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ELABORATION OF LEARNED LINGUISTIC DESCRIPTIONS IN THE FRAME OF LFLC[1]

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1. Introduction

In this paper we deal with the concept of the Linguistic Fuzzy Logic Controller as presented, e.g. in [9]. Recall that its linguistic description is given by the set of linguistically formulated IF–THEN rules

$$\mathcal{R} = \{\mathcal{R}_1, \mathcal{R}_2, \dots, \mathcal{R}_m\}. \tag{1}$$

The difference from standard interpretation is that these rules are taken as *linguistically expressed logical implications* and the inference method is the *modus ponens* in fuzzy logic in broader sense (cf. [6]). In paper [11] the method for learning of the linguistic description from data was presented. In this method, one of the key roles has been played by the concept of *linguistic context* which means specification of the meaning of terms such as "small ", "rather big", etc. which is given not only by shape of the membership function but also its width and position on the numerical scale. As the universe of discourse is in our case some interval of real numbers, the linguistic context may be specified by setting of its smallest and the highest values, respectively.

Each rule takes the form

$$\begin{aligned} \mathcal{R}_i \quad = \quad & \texttt{IF } X_1 \texttt{ is } \mathcal{A}_{i1} \texttt{ AND } \dots \texttt{ AND} \\ & X_n \texttt{ is } \mathcal{A}_{in} \texttt{ THEN } Y \texttt{ is } \mathcal{B}_i \end{aligned}$$

The variables $X_1, \dots, X_n$ are independent and Y is dependent. As is well known, form of these rules determines the kind of fuzzy controller, i.e. PI, PD or PID. In LFLC the linguistic context of the independent variables is determined automatically. Originally, the context of the dependent variable had to be set by the user. Our recent results make now possible to interpolate the context of the dependent variable from known values ([1]).

In [11] we have introduced a method for automatic generation of the linguistic description for fuzzy control from the data and have shown that it successfully controls the process in a way similar to the fuzzy control designed "by hand". For demonstration we have used the software packet LFLC 1.5 (see [10]) which has been developed at the University of Ostrava. This packet makes possible to design and tune the linguistic descriptions as well as simulate fuzzy control of simple processes in a closed feedback loop.

The basic idea is the following. Suppose that a successful fuzzy control of a plant be provided, for example, by skillful operator. When monitoring this control, we obtain data which can be used for the generation of the linguistic description. The goal is to control successfully the plant using the generated linguistic description. Hence, successful automatic generation can replace the laborious period of the design and tuning of the linguistic description.

For the experiments, we have used the following procedure.

1. Set the kind of fuzzy controller, whose linguistic description will be generated, i.e. PI, PD of PID fuzzy controller.

2. Set the linguistic context for each variable (error, its derivative and control action of its derivative).

3. Generate linguistic rules from the data.

The method we have used finds a typical term for the given value in the given linguistic context. The procedure which makes this possible is implemented in LFLC.

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Furthermore, the generated linguistic description is used to simulate the fuzzy control of the same process and using the same context (and time samples) as were assumed for the imitation of the control (see [11]). In our demonstration we considered the PI fuzzy controller and a simple process $y' + y = u(t)$ whose control will be simulated.

One of the problems of the generated linguistic description is that a rule is generated to each data item. For larger data this might lead to extremely big descriptions which, moreover, would contain a lot of superfluous information. Hence, the subsequent goal is to find methods for its reduction. Two basic approaches can be employed. First, we have to realize that the linguistic description is a set of logical formulas representing content of the linguistic statements. Hence, one way of reduction consists in its logical analysis. The second approach can be based on filtering of the input data and finding smaller number of significant points which can be used for the generation of the rules. In this paper, we focus mainly on the second approach.

2. Properties of the linguistic description

We consider the linguistic description with the independent variables *error* (E) and *change of error* (dE) and the dependent variable *change of control action* (dU).

The linguistic values used have the following form:

$$\langle \text{modifier} \rangle \langle \text{atomic term} \rangle$$

In this basis three basic atomic terms *small* (Sm), *medium* (Me), *big* (Bi) and the term *zero* (Ze) are used. The meaning of each terms can be modified by linguistic modifiers *extremely* (Ex), *significantly* (Si), *very* (Ve), *rather* (Ra), *more or less* (ML), *roughly* (Ro), *quite roughly* (QR), *very roughly* (VR) for atomic terms *small* and *big* and linguistic operators *rather* (Ra), *more or less* (ML), *roughly* (Ro), *quite roughly* (QR) and *very roughly* (VR) for atomic terms *medium*.

