Perspectives of Fuzzy Systems and Control

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Abstract

Although fuzzy control was initially introduced as a model-free control design method based on the knowledge of a human operator, current research is almost exclusively devoted to model-based fuzzy control methods that can guarantee stability and robustness of the closed-loop system. State-of-the-art techniques for identifying fuzzy models and designing model-based controllers are reviewed in this article. Attention is also paid to the role of fuzzy systems in higher levels of the control hierarchy, such as expert control, supervision and diagnostic systems. Open issues are highlighted and an attempt is made to give some directions for future research.

Key words: Fuzzy control, modeling, stability, LMI, nonlinear systems, intelligent control

1 Introduction

Feedback control is a powerful tool to handle uncertainty in dynamic systems, through reducing their sensitivity to external disturbances and parameter changes, and to modify their dynamic behavior (e.g., stabilize an unstable plant or speed up a slow system). However, as feedback can potentially destabilize open-loop stable systems, stability analysis is a major issue in control design. To guarantee stability, one needs a mathematical model of the plant.

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In contract to conventional control, fuzzy control was initially introduced as a model-free control design method based on a representation of the knowledge and the reasoning process of a human operator [65,37]. Fuzzy logic can capture the continuous nature of human decision processes and as such is a definite improvement over methods based on binary logic (which are widely used in industrial controllers). Hence, it is not surprising that practical applications of fuzzy control started to appear very quickly after the method had been introduced in publications. A drawback of knowledge-based, model-free fuzzy control is that it does not allow for any kind of stability or robustness analysis, unless a model of the process is available. However, if that is the case, one can of course use the model for design, as in standard control. The possibility to analyze stability, performance and robustness gave rise to the recent interest in model-based fuzzy control design and in identification for obtaining fuzzy models from process data. It has been recognized that fuzzy systems are universal function approximators and hence can be used to model a wide class of processes.

The present situation in the area of fuzzy systems and control is characterized by a certain mismatch between the main motivation of readability (using understandable rules, computing with words) and the use of mathematically involved and rather non-transparent techniques to ensure robust performance, in direct analogy with mainstream (nonlinear) control. From a research point of view, in the low-level control loop the knowledge-based approach seems to have been superseded by the model-based one. The knowledge-based approach mainly remains an option in higher control levels (supervision, diagnosis).

This paper outlines the state of the art of fuzzy techniques (from the control point of view), and puts forward some perspectives regarding the future role of fuzzy systems. Fuzzy plant models and the procedures to obtain them are discussed in Section 2. Model-based fuzzy controllers are discussed in Section 3 and adaptation in Section 4. The knowledge-based approach in control engineering is addressed in Section 5 while Section 6 concludes the paper.

2 Fuzzy modeling and identification

Initially, fuzzy modeling was introduced as an approach to building models based on expert knowledge in a linguistic form [65,36]. Later on, the focus gradually shifted toward methods for constructing fuzzy systems from data and applying them in areas like data mining, pattern recognition and systems identification [24]. In such applications, fuzzy approaches serve as an alternative or complement to other inductive methods, including neural networks, machine learning or statistical inference techniques. The most prominent feature that distinguishes fuzzy systems from black-box methods is their transparency and interpretability. Fuzzy models are suited for explaining solutions to users, especially to those who do not have a strong mathematical background. The linguistic interpretability and transparency of fuzzy models constructed from data therefore became important research items in the literature [45,46,15,43,29].

