Optimization of evolutionary strategies to achieve knowledge in faded temporal fuzzy logic controllers

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Abstract

In this document we carry out a comparative analysis of the reasoning strategies implemented in Fuzzy Logic Controllers (hereinafter FLCs) and Faded Temporal Fuzzy Logic Controllers (hereinafter FTFLCs). Starting from the problems associated to FLCs, we propose as a solution the use of FTFLCs. To improve the process of knowledge achievement in FTFLCs, it is introduced a mixed technique which combines the genetic learning in FLCs followed by the genetic learning in FTFLC.

Key-Words: fuzzy logic controller, faded temporal fuzzy logic controller, fading, temporal consequent, genetic algorithms.

1. Introduction.

Some applications of the systems based on knowledge [1] need to manage facts that happen and vary as time goes by. That's why several models have been developed to represent and process the temporal knowledge [2,3,4].

In FTFLCs it is spread the model proposed in [2], which introduces the concept of temporal fading [5,6,7], which includes a non linear perception of time and gives a higher accuracy, reliability and certainty to the observations and actions near in the time. This effect is achieved by the "fading" of the temporal FSs. To obtain knowledge used in FTFLCs with a reasonable computational cost, it is presented a method of genetic learning which combines the common Genetic Algorithms (hereinafter GA) applied over FLCs, followed by GA applied over FTFLCs. In GA applied over FTFLCs, the initial population has been developed from the best KB obtained in the first genetic process. In the GA applied over FTFLCs, the searching area is limited to temporal and fading parameters and it is forced the appearance of pairs of temporal and non temporal rules with the same antecedent. This method offers best results than the presented one in [5], which applies GA over TFLC and generate the initial population over which the GA limited to the fading parameters are applied.

The document is organised as following: in section 2 we show the similarities and differences in the reasoning strategies followed in FLCs and FTFLCs. In section 3 we analyze the problems associated to the control with FLCs, in addition, it is included a theoretical justification of the improvements added by the FTFLCs. In section 4 it is shown a comparison referred to the KB structure and the achievement process of the new KB in the GA applied on FLCs and FTFLCs. In section 5 it is introduced a mixed method which uses GA on FLCs (hereinafter GA_{FLCs}) and FTFLCs (hereinafter GA_{FTFLCs}), and the results of its application to a specific control system. In section 6 we spread the results of section 5.

2. Reasoning strategies followed in FLCs and FTFLCs.

FTFLCs can be a variant of FLCs, therefore the reasoning strategy of the FTFLCs will have a common and a different part as the FLCs.

a) The common part of the strategy means that in both controllers the output of the inference engine is achieved defuzzificating all the FSs created by the fired rules, existent in that moment.

b) The FTFLCs specific part of the reasoning strategy has 3 steps:

1. Implementation of a non-linear transformation through the time, that allows the concentration of the

closer temporal region and the spreading of the farthest temporal region.

2. Generation of temporal transformed FSs. For each activated rule and for each one of the output variables of the control system (hereinafter output variables), we generate a transformed temporal FS, created from the original temporal FS to which we have subjected to one mathematics transformation, allowing the generation of more accurate FSs close to the temporal origin, with less base and bigger height, and less accuracy far from the origin with bigger base and less height.

3. Generation of Contributory Components. For each fired activated rule, there is a temporal FS associated to any output variable. This FS will create a contributory component (FS of the output variable) in each moment of inference in which the membership function of the temporal FS has a value different to zero. This component will be proportional to the value existing in this membership function in that moment.

The output of the inference engine for each output variable at any moment (value taken for the output variable) is achieved defuzzificating the set of contributory components (truncated FSs) existing in that moment [5].

3. Justification of the improvements added by the FTFLCs.

3.1. Problems associated to FLCs.

In these systems, where the change of the input variables of the control system (hereinafter input variables) is spread with certain ease in the time, it will be necessary to adapt adequately the value given to the output variables in order to correct the detected failures in the states of the input variables when the temporal interval of spreading of each action finishes [6,7].

3.2. Solutions proposed in FTFLCs.

To solve this problem, an adequate solution could consist in including in the rules list of the KB a series of rules with the same antecedent as that one we want to complement, with FSs values in the consequent that provoke the change in the states of the system, in the adequate way. At that time we include the temporal consequent where its FSs will take values that delay adequately the application of the support action.

