Contradiction Sensitive Fuzzy Model-Based Adaptive Control

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Summary

In fuzzy control, an alternative to the direct acquisition of the knowledge by means of a human expert is the use of adaptive techniques for system identification, achieving the so-called fuzzy model-based adaptive controllers. However, they show no interest in the state of contradiction existing in the rule base, which often causes inconsistent rule base configurations in the learning stage. In this paper, the inclusion of the knowledge base contradiction analysis is proposed as an additional mechanism to guide the search of the optimal controller configuration.

Keywords: Fuzzy model-based adaptive control; fuzzy identification; consistency analysis.

1 Introduction

Fuzzy control ([9], [6]) tries to integrate the knowledge acquired by the expert in a system by means of a set of fuzzy rules, instead of trying to get a mathematical formalism of the process to be controlled. Moreover, in the last years approaches have arisen that, using identification adaptive techniques, construct fuzzy models of the process to be controlled ([1], [5]), being not necessary then the existence of a previous algorithm in the expert's mind and resulting in the fuzzy model-based adaptive control (FMBAC).

Regardless the expert knowledge acquisition method, it has been paid little attention to the consistency of the knowledge finally obtained or in the course of acquisition. In the first case, this analysis can warn of the existence of anomalous situations introduced by the knowledge engineering or the expert himself. In the second case, it can help and accelerate the search of the optimal process description.

2 Contradiction in a Fuzzy Environment

In classical logic, two rules are contradictory if their antecedents are identical and their consequents are opposite. An approach for extending this classical definition to the fuzzy one consists of replacing the binary nature of contradiction by a multivalued nature enabling a gradation of the contradiction. In order to do that, the concepts of identical antecedents and opposite consequents are replaced by the concepts of similarity between antecedents and dissimilarity between consequents. The main idea is that the more the similarity between their antecedents and the dissimilarity between their consequents, the more the degree of contradiction between two rules.

In [2] and [3], the authors propose a measure of the degree of contradiction underlying that idea. In short, given two fuzzy rules

if A_1 is LA_{1,i_1} and ... and A_n is LA_{n,i_n} then B is LB_{l_1}

if A_1 is LA_{1,j_1} and ... and A_n is LA_{n,j_n} then B is LB_{l_2}

the degree of contradiction between them is defined as

$$C_x = \frac{\sum_{k=1}^{n} 1 - d_x(LA_{k,i_k}, LA_{k,j_k})}{n} \times d_x(LB_{l_1}, LB_{l_2})$$

where d_x is some normalized measure of dissimilarity between fuzzy values. In [4] several measures of dissimilarity between fuzzy sets are studied and a comparative analysis between them is accomplished.

Notice that the first factor of the measure represents the similarity between the antecedents. The use of the averaging operator *arithmetic mean* enables the appropriate combination of the partial similarity degrees between each pair of premises. The second factor represents the dissimilarity between the consequents. Both values are combined using a t-norm in order to obtain the final degree of contradiction.

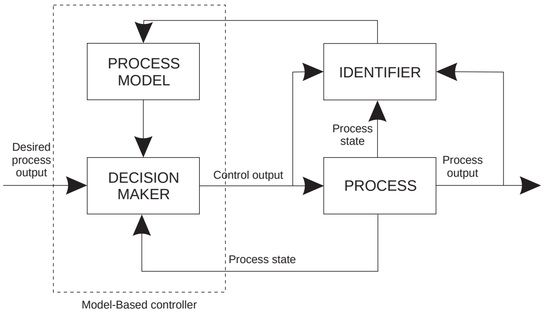

Figure 1: FMBAC Scheme

3 Fuzzy Model-Based Adaptive Controllers

FMBAC focus its operation scheme on the simultaneous development of a task of identification of the process to be controlled and a task of application of control actions on it (figure 1).

On the one hand, the aim of the identification task will consist of obtaining a fuzzy process model. In general, it will be represented by a set of fuzzy rules $R^{(i_1 \ldots i_m, j_1 \ldots j_n)}$ in the following form:

if X_1 is LX_{1,i_1} and ... and X_m is LX_{m,i_m} and

U_1 is LU_{1,j_1} and ... and U_n is LU_{n,j_n} then Y is LY_k

where X_i are process state variables and take their values from the fuzzy domains $\{LX_{i,1}, LX_{i,2}, ..., LX_{i,p_i}\}$, U_i are process input variables (control actions) and take their values from the fuzzy domains $\{LU_{i,1}, LU_{i,2}, ..., LU_{i,q_i}\}$ and Y is the process output variable (controlled variable) and takes its values from the fuzzy domain $\{LY_1, LY_2, ..., LY_r\}$.

On the other hand, the selection of the control action to be taken will be determined by the state of the system and the fuzzy process model so far available at that time, because it is possible to take from both of them which the control action will be that produces the output process closest to the desired one.

Therefore, in short, the operation of a FMBAC can be described as the continuous repetition of the following two steps, where $t-1$, t and $t+1$ are the previous, the current and the following instants, respectively:

1. Updating the fuzzy process model from the previous state vector $\{LX^{(t-1)}_{1,i_1}, ..., LX^{(t-1)}_{m,i_m}\}$ and process input vector $\{LU^{(t-1)}_{1,j_1}, ..., LU^{(t-1)}_{n,j_n}\}$ and also from the process output value $LY^{(t)}_k$ they produce, using some identification mechanism.