2.1 Preliminaries

In system identification, a fuzzy system typically approximates a nonlinear dynamic regression model $y(k+1) = f(\mathbf{x}(k))$, where the regression vector $\mathbf{x}(k)$ contains a collection of previous process inputs u and outputs y. Both Mamdani and TS models are used, but in the context of dynamic systems the TS model is more common:

$$\text{If } \mathbf{z}(k) \text{ is } F_i \text{ then } y(k+1) = \boldsymbol{\theta}_i^T \mathbf{w}(k), \quad i = 1, 2, \ldots, r, \tag{1}$$

where the antecedent and consequent variables $\mathbf{z}$ and $\mathbf{w}$ are usually selected from the regression vector $\mathbf{x}$. The model has two sets of parameters, the consequent parameters $\boldsymbol{\theta}$ and parameters defining the membership functions for the fuzzy sets F_i. The TS model can approximate nonlinear processes with both smooth and abrupt nonlinearities (through the form of the membership functions), specific choice of the antecedent and consequent variables (e.g., Wiener and Hammerstein systems), and for modeling processes where the dynamic structure varies with some known variables (switching systems, failure modes, etc.).

2.2 The identification problem and its solutions

The two basic steps in system identification are *structure identification* and *parameter estimation*. The choice of the model's structure (variables, number of membership functions, etc.) is very important, as it determines the flexibility of the model in the approximation of (unknown) systems. A model with a rich structure can approximate more complicated functions, but, at the same time, will have worse generalization properties. The parameter estimation problem can be formulated as the minimization of a nonlinear least-square criterion:

$$\{\boldsymbol{\alpha}_1, \ldots, \boldsymbol{\alpha}_r, \boldsymbol{\theta}_1, \ldots, \boldsymbol{\theta}_r\} = \arg\min \sum_{k=1}^{n} \left(y_k - \sum_{i=1}^{r} h_i(\mathbf{z}_k, \boldsymbol{\alpha}_i) \boldsymbol{\theta}_i^T \mathbf{w}_k \right)^2 \tag{2}$$

for the available set of n data pairs: $(\mathbf{x}_k, y_k)$, $k = 1, 2, \ldots, n$. The free parameters are the consequent and antecedent parameters vectors, $\boldsymbol{\theta}_i^T$ and $\boldsymbol{\alpha}_i$, respectively, and $h_i(\mathbf{z})$ denotes the degree of fulfillment of the ith rule (there are r rules in the rule base). The commonly used optimization techniques can be divided into two main categories:

(1) Methods based on global nonlinear optimization of all the parameters, such as genetic algorithms, neuro-fuzzy learning techniques (backpropagation and variants thereof), product-space fuzzy clustering, etc.
(2) Methods that exploit of the fact that (2) is nonlinear in $\boldsymbol{\alpha}_i$ (due to inherently nonlinear parameterization of the membership functions), while it is linear in $\boldsymbol{\theta}_i$. Typically, the linear estimation problem is solved as a local problem within one iteration of the antecedent parameter optimization problem or after the antecedent parameters were determined in some other way (e.g., using prior knowledge).

As virtually all nonlinear regression methods can be adopted for fuzzy modeling, the spectrum of available techniques is enormous.

2.3 Remarks and open issues

The construction of a fuzzy model involves a tradeoff between the accuracy and transparency of the model. Much research has therefore been devoted to methods for reducing complexity of fuzzy systems, e.g., by using similarity measures [45] or orthogonal transformations [62]. This issue still cannot be considered satisfactorily solved, as, especially in applications, fuzzy models are often used as purely black-box methods.

Fuzzy identification for control. Surprisingly little attention has been devoted to the identification of fuzzy models for fuzzy control design. There are quite some discrepancies between the assumptions made on fuzzy models for control design (mostly in a continuous-time state-space framework) and the possibilities of current identification techniques, which are developed primarily for discrete-time input-output models. The ‘identification for control’ paradigm that is currently being investigated in the control community should also be adopted in the fuzzy control community. The issues of effective experiment design, model class, modeling error, target control specifications, etc., have not been sufficiently addressed in the fuzzy modeling and identification literature. Very few publications are concerned with dynamic properties of fuzzy models [31].

Application examples and benchmarks. The performance of fuzzy identification techniques is typically assessed by using relatively simple simulation examples. It can be argued that many of these examples are not suitable as benchmarks or demonstrators of nonlinear (fuzzy) modeling methods. Results obtained for simple illustrative examples often do not carry over to more complex problems. In addition, standard regression methods will often solve the simple problems as well.

