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Design of Neuro Fuzzy Systems

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Abstract

Classical control theory is based on the mathematical models that describe the physical plant un-der consideration. The essence of fuzzy control is to build a model of human expert who is capa-ble of controlling the plant without thinking in terms of mathematical model. The transformation of expert's knowledge in terms of control rules to fuzzy frame work has not been formalized and arbitrary choices concerning, for example, the shape of membership functions have to be made. The quality of fuzzy controller can be drastically affected by the choice of membership functions. Thus, methods for tuning the fuzzy logic controllers are needed. In this paper, neural networks are used in a novel way to solve the problem of tuning a fuzzy logic controller.
The neuro fuzzy controller uses the neural network learning techniques to tune the member-ship functions while keeping the semantics of the fuzzy logic controller intact. Both the architec-ture and the learning algorithm are presented for a general neuro fuzzy controller. From this gen-eral neuro fuzzy controller, a proportional neuro fuzzy controllers is derived. A step by step algo-rithm for off-line training is given along with numerical examples.

Keywords: Component; formatting; style; styling; insert (key words)

1. Introduction

Fuzzy systems and neural networks have attracted the interest of researchers in various scientific and engineering areas [1,2]. The number and variety of applications of fuzzy logic and neural networks have been increasing, ranging from consumer products [3,4] and industrial process control [5] to medical instrumentation [6,7], information systems [8] and decision analysis [9].

The main idea of fuzzy logic control (FLC) is to build a model of a human control expert who is capable of controlling the plant without thinking in terms of a mathematical model. The control expert specifies his control actions in the form of linguistic rules.

These control rules are translated into the framework of fuzzy set theory providing a calculus which can simulate the behavior of the control expert. The specification of good linguistic rules depends on the knowledge of the control expert, but the translation of these rules into fuzzy set theory framework is not formalized and arbitrary choices concerning, for example, the shape of membership functions have to be made. The quality of fuzzy logic controller can be drastically affected by the choice of member-ship functions. Thus, methods for tuning fuzzy logic controllers are necessary.

A combination of neural networks and fuzzy logic offers the possibility of solving tuning problems and design difficulties of fuzzy logic [10]. The resulting network will be more transpar-ent and can be easily recognized in the form of fuzzy logic control rules or semantics [11]. This new approach combines the well established advantages of both the methods and avoids the drawbacks of both. In this paper, a neuro-fuzzy controller architecture is proposed, which is an improvement over the existing neuro fuzzy controllers. It overcomes the major drawbacks of the existing neuro-fuzzy approaches; of either keeping neural networks and fuzzy logic as separate entities (co-operative models) working towards a common goal or in most of the existing neuro-fuzzy approaches, the trained controller no longer can be interpreted as fuzzy logic controller. The novelty of this scheme is that the fuzzy controller itself is interpreted as a neural network. So, an error in the resulting control value can be distributed back among the control rules, instead of the integrating neural networks in certain parts of the controller, acting as black boxes to optimize the weights. One of the objective of this paper is to understand adaptation of the membership functions as a reverse mechanism deduced from the forwarding inference machinery of the fuzzy logic controller. The architecture and the learning algorithm of a proportional fuzzy controller (PFLC) is presented. A step by step algorithm for the off-line training of a PFLC is demonstrated by a numerical example.

2. The Neuro-fuzzy Controller

We consider a multi-input, single-output dynamic system whose states at any instant can be defined by “n” variables $X_1, X_2,...,X_n$. The control action that derives the system to a desired state can be described by a well known concept of “if-then” rules, where input variables are first transformed into their respective linguistic variables, also called fuzzification. Then, conjunction of these rules, called inferencing process, determines the linguistic value for the output. This lin-guistic value of the output also called fuzzified output is then converted to a crisp value by using defuzzification scheme. All rules in this architecture are evaluated in parallel to generate the final output fuzzy set, which is then defuzzified to get the crisp output value.

The conjunction of fuzzified inputs is usually done by either min or product operation (we use product operation) and for generating the output max or sum operation is generally used. For defuzzification, we have used simplified reasoning method, also known as modified center of area method.

For simplicity, triangular fuzzy sets will be used for both input and output. The whole work-ing and analysis of fuzzy controller is dependent on the following constraints on fuzzification, defuzzification and the knowledge base of an FLC, which give a linear approximation of most FLC implementations.

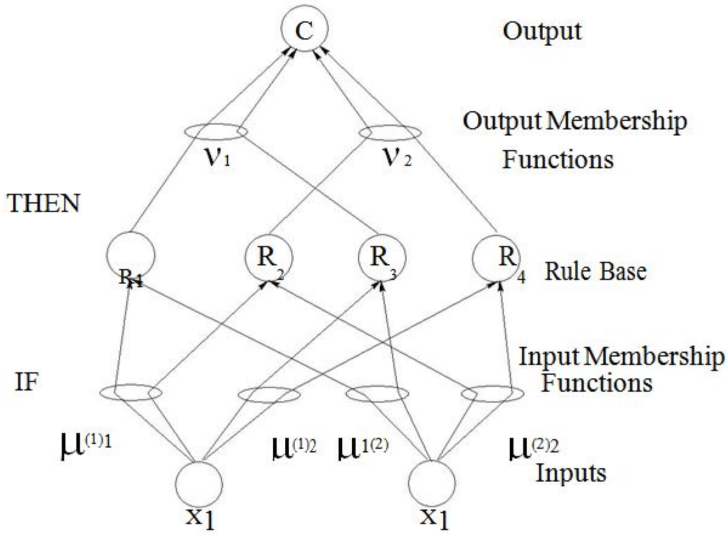

Figure 1: Architecture of four rule fuzzy controller from neural networks point of view.

3. The Learning Procedure

The actual output signal, C_a, is generated by the controller and now if the desired output of the controller, C_d, is also known at every instant, then error, e_c, can be generated. The goal now is to generate the adjustments of the input and output membership functions, by back- propagating the error through the "neural-like" architecture of the fuzzy controller.

The essence of back propagation algorithm in this case is to reward those rules which con-tribute towards taking the actual control action towards the desired control action and to discour-age the rules which tend to take the control action away from the desired path.

The error, e_c, is assumed to be due to the bad choice of membership functions. Membership functions can be adjusted by laterally moving the domain or by bending the segments of the func-tion. The error, e_c, is due to a combination of errors resulting from wrong lateral placement of the domains and from specification of function shapes. These partial errors are then distributed back to the architecture. The error due to lateral placement of domain goes on to affect the output membership function domain, whereas the error due to function shapes modifies the input mem-bership function in order to reduce that error.

4. Conclusion

Classical control theory is based on mathematical models that describe the system under consideration.

The underlying principle of fuzzy control is to build a model of a human expert who is capable of controlling the plant without thinking in terms of a mathematical model. The control expert specifies the control actions in the form of linguistic rules, generated from heuristic knowledge of the system. The specification of good linguistic rules depends on the heuristic knowledge of control expert. However, the translation of these linguistic rules into fuzzy sets theory framework is not formalized and arbitrary choices concerning, for example, the shape of the membership functions have to be made. The quality of fuzzy logic controller can be drastically affected by the choice of membership functions. Thus, methods for tuning fuzzy logic controllers are necessary.

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