In the previous experiment, we have generated the following linguistic description (see Fig. 1).

It is assumed that, in general, every linguistic description should have the following properties:

- completeness,

  Definition 1 (see [4]) *A linguistic description is complete if any combination of input values results in an appropriate output value.*

  When checking the above linguistic description, we see that it is not complete (in practical applications almost no rule base is complete).

- consistency,

  Definition 2 (see [4]) *A linguistic description is inconsistent if there are two rules with the same rule-antecedent but different rule-consequent.*

  Concerning the consistency an alternative definition says that a linguistic descriptions is inconsistent if there are two rules with the same rule-antecedents and mutually exclusive rule-consequents.

  If we look at rules number 17 and 18 (see Fig. 1) then there are two rules with the same rule–antecedents but rule consequents are not mutually exclusive. Hence, our linguistic description is not inconsistent.

- continuity,

  Definition 3 (see [4]) *A linguistic description is continuous if it does not have neighboring rules with output fuzzy sets that have empty intersection.*

Concerning the continuity we will consider the linguistic description in matrix structure. Then two rules are neighbors if their cell are neighbors. When checking our linguistic description we can see that it is continuous. In [4] the authors concentrate on the Mamdani's type of inference which, in principle, is an interpolation of some (precise) function $dU = f(E, dE)$ unknown to us and characterized only vaguely (cf. [6]).

Our approach is based on the assumption that the rules are logical implications. In this case, the information about continuity is not so important for us.

3. Reduction of the linguistic description by interpolation

Koczy in [7] proposed to reduce a dense rule basis using interpolation. The result is minimal necessary number of rules and all other rules in the original rule basis are replaced by interpolation algorithm (he used Lagrange-method) and can be generated with a certain accuracy which is prescribed before interpolation.

Our approach is based on interpolation of the data having been obtained as a result of successful control by hand (see Fig. 4). In our case, the data consist of triples

$$(E, dE, dU), \tag{2}$$

i.e. they represent PI fuzzy control of the process. The linguistic description is generated from these data.

Our goal is to reduce number of rules in the linguistic description. Therefore, we find a good interpolation, omit some of the data and generate the new reduced linguistic description. The goal is to obtain approximately the same results as when using non-reduced description.

First, we have tried the Lagrange interpolation method. After many experiments we found that by omitting some of the values the obtained results after applying the interpolating algorithm were unsatisfactory. Obviously, this is caused by the fact that the Lagrange interpolating method is not very useful for practical applications.

Therefore we were looking for better method. We used the program *Mathematica* and one of its facilities for finding least-squares fits to data. We had to specify a list of functions and tried to find a linear combination of them which approximated our data very well. The optimal fitting function is obtained by minimizing the quantity $\chi^2 = \sum_i (F_i - f_i)$ where F_i is the value of the i^{th} data point and f_i is the value which we obtain from the fit. The Mathematica *Fit* function finds the result by computing product of the response vector with the pseudoinverse of the design matrix.

The function we have used had the form

$$Fit[B, \{1, x, y, x \cdot y\}, \{x, y\}]$$

where B is the above mentioned data. The best fitting function is

$$\begin{aligned} f(x, y) &= -0.0444144 + 0.00807156 \cdot x \\ &\quad - 0.780903 \cdot y - 0.0137213 \cdot x \cdot y. \end{aligned}$$

Using this function, we have generated new data and from them we generated new linguistic description (see Fig. 2). As in the previous case, this linguistic description is incomplete, consistent and continuous.

The PI control using this description is a little worse than using the original one (see Fig. 5). However, when the method for learning of the linguistic context (see [1]) has been introduced, the control has significantly improved (see Fig. 6). Recall that the linguistic context learning method is based on the interpolation of the linguistic context of the dependent variable from known values.

Finally, we tried to omit some of the rules. We checked the situations

$$(E_1, dE_1, dU_1), \qquad (E_2, dE_2, dU_2)$$

in which the difference $|dU_1 - dU_2|$ is small. Then one of these triples can be omitted. At present, this procedure has been made manually.