Relation to other techniques. The quality of newly proposed fuzzy identification methods should be evident from a comparison with state-of-the-art regression or classification techniques. Critical analysis of the results should be made and linear models must be regarded as a lower bound on the acceptable performance. Fuzzy models certainly have the potential to outperform other techniques, but this must be clearly shown by comparisons with non-fuzzy approaches. Only in this way, fuzzy techniques can gain higher credibility outside the fuzzy community.

3 Stable and robust model-based fuzzy control

An available fuzzy or neuro-fuzzy model can be used in the design of a controller in two ways. First, any (nonlinear) model-based technique such as feedback linearisation (see later eq. (11)), predictive and inverse-model-based techniques can be applied to the fuzzy model [3]. Second, the controller itself can be a fuzzy system whose structure matches the structure of the fuzzy plant model. This idea, for TS fuzzy systems called *parallel distributed compensation* [53], has proven very fruitful. By far the largest number of results have been published for the stabilization of Takagi–Sugeno models in continuous and discrete time. In this paper we therefore focus on this class of methods.

3.1 Preliminaries

Consider the continuous Takagi–Sugeno (CTS) model in the state-space form:

$$\begin{aligned} \dot{x}\left(t\right) &= \sum_{i=1}^{r} h_i\left(\mathbf{z}\left(t\right)\right)\left(A_i x\left(t\right) + B_i u\left(t\right)\right) \\ y\left(t\right) &= \sum_{i=1}^{r} h_i\left(\mathbf{z}\left(t\right)\right) C_i x\left(t\right) \end{aligned} \tag{3}$$

where $h_i\left(\mathbf{z}\left(t\right)\right) \geq 0$ are the degrees of fulfillment of the rules (in an interpretation similar to (1), but in the state-space form), satisfying the convex sum property $\sum_{i=1}^{r} h_i\left(\mathbf{z}\left(t\right)\right) = 1$. The parallel distributed compensation (PDC) law for system (3), is given by:

$$u\left(t\right) = -\sum_{i=1}^{r} h_i\left(\mathbf{z}\left(t\right)\right) F_i x\left(t\right) \tag{4}$$

In the discrete-time TS (DTS) model, $\dot{x}\left(t\right)$ is replaced by $x\left(t+1\right)$.

The so-called sector nonlinearity approach [53] provides a systematic method to exactly represent affine nonlinear systems

$$\begin{aligned} \dot{x}\left(t\right) &= f\left(x\left(t\right)\right) + g\left(x\left(t\right)\right)u\left(t\right) \\ y\left(t\right) &= h\left(x\left(t\right)\right) \end{aligned} \tag{5}$$

in terms of (3) if the state is assumed to lie on a compact set. However, the number of rules r grows exponentially with the number of nonlinearities being involved in (5) [52]. Note also that the TS representation of (5) is not unique.

3.2 The control design problem and its solutions

The goal is to design a robust control law for model (5) using its equivalent representation (3). The main interest is in finding a context where linear design tools can be applied. Then, the result will only depend on the linear models (A_i, B_i, C_i), which are supposed to be observable and controllable. Consider the above scalar functions $h_i(\cdot)$, and symmetric matrices $\Upsilon_{ij} = \Upsilon_{ij}^T$. Many control design problems can be stated as finding the least conservative conditions ensuring:

$$\sum_{i=1}^{r} \sum_{j=1}^{r} h_i(\mathbf{z}(t)) \, h_j(\mathbf{z}(t)) \, \Upsilon_{ij} < 0 \tag{6}$$

The basic result considers the following quadratic Lyapunov function:

$$V(x) = x^T(t) P x(t) \quad \text{with} \quad P = P^T > 0 \tag{7}$$

whose derivative along the trajectories of the CTS (3) in the closed loop with the PDC law (4) result in (6) with:

$$\Upsilon_{ij} = (A_i - B_i F_j)^T P + P (A_i - B_i F_j) \tag{8}$$

The main approach is based on the use of Linear Matrix Inequality (LMI) techniques [6], where conditions valid for any h_i verifying the convex sum property are used. The fact that the actual scalar functions $h_i(\cdot)$ are not introduced in the LMI conditions will give only sufficient results.

