") to outputs ("control actions"). The membership functions provide a smooth interface from the linguistic knowledge to the numerical process variable. The fuzzification module determines the membership degree of the inputs to the antecedent fuzzy sets. The reasoning mechanism combines this information with the rule base and determines the fuzzy output of the rule-based system. In order to obtain a crisp signal, the fuzzy output is defuzzified and scaled.

Simple fuzzy control rules can be defined as relations between the control error e, the error derivative Δe and the control action u. As an example, assume that the following two rules are a part of a fuzzy controller's rule base:

If e e is *small* and Δe is *medium* Then u u is small

If e e is *medium* and Δe is *big* Then u is medium

Triangular membership functions are defined for the terms *small, medium* and *big* in the respective domains, see Figure 2. The computational mechanism of the FLC proceeds in five steps:

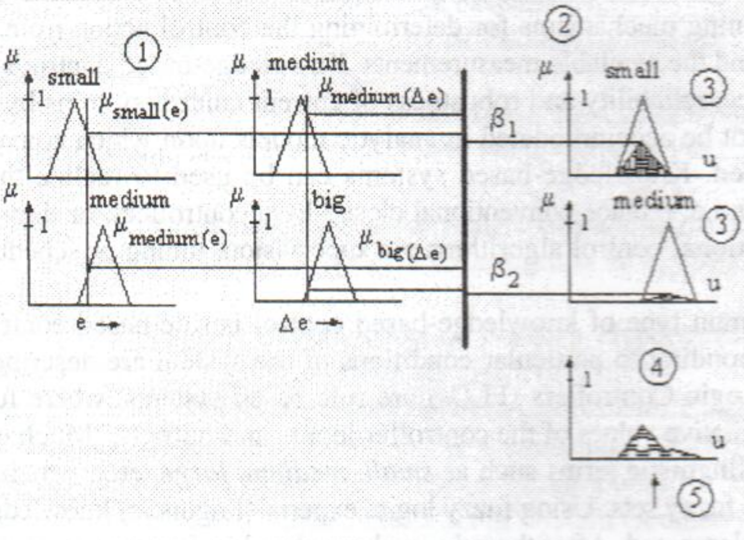

Figure 2: Computational mechanism of a FLC.

1. *Fuzzification:* The membership degrees of the antecedent variables are computed $\mu_{small}(e)$, $\mu_{medium}(e)$, $\mu_{medium}(\Delta e)$, $\mu_{big}(\Delta e)$.

2. *Degree of fulfillment:* The degree of fulfillment for the antecedent of each rule is computed using fuzzy logic operators. The degree of fulfillment β_i determines to which degree the i-th rule is valid. In the example, the product operator is used:

$$\beta_1 = \mu_{small}(e) \cdot \mu_{medium}(\Delta e)$$

$$\beta_2 = \mu_{medium}(e) \cdot \mu_{big}(\Delta e)$$

3. *Implication:* The degree of fulfillment is used to modify the consequent of th *cxg* e corresponding rule accordingly. This operation represents the if-then implication defined as a t-norm, i.e. a conjunction operator (e.g. product). Hence, the fuzzy outputs of the rules become:

$$\mu_1'(u) = \beta_1 \cdot \mu_{small}(u)$$

$$\mu_2'(u) = \beta_2 \cdot \mu_{medium}(u)$$

4. *Aggregation:* the (scaled) consequents of all rules are combined into a single fuzzy set. The aggregation operator depends on the implication function used; for conjunctions, it is a disjunction operator (e.g. max):

$$FLS\ \ output(u) = \max(\mu_1'(u), \mu_2'(u)) \quad \forall u \in U$$

5.*Defuzzification:* the resulting fuzzy set is defuzzifed to a crisp value. Defuzzification can be considered as an operator that replaces a fuzzy set by a representative value. There exists of defuzzification methods, such as the center of area method. In Figure 2, a small arrow marks the defuzzified value.

To different methods can be used for designing fuzzy logic controllers:

- design the controller directly from the knowledge available from the domain experts;
- develop a fuzzy model of the plant from measurements, first principles and expert knowledge, and use this model to design a controller or incorporate this model in a model-based control scheme.