The result are 8 triples (2) on the basis of which, new reduced linguistic description has been obtained (see Fig. 3). This description successfully controls the process in a way analogous to the imitated control above (the linguistic context learning method has been used again) (see Fig. 7). Obviously, the reduced linguistic description is incomplete, consistent and continuous.

4. Conclusion

The method for learning of linguistic description from data of linguistic oriented fuzzy control was recalled (see [11]) and methods for reducing the linguistic description using interpolation were investigated. Two methods were considered. The first one was the Lagrange-method and the second one the function *Fit* of program *Mathematica*. The second approach seems to be more suitable because the reduced linguistic description successfully controls the process. If the method for learning of linguistic context is used then the results will be better. Recall that all the experiments have been realized using the Linguistic Fuzzy Logic Controller (see [9]).

In future, we will further develop the method of reduction of the linguistic description based on the data. Furthermore, as it is a set of logical implications, we will also study the methods for its reduction on the basis of the logical analysis. It may be expected that combination of both methods will lead to satisfactory results.

References

[1] BŘlohlávek R., Novák V.: *Learning linguistic context for linguistic oriented fuzzy control.* To appear in Proc. FUZZ–IEEE'97

[2] astorál Z.: *Programming system for the automatic setting of fuzzy controller for industrial applications.* Diploma work, Plzeĺ, 1995 (in Czech).

[3] Dubois D., Prade H.: *Fuzzy sets and systems.* Theory and Applications. Academic press, New York 1980.

[4] Driankov D., Hellendoorn H., Reinfrank M.: *An Introduction to Fuzzy Control.* Springer–Verlag, Berlin 1993.

[5] Fantuzzi C.: *Linguistic rule synthesis of a fuzzy logic controller.* IECON'94, 1354–1358

[6] Klawonn F., Novák V.: *The relation between inference and interpolation in the framework of fuzzy systems.* Fuzzy Sets and Systems **81**(1996), 331–354.

[7] Koczy L.: *The reduction of fuzzy rule bases by interpolation.* Proc. First Asian Fuzzy Systems Symposium. Singapore 1993.

[8] Novák, V.: *Fuzzy sets and their applications.* Adam Hilger, Bristol, 1989.

[9] Novák V.: *Linguistically Oriented Fuzzy Logic Control and Its Design.* Int. Journal of Approximate Reasoning **12**(1995), 263–277.

[10] Novák V.: *LFLC-edu 1.5 — Linguistic Fuzzy Logic Controller for Education. User's and Programmer's Guide.* University of Ostrava, 1995.

[11] Novák V., Smolíková R.: *On learning of linguistic descriptions from data in LFLC.* Proc. Int. panel. Conf. on Soft and Intelligent Computing. Technical Univ. of Budapest, Budapest 1996, 229–234.

Fig. 1. The original linguistic description generated from data.

1.	If	E is +ExBi	and	dE is -VeSm	then	dU is +ExBi
2.	If	E is +ExBi	and	dE is -Sm	then	dU is +VeBi
3.	If	E is +RaBi	and	dE is -Sm	then	dU is +VeBi
4.	If	E is +QRBi	and	dE is -Sm	then	dU is Bi
5.	If	E is MLMe	and	dE is -VeSm	then	dU is +RaBi
6.	If	E is +QRSm	and	dE is -VeSm	then	dU is +RaBi
7.	If	E is +RaSm	and	dE is -VeSm	then	dU is +VRBi

8. If	E is +VeSm	and	dE is -SiSm	then	dU is +RaMe
9. If	E is +ExSm	and	dE is -SiSm	then	dU is +RoSm
10.If	E is -ExSm	and	dE is -ExSm	then	dU is +VeSm
11.If	E is -SiSm	and	dE is -RoZe	then	dU is -SiSm
12.If	E is -SiSm	and	dE is +RoZe	then	dU is -SiSm
13.If	E is -ExSm	and	dE is +ExSm	then	dU is -VeSm
14.If	E is -RoZe	and	dE is +RoZe	then	dU is -ExSm
15.If	E is +RoZe	and	dE is +RoZe	then	dU is Ze
16.If	E is +RoZe	and	dE is -RoZe	then	dU is +ExSm
17.If	E is -RoZe	and	dE is -RoZe	then	dU is +RoZe
18.If	E is -RoZe	and	dE is -RoZe	then	dU is Ze

Fig. 2. The new linguistic description generated from data.