In the pioneering works (see [53] and the references therein), the basic problem is solved without taking into account additional aspects like performances and robustness specifications and the use of state observers. The extension to output feedback with a state observer is quite straightforward when the premise variables $\mathbf{z}$ in (3) are measurable, in which case the separation principle holds [28]. In [53] and [2] dynamic output-feedback control is considered.

It should be stressed that contrary to claims often made in the literature, fuzzy controllers are not 'inherently robust', unless an uncertainty description is explicitly associated with the fuzzy model and taken into account in the design procedure. Norm-bounded uncertainties were introduced in [66,58,51,13]. Pole placement constraints for the individual linear models can be used to impose performance requirements [30,27].

Following the first works on nonlinear models in the form of (3), several extensions were explored. Some of them are direct extension of previous results, for example TS time-delay models with or without uncertainties [53,63]. Others try to extend to this representation standard results from the linear framework, for example control laws based on a descriptor form of CTS models or optimal fuzzy control design [53].

The methods remain conservative and the challenge is to find some new ways to reduce this conservatism. One possibility is to modify the Lyapunov function. Alternatives for the classical quadratic Lyapunov function (7) were proposed; a piecewise quadratic Lyapunov function [7,19,32], and a fuzzy Lyapunov function [4,54] for CTS models and a non-quadratic function for DTS models [22]. Another approach is to use some matrix properties: specific transformations, elimination lemma [59] and/or relaxation of the basic inequality (6), see for example [52,35].

3.3 Remarks and open issues

Two main issues can be mentioned. The first one concerns the preliminaries stated implicitly when addressing TS models stabilization. The first preliminary is the controllability and observability. If the nonlinear system (5) is controllable and observable (at least locally), how can we ensure that these properties are preserved in its TS representation (3)? These issues are rather complex in TS models. For instance, one can have a TS model with all linear submodels controllable and still obtain a locally uncontrollable nonlinear model. Vice versa, a controllable nonlinear model may be represented by a TS model with some uncontrollable linear models. The second concern is related to the lack of the separation principle in the general case. If dynamic output feedback is needed, the control law cannot be designed apart from the observer. Then we need to understand and to quantify the connection between the control law and the observer for the general case and/or for a more general class of TS models (with uncertainties, delays, etc.). The last concern is the tractability of the LMI problem. Many LMI variables are needed in the currently available least conservative results. Hence, in this context, although LMI algorithms have polynomial complexity with respect to the system order and the number of models, the polynomial exponents are large, so only low-order systems can be handled by the available solvers.

The second issue concerns future perspectives. It seems now that the classical approach using the quadratic Lyapunov function has been very well and deeply explored. Nevertheless, as the results only use sufficient conditions, the main problem is what can be done if the conditions are too restrictive? What happens when there is no solution to the constrained problem under consideration? This question is directly related to the definition of the kind of 'best' TS representation (3) of the nonlinear model (5) – 'best' in the sense of feasible LMI problem. Apart from introducing additional conditions, another way is to find new Lyapunov functions able to cope with the degrees of fulfillment. This includes the works already done with piecewise Lyapunov function [7,19,32] or with non quadratic ones [22]. A further possibility would be to leave the Lyapunov direct approach and introduce alternative methods, maybe a linguistic approach to stability analysis.

