Learning Fuzzy Control with Hybrid Symbolic, Connectionist Networks

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Abstract

The problem of deriving membership functions as a means for describing linguistic variables (for some control process) and the choice of fuzzy inference operators and connectives is at the heart of developing fuzzy control systems. To this date much of the selection process is under the control of the system engineer, and dependent on his or her ability to make the right choice for the right application. In this paper, it will be shown by means of a real world example for controlling a steam engine, how hybrid learning systems can be employed for automating the design of fuzzy controllers. Deriving the necessary linguistic variables and accompanying membership functions from raw data by use of machine learning is addressed. Finally, the viability of such a system is emphasized to act not only as a fuzzy controller, but more importantly independent of human intervention, automatically derive acceptable control strategies.

1 Introduction

1.1 Fuzzy Control

In the classical case of fuzzy control a process operator may formulate a verbal description of some process behavior using fuzzy sets to formalize the verbal description. This results in building a fuzzy model of the real process versus constructing a mathematical model of the system, which may be cumbersome to realize due to its increased complexity. Models derived from fuzzy set theory may be equivalent to simulated models with respect to their performance capabilities, but easier to construct. Nonetheless, they require human intervention at two levels: First, a technique for formulating the verbal description of process behavior that can yield an adequate description of the linguistic variables, needs to be developed (Rules and Membership functions). Second, a reliable mathematical apparatus that is used by the system designer for formalizing accurate verbal description for the fuzzy model, needs to be created (Selection of fuzzy inference operators) [3]. The purpose of this paper is to point out how learning systems - specifically hybrid symbolic/connectionist - can be utilized to support the fuzzy control process. Emphasis will be placed on practical results showing how membership functions and linguistic variables can be derived by means of an autonomous learning system. The problem to be studied is the control of a steam engine.

1.2 Overview of SC-net

SC-net has been primarily developed as a tool to support the knowledge engineer in the difficult task of knowledge acquisition [4] [6] [8] for expert systems [10]. Machine learning and knowledge representation in a hybrid/symbolic connectionist environment, together with uncertainty management through means of fuzzy logic, form the corner stones of the system. Learning is analogous to instance-based learners in that only a single pass through the training data is required and examples are encoded through Recruitment of Cells Algorithm (RCA). During RCA pass an instance is either identified (Difference in actual and expected output of network within ϵ), the bias of one or more cells - representing encoded instances - is modified (Difference within 5ϵ), or a new cell is recruited to encode the presented instance. For more detail on the RCA algorithm see [7] [8].

The choice of a connectionist architecture was motivated by the following three desirable features:

1. A highly parallel and uniform representation of knowledge (the SC-net network).

2. Fault tolerance and noise resistance.

3. A built-in ability to deal with non-crisp inputs and outputs.

On the other hand it proved beneficial to incorporate some of the strong points of symbolic machine learning. From the symbolic side we can identify:

1. The ability to encode rules to support knowledge refinement.

2. Allow for rule extraction as a direct means to elicit learned knowledge and support the implementation of expert system standards such as, consulation and explanation facilities.

3. Provide a means to represent symbolic constructs such as variables, comparators and quantifiers. This leads to a more powerful language for describing knowledge and augmenting the learning process through use of domain specific meta knowledge.

The quintessence of SC-net is to combine the virtues of both symbolic and connectionist representations, that is to yield a more powerful environment for automating the knowledge acquisition process.