1. If	E is +ExBi	and	dE is -VeSm	then	dU is Bi
2. If	E is +ExBi	and	dE is -Sm	then	dU is +ExBi
3. If	E is +RaBi	and	dE is -Sm	then	dU is +SiBi
4. If	E is +QRBi	and	dE is -Sm	then	dU is Bi
5. If	E is MLMe	and	dE is -VeSm	then	dU is +MLBi
6. If	E is +QRSm	and	dE is -VeSm	then	dU is +RoBi
7. If	E is +RaSm	and	dE is -VeSm	then	dU is +VRBi
8. If	E is +VeSm	and	dE is -SiSm	then	dU is +RaMe
9. If	E is +ExSm	and	dE is -SiSm	then	dU is +QRSm
10.If	E is -ExSm	and	dE is -ExSm	then	dU is Sm
11.If	E is -SiSm	and	dE is -RoZe	then	dU is +ExSm
12.If	E is -SiSm	and	dE is +RoZe	then	dU is -ExSm
13.If	E is -ExSm	and	dE is +ExSm	then	dU is -SiSm
14.If	E is -RoZe	and	dE is +RoZe	then	dU is -SiSm
15.If	E is -RoZe	and	dE is +RoZe	then	dU is -ExSm
16.If	E is +RoZe	and	dE is +RoZe	then	dU is -ExSm
17.If	E is +RoZe	and	dE is -RoZe	then	dU is -ExSm
18.If	E is -RoZe	and	dE is -RoZe	then	dU is -ExSm

Fig. 3. The new reduced linguistic description.

1. If	E is +ExBi	and	dE is -VeSm	then	dU is Bi
2. If	E is +RaBi	and	dE is -Sm	then	dU is +SiBi
3. If	E is MLMe	and	dE is -VeSm	then	dU is +MLBi
4. If	E is +VeSm	and	dE is -SiSm	then	dU is +RaMe
5. If	E is +ExSm	and	dE is -SiSm	then	dU is +QRSm
6. If	E is -SiSm	and	dE is -RoZe	then	dU is +ExSm
7. If	E is -ExSm	and	dE is +ExSm	then	dU is -SiSm
8. If	E is +RoZe	and	dE is -RoZe	then	dU is -ExSm

Fig. 4. Generating of the linguistic description on the basis of the imitated control.

Generating of linguistic description for LFLC

	Error	Change of error	Change of cont. action	Linguistic description
0.	35.0000	-0.0000	0.0000	
1.	31.8394	-3.1606	5.0000	+ExBi & -VeSm => +Bi
2.	27.8321	-4.0073	4.5000	+ExBi & -Sm => +ExBi
3.	23.5134	-4.3187	4.5000	+ExBi & -Sm => +ExBi
4.	19.0801	-4.4333	4.5000	+RaBi & -Sm => +HiBi
5.	14.9207	-4.1594	4.0000	+QRBi & -Sm => +Bi
6.	10.9885	-3.9322	3.8000	+MLMe & -VeSm => +MLBi
7.	7.1398	-3.8486	3.8000	+QRSm & -VeSm => +RoBi
8.	4.1437	-2.9961	2.5000	+RaSm & -VeSm => +VRBi
9.	1.7772	-2.3665	2.0000	+VeSm & -HiSm => +RaMe
10.	0.1481	-1.6291	1.2000	+ExSm & -HiSm => +QRSm
11.	-0.6408	-0.7890	0.3000	-ExSm & -ExSm => +Sm
12.	-0.8047	-0.1638	-0.2000	-HiSm & -RoZe => +ExSm
13.	-0.7385	0.0662	-0.2000	-HiSm & +RoZe => -ExSm
14.	-0.5245	0.2140	-0.3000	-ExSm & +ExSm => -HiSm
15.	-0.2562	0.2684	-0.3000	-ExSm & +ExSm => -HiSm
16.	-0.0942	0.1619	-0.1000	-RoZe & +RoZe => -HiSm
17.	-0.0031	0.0912	-0.0500	-RoZe & +RoZe => -ExSm
18.	0.0305	0.0335	0.0000	+RoZe & +RoZe => -ExSm

Fig. 5. Simulation of fuzzy control using the original linguistic description.