4 Adaptive fuzzy control

4.1 Preliminaries

Recently, there has been an increased interest in adaptive fuzzy control (AFC) for input-affine nonlinear systems in the controllable canonical form:

$$x^{(n)} = f(\mathbf{x}) + g(\mathbf{x})u \tag{9}$$

$$y = x \tag{10}$$

where $\mathbf{x} = \left[x, \dot{x}, \ldots, x^{(n-1)}\right]^T$ is the state vector. The control goal is to track a desired trajectory y_m while keeping all the signals in the closed-loop bounded. If the functions $f(\mathbf{x})$ and $g(\mathbf{x})$ are known, the ideal feedback linearizing control law can be applied:

$$u = \frac{1}{g(\mathbf{x})}\left(-f(\mathbf{x}) + y_m^{(n)} + \boldsymbol{k}^T\boldsymbol{e}\right) \tag{11}$$

where $\boldsymbol{e}$ is the vector containing the tracking error $e = y_m - y$ and its $n-1$ derivatives and $\boldsymbol{k}$ is a feedback gain vector which can be chosen such that the roots of the polynomial $h(s) = s^n + k_1 s^{n-1} + \ldots + k_n$ are in the open left half of the complex plane.

4.2 Indirect and direct adaptive fuzzy control

The basic idea of *indirect AFC* is to approximate the unknown functions $f(\mathbf{x})$ and $g(\mathbf{x})$ in the control law (11), by using two linearly parameterized singleton fuzzy systems [60,61]:

$$\begin{aligned}\hat{f}(\mathbf{x}) &= \boldsymbol{\theta}_f^T \mathbf{h}_f(\mathbf{x}) \\ \hat{g}(\mathbf{x}) &= \boldsymbol{\theta}_g^T \mathbf{h}_g(\mathbf{x})\end{aligned} \tag{12}$$

where $\boldsymbol{\theta}_f$ and $\boldsymbol{\theta}_g$ are the consequent parameters to be adapted, $\mathbf{h}_f(\mathbf{x})$ and $\mathbf{h}_g(\mathbf{x})$ are the normalized degrees of fulfillment of the (fixed) fuzzy rule antecedents. The consequent parameters are adapted on-line by means of stable adaptive laws derived through Lyapunov synthesis. These methods, here stated for SISO systems, have also been extended to square MIMO systems [56].

In *direct AFC*, the control law is represented by a single fuzzy system whose parameters are adjusted to meet the required control objective [34,10,11,41,49]. In this case, however, the assumptions made on $g(\mathbf{x})$ can be very restrictive. For instance, in [34,10], the authors assume that $g(\mathbf{x})$ is exactly known, and in [41] $g(\mathbf{x})$ is assumed to be strictly diagonal dominant with known state dependent upper bounds for the time derivatives of the main diagonal entries.

The design of such adaptive fuzzy controllers must inherently consider robustness issues since any finite dimensional fuzzy approximator unavoidably introduces an approximation error. Such an error is usually handled as a disturbance acting on the system by means of modifications such as:

- *An additional damping term*, usually in the sliding mode framework [50,20,49], [12,57,10].
- *A modified adaptive law* such as a projection [60,61], dead-zones [33], $\sigma-$modification or $\epsilon-$modification [48].

Adaptive controllers with composite adaptive laws, based on both the tracking and model prediction error, have been also proposed in the literature [64,25].

4.3 Remarks and open issues

Fuzzy systems have the potential to play an important role in nonlinear adaptive control, mainly thanks to their *universal function approximation* property and their amenability to (linguistic) interpretation of the input-output relationships. The use of fuzzy systems instead of a black-box technique is advantageous not only because fuzzy systems can provide a good guess for the initial system model (by the including prior qualitative knowledge), but also to gather more insight about the unknown systems dynamics and/or control law during or at the end of adaptation. These issues are, however, still to be explored and exploited.

The efforts in current research on AFC are directed toward:

- the use of more general (nonlinear) parameterizations for the fuzzy systems [23,1];
- the extension of AFC to discrete-time systems [39] and other classes of systems (e.g., systems described by a TS fuzzy model rather than the canonical controllable form (10) [42,16]);

- the assessment not only of the closed-loop stability but also of the performance of the adaptive controller (e.g., in terms of control effort [39]).

Finally, note that the class of input-affine nonlinear systems is still very restricted and the hypothesis of having a measurable state vector is unrealistic. The next step should be to investigate the use of state observers to eliminate this drawback.