The external noise and the fired rules during the delay interval provoke the displacement of the moment in the time when the unwanted state we wish to correct, is produced. The displacement will depend specially on the external actions suggested by the environmental noise during the delay interval.

To solve this problem a good solution may consist in increasing the interval of temporal performance of the correcting action, without increasing its global influence over the system. This effect is achieved distorting the temporal FSs, increasing their base and decreasing their height, so that their area will be the same as the original FS. The distortion will have to increase as the time among the observation of the system and the action programmed to its control passes, in order to compensate the decrease in the probability of placing adequately the correcting action. That means a lack of accuracy in the temporal placing of the control actions, but supposes an increase in the probability of placing adequately such actions.

To place correctly the delayed actions it is necessary an adequate number of temporal FSs which covers all the possible delay interval of time, "period".
To achieve that aim it is necessary:

a) A concentration of the closer temporal region.
Considering that the bases of the temporal FSs decrease as they come to their origin, a higher number of FSs with a lower separation between them will be necessary in that zone, if we want to maintain its overlap level.

b) A spreading of the farthest temporal region.
As the correcting action is delayed, the base of their associated temporal FSs will increase. Thus the temporal FSs will be overlapped for two rules which program actions placed in two far consecutive moments, therefore concerning to control effects, the temporal FSs would have almost the same temporal place. The target of programming two control actions with a different temporal performance will be only achieved if the time is spread (it is separated the placing of the consecutive moments). This spreading of time will have to be higher if the delay time of the rules is increased, in order to compensate the increase in the overlapping of the faded temporal FSs. [5,6,7].

4. Learning process. GAs over FLCs and GAs over FTFLCs comparison.

4.1. Structure of KB.

In the KBs used in GA_{FLCs}, the knowledge is stored in:

a) Groups of immediate application rules: groups of rules that present only one variable in the consequent, which is the same in all the rules.
b) The definition of membership function associated to antecedent and the consequent FSs variables.
c) The "fitness" parameter of the KB.

In the KBs used in GA "heading" for FTFLCs (hereinafter GAh_{FTFLCs}), the knowledge is stored in:

a) Duplicated groups of rules, set by:
1. A group of non temporal rules.
2. A group of deferred application temporal rules, set by rules with the same antecedent to any rule of the non temporal group, considering that its consequent is the same or different to the above mentioned rule, and those which a temporal consequent is added.

b) The definition of membership function associated to temporal FSs (triangular function).
c) The "fitness" parameter of the KB.
d) The "period" parameter, that informs about maximum temporal operating interval of the rules,
e) The fading parameters: "a", "b" and "c", which model the precision and temporal accuracy variation.

4.2. New KB obtaining.

To implement the GA_{FLCs} and the GAh_{FTFLCs}, it has been used the Pittsburgh approach, taking as elements of the initial population 20 KBs filled at random and applying on each case the structure explained on the above section.

To achieve the KBs applying GA_{FLCs}, the genetic process is divided into four stages: 1. KB selection, proportionally to its "fitness". 2. A crossover in rules and FSs definitions. 3. A mutation in variables, FSs in rules, and FS definition. 4. Old individual substitution by new ones, after comparing their "fitness".

To achieve the KBs applying GAh_{FTFLCs}, the genetic process is divided into four stages: 1. KB selection, proportionally to its "fitness". 2. A crossover in temporal rules. 3. Mutation of variables in the rules, limited to the output variables and its associated temporal variable, and the temporal and fading parameters. 4. Old individual substitution by new ones, after comparing their "fitness".

5. Improvement due to the combination of genetic learning in FLCs and FTFLCs.

5.1. Method description.

There are two different ways to apply the GA in our method. On one hand, the GA_{FLCs} are applied to obtain non optimum good KB.

