Experiments and Design of an Inference Fuzzy System

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Abstract: The aim of this paper is to propose a criterion to estimate the design, from experimental data, of a fuzzy infer-
              ence system, when data are sparse. This lack of data is important and may improve the generalisation ability
              of fuzzy systems (Isao Ishibuchi, 2002).
              Several methods have been proposed to obtain automatic fuzzy rules from sparse training data. In (Cruz
              Vega Israel, 2010), the authors first construct fuzzy rules from collect data. Then, they use kernel regressions
              for generate training data.
              Another technique used when classical inference methods produce sparse fuzzy rules is a diffusion proce-
              dure based on interpolation to initialize incomplete rules (Benmakrouha, 1997), (Glorennec, 1999), (Baranyi,
              1996). Our method has the advantage of occuring before initialization step and therefore avoiding unfired
              rules which make difficult to produce an accurate output.

1 INTRODUCTION

The lack of data is important and is pointed out by
M Lutaud-Brunet in (Lutaud, 1996). Sugeno and Ya-
sukawa underline in (Sugeno and Yasukawa, 1993)
how difficult it is to build a fuzzy model when data are
scarce and membership functions don't sweep over all
the universe of discourse. This may improve the gen-
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procedure based on interpolation to initialize incom-
plete rules (Benmakrouha, 1997), (Glorennec, 1999),
(Baranyi, 1996).

The objective of this paper is to measure the im-
pact of datum plane covering on the outcome of a
fuzzy inference system. Most of optimization meth-
ods make the assumption that datum plane is suffi-
ciently covered. If this assumption no longer holds,
we will see that these methods cannot work, since it
implies that, before optimization, the fuzzy system gi-

ves acceptable results. In (Benmakrouha et al., 2010),
we analysed the relationship between learning set Ω
and labels of fuzzy inference system. In this paper,
we take into account a data density repartition, by the
measure of number of available data on intervals of
each input variable domain.

All these tecniques take place during optimisation
step when our method is used before initialization
step. This in turn allows one to isolate unfired rules
and to proceed, if necessary, to a partial remodelling
of the FIS before training and optimization.

2 THE TAGAKI-SUGENO MODEL

The model under consideration in this section is
a Tagaki-Sugeno model, which corresponds to dis-
cretized linear models of order 1, combined with non-
linear functions.

$$y(t) = \sum_{i=1}^{r} h_i(z(t))(a_1^i.y(t-idecal) + b_1^i.u(t-idecal))$$

$y(t)$ is the output,
r is the number of linear models,
$z(t)$ a vector which depends lineary or not on the
state,
$h_i(z(t)) >= 0$, $i = 1, \cdots, r$ nonlinear functions
verifying the convex sum property.

idecal is the time lag between input and its effect, which is specially interesting in our application. We have measures about every five minutes and we admit that the effect of insulin (considered in our application)is fast and noticeable ten (idecal=2) minutes later, up to half an hour(idecal = 6).

The determination of unknown parameters a_1^i and a_2^i is done by the algorithm of recursive least square.

3 APPLICATION TO THE INSULIN/GLYCAEMIA BEHAVIOR OF DIABETICS

3.1 The Available Data

The correlated data "'insulin infusion delivery/glycaemia'" has been provided by the team of Pr. Pinget, CHU of Strasbourg. They concern the same person and the same insulin.The insulin infusion has been done by an intra-peritoneal route and the glycaemia has been checked by a subcutaneous sensor. Measures of glycaemia have been made every five minutes during 7 days, which corresponds to 1700 measures.
A bolus is a dose of insulin infused manually, in addition to the basic dose, since postprandial glycemia cannot be regulated satisfactorily. The insulin file contains crude data about basic insulin doses as well as boluses. So, a pretraitement of the insulin file has been necessary to produce a file of insulin delivery for the same person every five minutes.

3.2 Experiments and Validation of the Model

The learning set is composed of the first measures(280 points) that corresponds to insulin infusion and blood glucose concentration of a patient during a day. We take 7 ($r = 7$)linear models, considering that each model is valid about three and half hours. The mean square error(MSE)is calculated on the totality of the measures(1700 points).

We make experiments by changing the parameter *idecal* of the model, time lag between an input and its effect.

The test of our modeling method shows that we can predict the glycaemia over a long period (7 days), by considering glycaemia and insulin delivery 15-minute (resp 30-minute) before with an error of about 6%(resp 16%), which is a good result compared with current results. However, we see that results obtained

Table 1: First table.

r	idecal	MSE
7	2	0.04
7	3	0.06
1		
7	6	0.16
7	24	1.02

are not so good in the last case, when we consider slow effect insulin (with 2-hours delay). In this case, our model has to be refined, by increasing its order.

4 DATUM PLANE COVERING

We propose a measure used to pre-validate a fuzzy model. We suppose that there exists a learning set $\Omega = \{(\mathbf{x}_j, d_j)\}$, where $\mathbf{x}_j$ is an input vector and d_j, the corresponding output. We also assume that the desired function f is defined in

$$V = [a_1, b_1] \times [a_2, b_2] \times ... \times [a_p, b_p]$$

Usually, to validate a fuzzy inference system, the mean square error (MSE) is calculated on a test set. If the MSE exceeds a threshold, then training is done, using a gradient method. This consists in modifying C_j at each presentation of examples from the error $(y(\mathbf{x}_j) - d_j)$.
Unfortunately, in case of model invalidation, we cannot determine never learned rules that cause the gap between the model and the real system. Moreover, if there is an insufficient covering of datum plane, training and finer splitting of input space are inefficient and useless. With the criterion proposed below, we estimate the datum plane coverage and we are able to isolate inactivated rules. Then, partial remodeling of the fuzzy inference system is possible. The study is investigating the relationship between a quantitative variable X, number of available data for each input, and a qualitative variable Y, labels of membership functions.