5 Expert control, supervision and diagnosis

Historically, the use of fuzzy systems in control started in a close relation to logic, inference and 'linguistic' information processing (based on knowledge of plant operators). Direct fuzzy controllers implementing heuristic rules from operators had a significant success in application areas such as cement kilns [38,26] or waste-water treatment [55]. However, closer analysis reveals that many proposed strategies are remarkably similar to the basic proportional, integral and derivative control actions. Their tuning involves adjustable 'scaling factors', and is thus not fundamentally different from adjusting gains in a conventional regulator (see [40] for an example).

Higher decision levels in process control also use rule bases for decision support. Supervision, diagnosis and condition monitoring are examples of successful application domains for fuzzy reasoning strategies [8,18]. Rule bases can be regarded as *compiled* dictionaries of faults (or operation modes) and symptoms, without resorting to a deep knowledge of the plant being monitored. If fuzzy logic is used, the plant condition may be expressed as a partial membership to one or several prototype situations (identifying membership with fault 'severity').

Setting up the rules seems an easy task if expert knowledge is available. However, there are three significant issues complicating this procedure:

- Rules are not always true (some rules hold in the majority of cases, but have exceptions, cumbersome to be detailed),
- A rule with a set of conditions 'if C_1 and C_2 and C_3 and ...' fails to fire if a measurement involved in any C_i is missing. Therefore, one unmeasured premise may prevent, say, a 30 symptom rule from firing, even if it is clear that the likelihood of the fault, based on 29 matching conditions, is very high.
- Some conditions are diagnosed by detecting patterns over time, so dynamics need to be considered.

In the fuzzy logic area, refinements have been worked out to deal with the first two situations above. For instance, 'certainty factors' can be used to weight the rule activations when deriving conclusions. However, the interpretation of certainty factors may be unclear. Many schemes for reasoning under uncertainty have been developed [21,47]. A promising approach is the possibilistic reasoning [17], in which symptoms have possibility and necessity measures in the interval $[0, 1]$ and extended deduction axioms are applied. In practical situations, possibility and necessity may be roughly understood as upper and lower probability bounds (or membership –severity– ones), respectively. For instance, in [9], a list of consistent faults is generated and further information may reduce the possibility or increase the necessity of a particular condition. However, if information is scarce, a lot of possible faults are generated and one needs to rank them. In the absence of probabilistic information, *abduction* techniques are used (the most evident is symptom counting, see [9] and the references therein).

5.1 Remarks and open issues

Fuzzy control. The inherent limitations of the PID-like control structure in dealing with nonlinear process are usually not recognized in the literature on knowledge-based fuzzy control. For instance, unless inversion or linearisation-based designs are pursued, to cope with significantly nonlinear systems the controller rule base must include additional inputs, such as the setpoint. However, the corresponding designs cannot be pursued using only heuristic knowledge in most cases: long ago, it has been recognized that a successful fuzzy control design relies on the mix of heuristic knowledge and solid control-theoretic insights. In general, the knowledge-based approach to direct control has been presently superseded by the developments described in previous sections.

Monitoring. Monitoring (supervision and diagnosis) can be regarded as estimating the plant's state based on measurements. Not so surprisingly, analytical model-based techniques have been developed, interpreting the monitoring process as setting up a (nonlinear) observer. Observation errors called residuals are generated by processing input output data (u, y), which depend on the process condition θ and unmeasurable disturbance inputs n. The task is to devise a dynamic system N_i such that $N_i(u(\theta, n), y(\theta, n))$ is near zero except when $\theta = \theta_i$, denoting a particular condition. That residual may also be generated from discrete-event and graph models of failure, or by parameter estimation techniques. The reader is referred to [14,5] and references therein for details. In a sense, there is a complementarity between rule-based designs and dynamic processing: the more elaborate and accurate the dynamic models are, the simpler and more reliable the post-processing rules will be.