2. Selecting the new controller action $\{LU^{(t)}_{1,j_1}, ..., LU^{(t)}_{n,j_n}\}$ using the fuzzy process model updated in the previous step and the current state vector $\{LX^{(t)}_{1,i_1}, ..., LX^{(t)}_{m,i_m}\}$, so that the new process output value $LY^{(t+1)}_k$ approaches as far as possible to the desired process output.

Usually, the initial process model is constructed using generic logical considerations.

Adaptation methods associated with self-organizing fuzzy controllers often carry out modifications in the knowledge base consisting of changes in the consequents of the rules (e.g., [7][8]). For example, Graham and Newell propose in [7] the following algorithm:

1. Let $\{LX^{(t-1)}_{1,i_1},...,LX^{(t-1)}_{m,i_m}\}$, $\{LU^{(t-1)}_{1,j_1},...,LU^{(t-1)}_{n,j_n}\}$ and $LY^{(t)}_k$ be the previous state and process input vectors, and the output fuzzy value they produce, respectively.

2. IF the rule

if X_1 is LX_{1,i_1} and ... and X_m is LX_{m,i_m} and

U_1 is LU_{1,j_1} and ... and U_n is LU_{n,j_n} then Y is LY_l

exist, THEN replace it by

if X_1 is LX_{1,i_1} and ... and X_m is LX_{m,i_m} and

U_1 is LU_{1,j_1} and ... and U_n is LU_{n,j_n} then Y is $LY_{k'}$

where k'=round((1-α)·l+α·k); $\alpha \in$[0,1],

ELSE add the rule

if X_1 is LX_{1,i_1} and ... and X_m is LX_{m,i_m} and

U_1 is LU_{1,j_1} and ... and U_n is LU_{n,j_n} then Y is LY_k

In case a rule with the same antecedents and a consequent with the value LY_l already exists, determining the new value $LY_{k'}$ by means of a weighting factor α is a way to preserve a combination of the previously acquired knowledge and the recently learned one.

4 Operation Scheme of a Contradiction Sensitive FMBAC

The adaptive algorithm presented in the previous section, as well as others used in the design of self-organizing fuzzy controllers (e.g., [8]), are based on the change of the consequent of the rules included in the knowledge base or on the addition of new rules.

Nevertheless, the extent in which those changes are consistent with the knowledge already included in the system are not considered at all in these algorithms. This can provoke the coexistence of high-degree contradictory rules in the knowledge base, mainly during the initial learning stage or during those stages following changes in the system operation caused by disturbances or alterations in any of its parameters, since it is in those stages where the extent of those changes in the consequents tends to be more significant.

The generic solution proposed here consist of studying the level of consistency existing on the rule base after every step of the identification process that leads to a change in the rules. In order to do that, the degree of contradiction between the adapted rule and the rest will be examined and, when it becomes too high, the latter will be changed in order to attenuate it.

Therefore, a CS-FMBAC will include within the model identification task and after every adaptation step an attenuation process whose goal will be to smooth the possible contradictions introduced in the rule base. For example, in Graham and Newell's algorithm, it will result in the inclusion of a third step: *Call to attenuate*($R^{(i_1 \dots i_m, j_1 \dots j_n)}$)

Below, an algorithm is presented to attenuate the contradiction between the rules, where $R^{(i_1 \dots i_m, j_1 \dots j_n)}$ is the modified/added rule during the adaptation process and C_x is the measure of contradiction between fuzzy rules described in section 2.

attenuate($R^{(i_1 \dots i_m, j_1 \dots j_n)}$) algorithm:

FOR x_1=1,...,p_1;...;x_m=1,...,p_m;

u_1=1,...,q_1;...;u_n=1,...,q_n DO

IF $C_x(R^{(i_1 \dots i_m, j_1 \dots j_n)}, R^{(x_1 \dots x_m, u_1 \dots u_n)}) > \mu$ THEN

REPEAT

replace in $R^{(x_1 \dots x_m, u_1 \dots u_n)}$ the consequent

...then Y is LY_z

by the consequent

...then Y is LY_{z-1}, if $LY_k < LY_z$

or

... then Y is LY_{z+1}, if $LY_z < LY_k$

UNTIL $C_x(R^{(i_1 \dots i_m, j_1 \dots j_n)}, R^{(x_1 \dots x_m, u_1 \dots u_n)}) \leq \mu$

attenuate($R^{(x_1 \dots x_m, u_1 \dots u_n)}$)

END IF

END FOR

This algorithm begins examining the degree of contradiction between the modified/added rule in the adaptation, $R^{(i_1 \dots i_m, j_1 \dots j_n)}$, and every one of the already existent in the rule base, replacing the value LY_z in the consequent of the rule $R^{(x_1 \dots x_m, u_1 \dots u_n)}$ that exceeds a threshold of contradiction μ by the adjacent value LY_{z+1} or LY_{z-1} nearest to the consequent value LY_k of $R^{(i_1 \dots i_m, j_1 \dots j_n)}$, in order to diminish the contradiction between both rules. After each attenuation, the process is applied to the modified rule $R^{(x_1 \dots x_m, u_1 \dots u_n)}$ again, resulting, that way, a recursive procedure.