When designing a fuzzy system, we attribute to each input I r modalities (or labels) noted $y_1, \cdots y_l, \cdots y_r$. We note X^I the variable for the input I of average $\bar{x}^I$ and variance $\sigma_{X^I}^2$. We note Ω^I the corresponding learning set . Each label y_l of I defines a subset Ω_l^I of Ω^I : we obtain a partition of Ω^I in m classes. We note $n_l^I = card(\Omega_l^I)$ and $n^I = card(\Omega^I)$. We have $n^I = \Sigma_{l=1}^m n_l^I$. Then, if we consider the restriction de X^I to Ω_l^I) ($l = 1, \cdots, m$), we may define

the average (noted $\bar{x}_l^I$)and the variance (noted $\sigma^2_{X_l^I}$ of X^I on this subset:

$$\bar{x}_l^I = \frac{\sum_{\omega \in \Omega_l^I} X(\omega)}{n_l^I}$$

$$\sigma^2_{X_l^I} = \frac{\sum_{\omega \in \Omega_l^I} (X(\omega) - \bar{x}_l^I)^2}{n_l^I}$$

We have an index of connection between the datum plane coverage (for an input I) and the learning set defined by :

$$s^I = \sqrt{\frac{\sigma_E^2}{\sigma_{XI}^2}}$$

where

$$\sigma_{XI}^2 = \sigma_E^2 + \sigma_R^2$$

and

$$\sigma_E^2 = \frac{\sum_{l=1}^{r} n_l^I * (\bar{x}_l^I - \bar{x}^I)^2}{n^I}$$

and

$$\sigma_R^2 = \frac{\sum_{l=1}^{r} n_l^I * \sigma^2_{X_l^I}}{n^I}$$

and

$$\bar{x}^I = \frac{\sum_{l=1}^{r} (n_l^I * \bar{x}_l^I)}{n^I}$$

This index of connection consists in detecting relationships between number of data of the learning set Ω^I and r_I labels. This index is low if the features of these labels are not so different (Test 1). When this index is high, it points to that there is a bad repartition of membership functions (Test 3). This gives an information about the repartition of data of learning set Ω^I between membership functions.

4.1 Experiments

We have made 3 tests for the first input (with two triangular membership functions) using our application. We give in these array the features of these functions. We obtain for the first test a low index(0.035), the second a medium index (0.28) and for the last test a high index (0.84). In the third test, the first membership function is useless and the corresponding rules are inactived. So, we can suppress them without affecting results. We have made a 4th test where three (out of four) membership functions and the associated rules were unnecessary.

Table 2: First membership function.

Test	Center	Left corner	Right corner
1	1.4	1.6	1.0
2	1.0	0.6	1.0
3	0.2	0.2	0.2

Table 3: Second membership function.

Test	Center	Left corner	Right corner
1	2.6	1.0	0.9
2	2.6	1.0	0.9
3	3.0	2.8	0.5

4.2 Graphic Representation

We represent sets of data by Box & Whiskers Plots to underline the relation between number of data and labels of membership functions. The first figure (resp figure 2 and figure 3) corresponds to Test1 (resp Test 2 and Test 3).
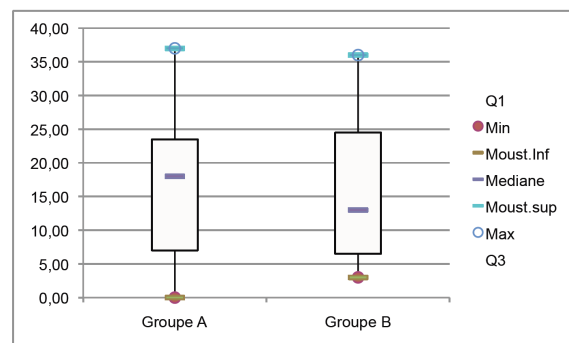

Figure 1.

5 CONCLUSIONS

We have proposed a measure for detecting useless rules and thus pre-validating a fuzzy inference system. When the model is not pre-validated, we have not to carry out next steps, particularly optimization step.

We have shown that this criterion gives useful information about datum plane coverage.
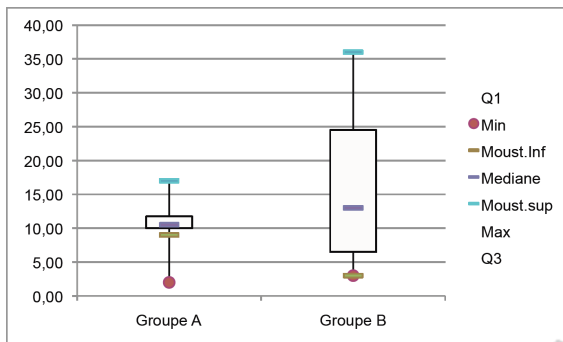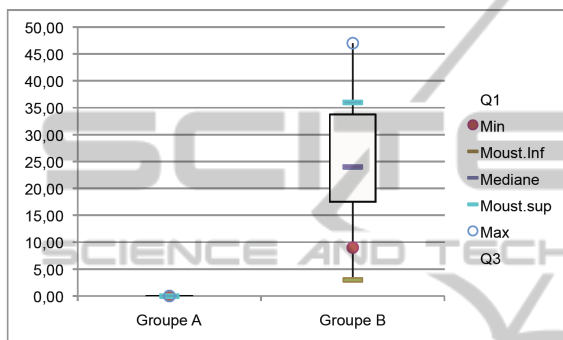
Figure 2.

Figure 3.

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