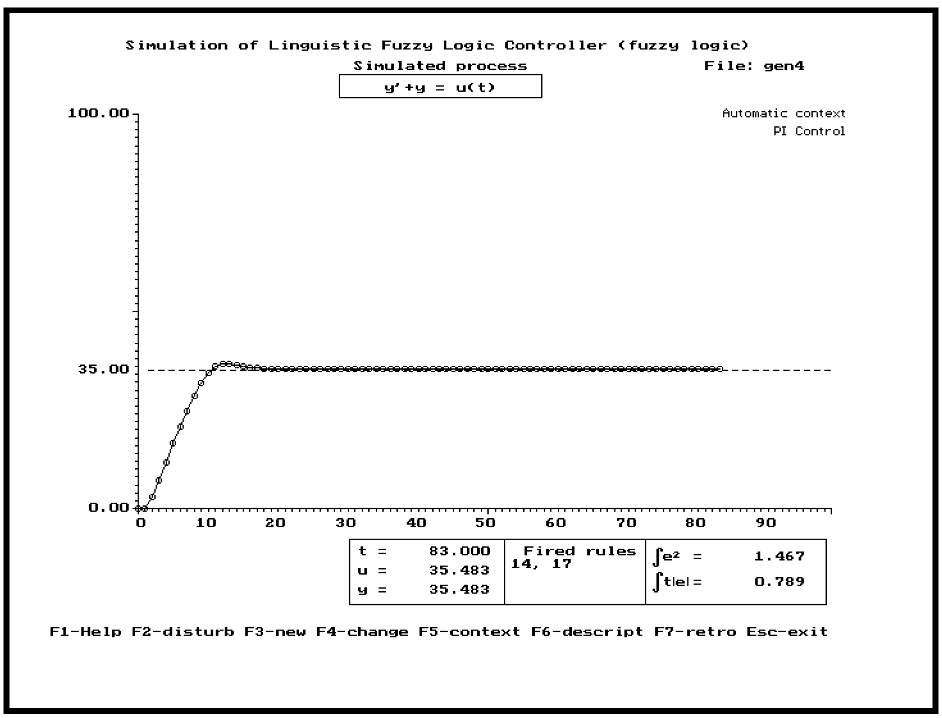

Fig. 6. Simulation of fuzzy control using the new linguistic description.

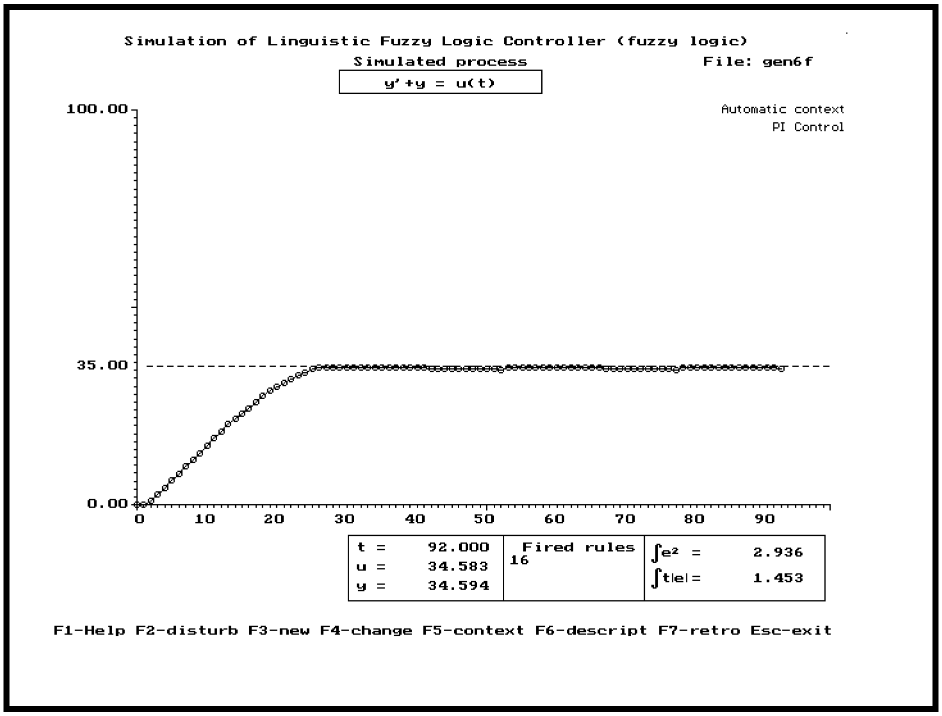

Fig. 7. Simulation of fuzzy control using the new reduced linguistic description.