The design the fuzzy controller characterizes by the following steps:

1. *Determine the controller inputs and outputs.* For this step, one needs basic knowledge about the character of the plant dynamics (stable, unstable, stationary, time-varying, low order, high order, etc.), the plant nonlinearities, the control objectives and the constraints. The simplified plant dynamics together with the basic control objectives determine the dynamics of the controller, e.g. PI, PD or PID type fuzzy controller. In order to compensate for the plant nonlinearities, non-stationary or other undesired phenomena, variables other than error and its derivative or its integral may be used as the controller inputs. It is, however, important to realize that with an increasing number of inputs, the complexity of the fuzzy controller (i.e. the number of linguistic terms and the total number of rules) increases considerably. In that case, rule base simplification and reduction techniques need to be used for keeping the number of rules small.

2. *Determine the rule base.* The construction of the rule base is a crucial aspect of the design, since the rule base encodes the control protocol of the fuzzy controller. Several methods of designing the rule base can be distinguished. One is based entirely on the expert's intuitive knowledge and experience over all operating conditions. Since in practice it may be difficult to extract all knowledge from the operators, this method is often combined with a good understanding of the system's dynamics. Another method is based on using a fuzzy model of the process from which the fuzzy control rules are derived.

3. *Define the membership functions and the scaling factors.* The designer must decide, how many linguistic terms per input variable will be used. The number of rules needed for defining a complete rule base increases exponentially with the number of linguistic terms per input variable. On one hand, the number of terms per variable should be low in order to keep the rule base maintainable. On the other hand, with few terms, the flexibility in the rule base is restricted with respect to the achievable nonlinearity in the control mapping. The membership functions may be a part of the expert's knowledge, for example the expert knows approximately what a "large roll angle error" means. If such knowledge is not available, membership functions of the same shape, uniformly distributed over the domain, can be used as an initial setting and can be tuned later. For computational reasons, triangular and trapezoidal membership functions are usually preferred to bell-shaped functions. Moreover, the latter functions introduce a nonlinear character, which may not be desirable in all cases.

Generally, the input and output variables are defined on closed intervals. For simplification of the controller design, implementation and tuning, it is more convenient to work with normalized domains, such as the interval [-1,1]. Scaling factors are used to transform the values from the operating ranges to these normalized domains. However, one should be aware that such scaling factors also scale the nonlinearity in the controller, which may not always be desirable.

4. *Inference options.* The choice of the inference operators also influences the shape of the mapping between inputs and outputs. The most used inference method is the max-min method, where the minimum operator is used for determining the degree of fulfillment and the implication, and the maximum operator for rule aggregation. Another method is the sum product inference. The latter combination is useful for an initial, linear setting of the FLC.

5. *Fine-tuning the controller.* The implementation of human heuristics is formalized by fuzzy logic in a systematic way. Although fine-tuning the performance of the controller is essentially a matter of trial-and-error, an understanding of the influence of various parameters can guide the process. The scaling factors, which determine the overall gain of the fuzzy controller and also the relative gains of the individual controller inputs, have mainly a global effect. The effect of a modification of membership functions and rules is more localized, for example changing the consequent of an individual rule. The effect of the change of the rule consequent is the most localized and influences only that region where the rule's antecedent holds.

6. *Stability analysis.* The analysis of the controller is mainly based on time responses. A stability analysis of the nonlinear FLC is in general difficult. However, results can be obtained by using techniques from nonlinear systems theory if a model of the process under control is available. The stability is only proven for the particular, simplified model. Recently, the stability results have also been extended to more general classes of systems. The resulting controllers are usually conservative because of the conservative nature of the stability criteria.

Conclusions. Designing controllers for task flying an aircraft particularly when extra situation appearing in the air such as failure of main systems and unites, collisions with birds in air and so on is very complicated. Because it is nonlinear task and conventional control may not be appropriate. One of the reasons is to necessity of using mathematical model for controlling the process. But it may be some difficulties in obtaining explicit mathematical model for controlling a nonlinear object. Another reason is that humans use various kinds of information and a combination of control strategies that cannot be easily integrated into an analytic control law. However, a lot of experience and knowledge is available from the experts (e.g. the pilot), which can be made explicit and programmed as a control strategy in a computer. The basic idea of a fuzzy logic controller is to formalize the control algorithm, which can be represented as a collection of if-then rules, (the first part of the rules (if) specifies the conditions, the second part (then) prescribes the corresponding control action). One of the main reasons put forward for using fuzzy logic is that an explicit mathematical model description is not required for the design of a FLC [3,4]. The criterion functions and task of optimal control is not required by using fuzzy logic control, because applying large number of a private rules instead traditional method where low of control is represented a one formula. We can offer working out of new principals of control based on fuzzy logic; together with traditional methods of control.

The list of literature

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