2 Fuzzy Variables and their Adaption through Learning

SC-net supports the representation of fuzzy variables, which allow either the user or the system itself to divide the numerical range of a variable into its fuzzy equivalent. In general fuzzy variables are described by a set of membership functions, where each function is associated with a linguistic hedge (variable) such as *high*, *small*, etc [11]. These membership functions correlate a given numerical value with a degree of membership indicating the strength (membership) of the numerical value being a member of the predefined fuzzy sets. In SC-net only pi-shaped membership functions are supported. An extension to more complicated membership functions is forthcoming [9]. A linguistic hedge in SC-net is defined by the 4 quantities:

$$< HedgeId >: Bound_{Lower} \ldots Bound_{Upper}$$
$$(Plateau_{Lower}, Plateau_{Upper}) \quad (1)$$

Whenever the value of a given fuzzy variable lies between $Bound_{Lower}$ and $Bound_{upper}$ $< HedgeId >$ takes on a membership value of 1. If the value falls outside the $Plateau_{upper}$ and $Plateau_{lower}$ range a membership value of 0 is assigned. In every other case a graded membership response is returned which in turn is described by a linear function (arms of pi-shaped membership function). Figure 1 shows the general network structure used by SC-net to represent a fuzzy variable (labeled attribute) and a linguistic hedge (labeled attribute[value]). Cells labeled with the numerical value of -1 return the minimum of the incoming activations, whereas cells with a 0 label return the strong negation $(1-Activation)$ of the incoming activation.

The weights are calculated as follows:

$$\begin{aligned}
&Weight-1 = \tfrac{1}{Plateau_{Upper}}\\
&Weight-2 = 1\\
&Weight-3 = \tfrac{Plateau_{Upper}}{Plateau_{Upper}-Bound_{Upper}}\\
&Weight-4 = \tfrac{1}{1-Plateau_{Lower}}\\
&Weight-5 = \tfrac{1-Plateau_{Lower}}{Bound_{Lower}-Plateau_{Lower}}
\end{aligned} \quad (2)$$

Finally, SC-net allows the arms of fuzzy membership functions to be dynamically adapted through use of the Dynamic Plateau Modification Algorithm (dubbed DPM) [7]. Initially $Plateau_{Lower}$ and $Plateau_{Upper}$ are set to the smallest and the largest variable range value, respectively. By presenting encoded instances of examples learned by RCA and represented into a network structure (the SC-net network) the membership arms of the pi-shaped functions are modified. The central idea of the algorithm is to place constraints on the degree of generalization provided by each of the arms. If the degree of membership

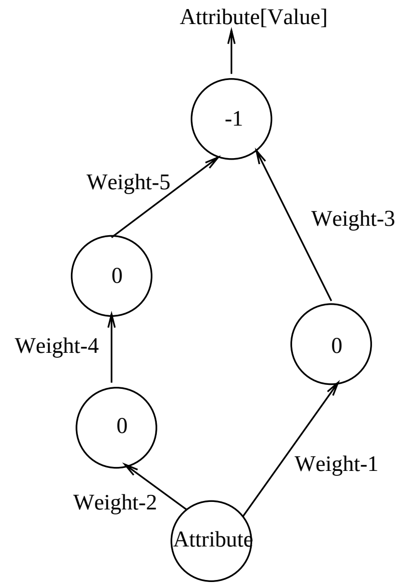

Figure 1: SC-net Network Representing Fuzzy Attribute

calculated by either arm is too high (for a given encoded example), it is lowered by appropriately moving either the $Plateau_{Lower}$ value closer to the $Bound_{Lower}$ or the $Plateau_{Upper}$ value closer to $Bound_{Upper}$. The amount of adjustment is determined by comparing the actual and the expected output response of a cell. For further detail on fuzzy variables, activation functions used by SC-net and the Dynamic Plateau Modification algorithm refer to [7, 8].

3 Experiments

3.1 Domain of Study

The control problem to be studied is concerned with the heat-pressure loop of a steam engine. The pressure error (PE) and the change in the pressure error (CPE) are two system inputs, whereas the heat input change (HC) is the only system output. Table 1 lists the abreviations of other linguistic variables used throughout the remainder of the paper.

Table 1. Abreviations for linguistic variables

Positive Big	PB
Positive Medium	PM
Positive Small	PS
Positive Zero	PO
Zero	ZO
Negative Zero	NO
Negative Small	NS
Negative Medium	NM
Negative big	NB

In Table 2 a set of sample rules used for the steam engine control problem is displayed. By decomposing the given rules into conjuncts (Ex. PE[x] and CPE[y]) a total of 42 conjuncts were obtained, and used during the first experiment testing SC-net's ability to act as a fuzzy controller.