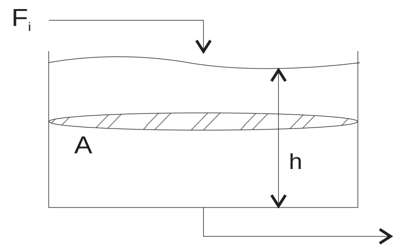

Figure 2: A storage tank

In order to avoid the modification of the identified rule and not to interfere negatively in the adaptation, it is necessary to add a new restriction to the attenuation process. This could be stated: *A rule will not be modified in recursive levels which descend from it.* This way, the modification of the consequent causing the attenuation process is avoided and the approach of the adjacent consequents to it, instead of the opposite, is favoured.

5 An Example

As an illustration of the method proposed in the previous section, now its application to the example in [7] is described: the control of a storage tank level. The figure 2 outlines the process dynamic, which is described by the following discrete-time non-linear equation:

$$\Delta e(t+1) = (1 - T/\tau_p) \cdot \Delta e(t) + (K_p \cdot T/\tau_p) \cdot \Delta F_i(t)$$

where $e(t) = h_s - h(t)$; $\tau_p = 2A\sqrt{h}/\beta$ and $K_p = 2\sqrt{h}/\beta$, being h_s the setpoint, A the cross-sectional of the tank, β a constant and T the sampling time. In the results presented here, the values 10, 20, 1 and 5, respectively, are considered.

This functional relationship can be described by rules of the form:

if ΔE(t) is LE_i and ΔF_i(t) is LF_j then ΔE(t+1) is LE_k

In figure 3 the definition of the fuzzy domains associated to the change of error ΔE to the change of the inlet flow ΔF_i.

A sequence of runs was carried out for the proposed algorithm in [7] and for its contradiction sensitive version suggested here. As no noise exists, a weighting factor α of one is used.

Different values for the threshold μ have been used in order to analyze the results produced by the contradiction attenuation in the rule base. We use two different initial rule bases: one designed by means of logical considerations and another one with consequents generated randomly and, therefore, equivalent to an a

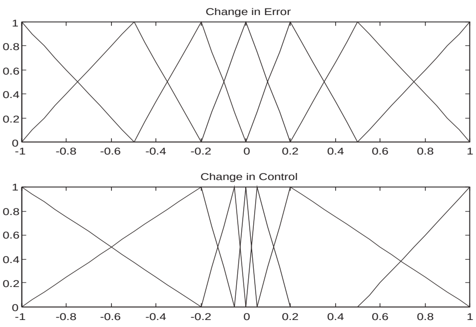

Figure 3: Fuzzy domains

Table 1: Sums of absolute error (SAE)

	CS-FMBAC (μ)			
initial model	0.25	0.30	0.35	FMBAC
random	342	178	162	no control
logical	684	747	960	950

priori nonexistent knowledge. In order to evaluate the controller response, there has been used he sum of absolute errors (SAE) of the height from setpoint. In the case of starting from an a priori logical model, a step change of five centimeters is added to the setpoint.

Table 1 summarizes the results obtained. It shows how the CS-FMBAC is able to keep control of the system in all cases, whereas the FMBAC is unable to do it when the original rule base is randomly generated. Moreover, in the case of starting from an a priori logical model, the CS-FMBAC exhibits, in general, a better behaviour than its contradiction non-sensitive version. Figure 4 shows an example of both control responses.

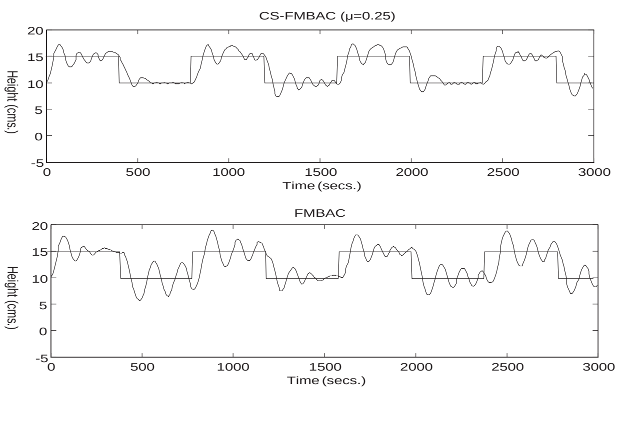

Figure 4: Control responses with logical initial model

6 Conclusions

In the present work, it has been proposed to consider the attenuation of the high degrees of contradiction between rules in the knowledge base as a searching additional heuristic criterion along the learning stage in the FMBAC framework. Thus, it is possible to eliminate the existing conflicts between rules without having to wait for those rules to reveal their inconsistencies during the control process. This way, theoretically, not only the number of identification/control iterations required to reach the desired configuration will be reduced, but also the error made when the controller operate on the system during the learning process.

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