In the AI community, Bayesian network approaches are gaining popularity, in contrast to traditional rule-based systems. In Bayesian nets, uncertainty (both in the rules and the individual premises) is treated under a probabilistic setting and missing observations are handled naturally, as well as some cases of learning from experience [44]. However, the Bayesian approach has some drawbacks. First, one needs to define a multitude of probability coefficients (many may be unknown to the expert) and even continuous multivariate probability density functions (if, instead of binary outputs, real-valued conclusions such as severity of faults are desired). Second, computational issues may render fuzzy conclusions an intractable problem in practice, unless partitioned into discrete states symbolizing intermediate membership ranges. Regarding practical applications there is certainly some room for mixed schemes including fuzzy or possibilistic inference combined with probabilistic information.

6 Concluding remarks and future perspectives

Theoretical results and possibilities of the fuzzy control approach have been reviewed in the preceding sections. Conclusions and more general open questions are given here.

First, the use of fuzzy logic as a reasoning tool in direct process control has been superseded by the model-based techniques. Clearly, the mainstream fuzzy control has become one of the nonlinear control design methods, with a strong mathematical basis and reliance on a (fuzzy) plant model. This is a departure from the original goals of fuzzy control, neglecting the fact that fuzzy systems provide an alternative representation scheme to incorporate extra relevant information that cannot be used in the standard control-theoretic framework. For instance, in the realm of possibility theory, fuzzy logic can be used to represent uncertainty. However, in the control area, fuzzy systems are not used as a framework for uncertainty representation, but rather as a nonlinear function approximation tool.

Questions about the difference between fuzzy and other non-linear control strategies arise. Indeed, the difference between some specific fuzzy-neural and nonlinear control applications is often unclear. Although emphasis is put on trying to show specific advantages, the opposite question can (and should) also be posed: which are the specific disadvantages of using fuzzy logic? Every methodology has its particular drawbacks.

The motivation behind the current fuzzy control approaches is still the simplicity of representation (albeit in a different interpretation than the original Zadeh's approach). Current fuzzy control tries to get as much performance as possible by using a convex combination of local linear models and local controllers, setting up conditions that depend on the models themselves rather than on the weighting coefficients (membership degrees). Indeed, intricate behaviors can be modeled as a combination of simpler ones and significant results are available (despite the inherent conservatism). However, the sophistication of the current LMI conditions for fuzzy control design is reaching practical computational tractability limits for high-order plants.

Another use of fuzzy logic is decision support at higher levels of the control hierarchy (supervision, planning, monitoring). With fuzzy models serving as a simplified representation of uncertain systems, near-qualitative decisions can be made at this level of abstraction. Different fuzzy models of the same process may coexist (from qualitative descriptions and diagnosis rules to precise settings approximating a nonlinear function). At higher levels, simple decision tables have limitations that can be overcome by incorporating possibilistic and probabilistic information.

Finally, a slightly provocative question arises whether the fuzzy control community should not adopt a more ambitious view to broaden its perspective in order to achieve some breakthrough results. Humans exhibit 'intelligent behavior' in controlling complex, poorly understood processes; they can learn from past experience, organize knowledge about the process and its surrounding environment and plan their future behavior. It can be assumed that for a large part, they achieve this thanks to their reasoning capabilities. Although fuzzy set methods have been considered as powerful reasoning tools with the potential to bridge traditional AI and control, the present use of them in the control area has adopted quite a restricted view.

Fuzzy systems may contribute to the solution of really hard control problems encountered in distributed and networked systems, autonomous agents, hybrid systems (switching, mix of symbolic and continuous variables, fault-tolerant systems), high-level coordination and control (enterprise-wide systems, supply chain management), systems interacting with humans, etc. Assuming that complex behaviors can emerge from the interaction of agents using simple sets of understandable fuzzy rules, how can this behavior be designed to accomplish some predefined goals? Finally, biological organisms are equipped with a highly efficient, redundant system for sensing the environment and for processing and storing the acquired information. Along with new sensor technologies, we need to develop tools for interpreting the vast amounts of acquired data and storing them in the form of knowledge relevant for on-line decision making and control. Here too, fuzzy set techniques can play an important role.

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