Table 2. Sample of rules used for steam engine control

Rule 1:

if and(or(fuzzy(PE[NB])=1.0, fuzzy(PE[NM])=1.0), fuzzy(CPE[NM])=1.0) then HC_PM (1.0).

Rule 2:

if and(or(fuzzy(PE[NS])=1.0, fuzzy(PE[PS])=1.0), fuzzy(CPE[NS])=1.0) then HC_ZO (1.0).

The membership functions for both pressure error and change in pressure error are shown in Tables 3 and 4. Since SC-net to this point only supports pi-shaped membership functions some change from the original membership functions used in [5] resulted. This change is only minor in that the drop-off of the original membership arms is not linear, but experiences a slight decrease.

Table 3. Membership definitions for pressure error PE

Label	LB	UB	LP	UP
PB	6.0	6.0	3.0	7.0
PM	4.0	4.0	1.0	7.0
PS	2.0	2.0	-0.5	5.0
PO	0.0	0.5	-0.5	3.0
NO	-0.5	0.0	-3.0	0.5
NS	-2.0	-2.0	-5.0	0.5
NM	-4.0	-4.0	-7.0	-1.0
NB	-6.0	-6.0	-7.0	-3.0

Table 4. Membership definitions for change in pressure error CPE

Label	LB	UB	LP	UP
PB	6.0	6.0	3.0	7.0
PM	4.0	4.0	1.0	7.0
PS	2.0	2.0	-1.0	5.0
ZO	0.0	0.0	-3.0	3.0
NS	-2.0	-2.0	-5.0	1.0
NM	-4.0	-4.0	-7.0	-1.0
NB	-6.0	-6.0	-7.0	-3.0

Table 5 shows the original membership definitions for linguistic variables PB and PM which are representative for the remaining variable definitions.

Table 5. Sample of original fuzzy sets

	-6-1	2	3	4	5	6
PB	0.0	0.0	0.0	0.3	0.7	1.0
PM	0.0	0.3	0.7	1.0	0.7	0.3

3.2 Description of Experiments

The first experiment attempts to determine SC-net's applicability as a fuzzy controller based on a connectionist architecture. The question that needs to be answered is by what degree do SC-net's control responses for any given input of PE and CPE differ from those of a classical fuzzy control system? Secondly, what impact does a priori knowledge have on the outcome of these results? Table 6 displays the original fuzzy decision matrix for the control problem, which will form the basis for all further comparisons. SC-nets performance (using rules) is shown in Table 7. Here, the breakdown of differences in the original and the SC-net generated fuzzy decision table is given in terms of responses, which differ by 0, 1, or 2+ (2 or more) linguistic variables. The first row of the table presents the results for using the membership functions defined earlier in Tables 3 and 4. As can be seen, over 87% of the time SC-nets response is identical to that of the fuzzy controller. Only in little over 3% of the cases the difference is greater than or equal to 2 in the predicted responses. This clearly shows that SC-net can perform adequately as a controller for the steam engine problem. For the results shown in the second row of Table 7, the same partitions (linguistic variables) were used as in the first experiment, but the Lower-Plateau and Upper-Plateau values were all reset to the minimum and maximum range values, respectively. This time DPM was applied to automatically determine the best set of membership arms for this problem. As the results indicate the performance of SC-net clearly improved. Over 91% of all responses were identical to those made by the original controller. More importantly, the number of false responses of 2 or more linguistic variables difference decreased by 33%. Finally, in the last experiment, using control rules SC-net is forced to derive its own linguistic variables using the APG algorithm [7] and then applying DPM to derive the final set of membership functions. Though no increase in the performance of the number of correctly given responses is achieved, the number of errors made in the third category is again decreased by 33% (moved into second category).