On the other hand, the GAh_{FTFLCs} are applied starting from an initial population set by a KBs group, which all of them has:

a) The same groups of non temporal rules as the ones obtained in the resulting KB after applying the GA_{FLCs}.
b) The same definitions of membership functions of the FSs as the ones obtained in the resulting KB after applying the GA_{FLCs}.
c) The same groups of temporal rules obtained after duplicating the groups of non temporal rules and adding to each rule a temporal consequent. The value given to the FSs associated to the output variable and the time variable in each rule is ascribed at random.
d) The same definitions of the membership functions of the temporal FSs, which present an uniform distribution.
e) The same "fitness" parameter value of the KBs, as the one which is ascribed a value next to zero.

In addition, each KB of the initial population has:

a) A different value for the "period" parameter.
b) A different value in the fading parameters.

We have called this technique GA "heading" for FTFLCs, due to the use of the theoretical knowledge we have about the right structure of the KB_{FTFLCs}, to build the KBs which form the initial population and change the genetic operator to use. This technique tries to increase the speed of learning and get improvements on the application separately of GA_{FLCs} and GA_{FTFLCs}.

5.2. Experimental results.

To obtain the experimental results we take the cart-pole as the system to be controlled. Playing the experiment from sixteen different positions, defined by different values of the input variables of the control system. In order to fill some wide representative initial situations so we give a reliable evaluation of the evaluated KB behaviour. To make the results obtained relevant, the system to control will present a reasonable temporal spreading in the variation of the input variables according to a punctual change of the output variables. So we have chosen a system with fairly small masses[7].

The experiment is divided into two parts:
a) In the first one, the genetic learning process in FLCs is carried out in the above mentioned conditions.
b) In the second one, the genetic learning process headed for FTFLCs is carried out according to the above section.

The results are shown that in figures 1 and 2, where it can be checked the evolution of the KB "fitness" obtained by applying GA_{FLCs} compared to the one obtained by applying GAh_{FTFLCs}, according to the generation number [5]. In the graphics, it is noticed that the line which shows the evolution of the KB "fitness" obtained by applying GA_{FTFLCs} starts from the generation number 770. The non optimum KB_{FLCs} is obtained in this generation, which is used as the base to get the KBs which will form the initial population of the GAh_{FTFLCs}.

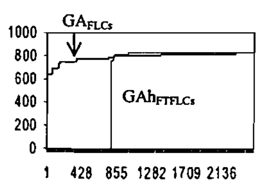

Figure 1. Evolution of the KB "fitness" obtained by applying GA_{FLCs} & GAh_{FTFLCs}

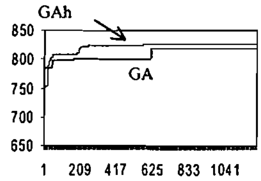

Figure 2. Part of the above graphic.

From the observation of the graphics it is noticed that to obtain a KB through the method given, for instance, with a 0,826 "fitness" it will be necessary 1352 generations, considering that 770 will be obtained by applying GA_{FLCs} and 582 (1352-770) by applying GAh_{FTFLCs}. In these graphics it can be noticed that the genetic learning through the combination of GA_{FLCs} and GAh_{FTFLCs} allows us to get a stronger KB with a less generation number compared to the GA_{FLCs}.

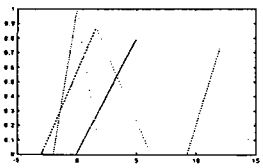

Figure 3. Transformed temporal FSs.

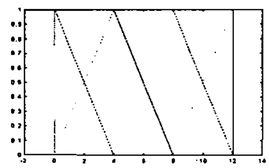

Figure 4. Original temporal FSs.

In the best KB obtained genetically, the values taken by the fading and temporal parameters are: a=1.355, b=0.886, c=6, "period"=12. Values that as it is shown in figure 3 and 4 model the non linear transformation of time and the distortion of the temporal FSs according to the concept of temporal fading [5,6,7].

6. Conclusions.

From the analysis of the experimental results obtained, it is noticed that the use of the mixed method of GA_{FLCs} and GAh_{FTFLCs} produce:

1. An improvement on the "fitness" of the KB obtained, for a reasonable number of generations, compared to the use of GA_{FLCs}.
2. An improvement on the learning speed compared to the use of GA_{FLCs}.

Improvements ascribed to force the appearance of a group of rules (temporal and non temporal) with the same antecedent, so that it is eliminated the random search.

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