Table 6. Fuzzy logic decision table for controlling steam engine

	-6	-5	-4	-3	-2	-1	0	1	2	3	4	5	6
-6	0	0	4	4	4	5	6	6	6	6	5	6	6
-5	0	0	4	4	4	5	6	6	6	6	5	6	6
-4	-2	-2	1	4	4	5	6	6	6	6	4	6	6
-3	-2	-2	-2	1	2	3	5	5	5	5	6	6	6
-2	-2	-2	-2	-1	0	2	4	4	4	5	6	6	6
-1	-3	-3	-3	-2	-1	1	2	2	4	5	5	5	5
-0	-4	-4	-4	-3	-2	-1	0	0	2	4	4	4	4
+0	4	4	4	3	2	1	0	0	-2	-4	-4	-4	-4
1	3	3	3	2	1	-1	-2	-2	-4	-5	-5	-5	-5
2	2	2	2	1	0	-2	-4	-4	-4	-5	-6	-6	-6
3	2	2	2	-1	-2	-3	-5	-5	-5	-5	-6	-6	-6
4	2	2	-1	-4	-4	-5	-6	-6	-6	-6	-4	-6	-6
5	0	0	-4	-4	-4	-5	-6	-6	-6	-6	-5	-6	-6
6	0	0	-4	-4	-4	-5	-6	-6	-6	-6	-5	-6	-6

Table 7. Steam Engine control results with using rules

	0-LVD	1-LVD	2+-LVD
PP and PMF	87.4%	9.3%	3.3%
PP	91.2%	6.6%	2.2%
Rules only	91.2%	7.7%	1.1%

The generated membership functions for pressure error and change in pressure error are displayed in Tables 8 and 9. It is interesting to note, that the number of partitions derived for PE and CPE is identical to the number original defined by human experts [5]. In the final experiment SC-net's learning ability is tested. For this test random partitions of the original decision matrix were generated (10) for various partitions sizes (10%-90%). The selected points of the partitions were then used for training. No information with regard to the fuzzy membership functions was provided. The results of this experiment are shown in Table 10. Figure 2 demonstrates graphically SC-net's generalization ability as the size of the training sets is increased in 10% increments.

Table 8. Membership functions derived by APG and DPM for pressure error

Partitions	Lower-Bound	Upper-Bound
p1	-6.0	-5.0
p2	-5.0	-3.0
p3	-3.0	-1.03
p4	-1.03	-0.0
p5	-0.0	1.02
p6	1.02	3.0
p7	3.0	5.0
p8	5.0	6.0

Table 9. Membership functions derived by APG and DPM for change in pressure error

Partitions	Lower-Bound	Upper-Bound
p1	-6.0	-5.0
p2	-5.0	-3.0
p3	-3.0	-1.0
p4	-1.0	1.0
p5	1.0	3.0
p6	3.0	5.0
p7	5.0	6.0

Table 10. Steam Engine control results for various training sizes anD different train set partitions

	0-LVD	1-LVD	2+-LVD
10%	63.0%	21.4%	15.6%
20%	75.8%	13.7%	10.5%
30%	80.5%	13.1%	6.4%
40%	83.9%	10.4%	5.7%
50%	88.1%	7.3%	4.6%
60%	90.6%	5.4%	4.0%
70%	93.3%	3.8%	2.9%
80%	95.7%	2.4%	2.0%
90%	97.8%	1.2%	1.0%
100%	100.0%	0.0%	0.0%

As expected SC-net shows a high degree of performance early on. At about 60% SC-net achieves over 90% exact responses in its choice of linguistic control variables. The other two categories of misses are about equal (difference around 1%). Importantly, throughout all tests the number in differences of 2 or more always remains lower than that of 1 difference. For control purposes, a difference of 0 or 1 in the choice of linguistic variable, will only have minimal affect on the controllers performance. It is therefore crucial that the third category remains low. This is exactly what can be observed in Figure 2. From the last experiment we can safely conclude that SC-net is capable of not only acting as a fuzzy controller, but can also be trained to perform the same task. Additionaly, no a priori knowledge in form of user defined fuzzy membership functions or fuzzy rules is required. The system can act as an autonomous entity and derive the best decisions without any human intervention. Lastly, Table 11 displays the fuzzy responses provided by SC-net for steam engine control.

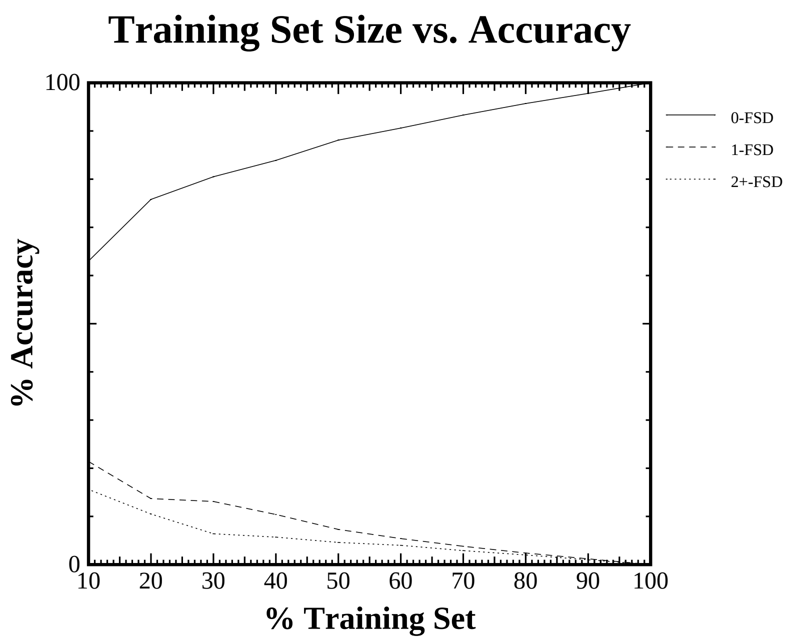

Figure 2: Performance Results for Steam Engine Control

Table 11. SC-net derived decision table using rules

	-6	-5	-4	-3	-2	-1	0	1	2	3	4	5	6
-6	1	5	4	4	4	5	6	6	6	6	6	6	6
-5	-2	2	4	4	4	5	6	6	6	6	6	6	6
-4	-2	-2	1	4	4	5	6	6	6	6	6	6	6
-3	-2	-2	-2	1	2	3	5	5	5	5	6	6	6
-2	-2	-2	-2	-1	0	2	4	4	4	5	6	6	6
-1	-4	-4	-4	-3	-2	-2	4	4	4	4	4	4	4
-0	-4	-4	-4	-3	-2	-2	0	0	0	4	4	4	4
+0	4	4	4	3	2	1	0	0	0	-4	-4	-4	-4
1	4	4	4	3	2	1	0	0	-4	-4	-4	-4	-4
2	2	2	2	1	0	-2	-4	-4	-4	-5	-6	-6	-6
3	2	2	2	-1	-2	-3	-5	-5	-5	-5	-6	-6	-6
4	2	2	-1	-4	-4	-5	-6	-6	-6	-6	-6	-6	-6
5	2	-2	-4	-4	-4	-5	-6	-6	-6	-6	-6	-6	-6
6	-1	-5	-4	-4	-5	-6	-6	-6	-6	-6	-6	-6	-6

4 Summary

This paper provided a series of experiments targeted to investigate the salience of the prototypical hybrid symbolic/connectionist expert system development tool SC-net to not only act as a fuzzy controller, but more importantly to independently derive the necessary fuzzy control strategies required to adequately control a steam engine. Deriving linguistic variables and their associated membership functions was stressed, as well as SC-nets ability to construct control strategies from raw training data, without intervention from any human party. In light of the positive results obtained, it would seem justified to conclude the viability of knowledge acquisition for fuzzy control problems - at least in the domain studied - by means of machine learning, and warrant to continue investigating SC-net's applicability in this area.

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