Hierarchical Neuro–Fuzzy Systems Part II

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INTRODUCTION

This paper describes a new class of neuro-fuzzy models, called Reinforcement Learning Hierarchical Neuro-Fuzzy Systems (RL-HNF). These models employ the BSP (**Binary Space Partitioning**) and Politree partitioning of the input space [Chrysanthou,1992] and have been developed in order to bypass traditional drawbacks of **neuro-fuzzy systems**: the reduced number of allowed inputs and the poor capacity to create their own structure and rules (ANFIS [Jang,1997], NEFCLASS [Kruse,1995] and FSOM [Vuorimaa,1994]).

These new models, named Reinforcement Learning Hierarchical Neuro-Fuzzy BSP (RL-HNFB) and Reinforcement Learning Hierarchical Neuro-Fuzzy Politree (RL-HNFP), descend from the original HNFB that uses **Binary Space Partitioning** (see Hierarchical Neuro-Fuzzy Systems Part I). By using hierarchical partitioning, together with the **Reinforcement Learning** (RL) methodology, a new class of **Neuro-Fuzzy Systems** (SNF) was obtained, which executes, in addition to automatically learning its structure, the autonomous learning of the actions to be taken by an agent, dismissing a priori information (number of rules, fuzzy rules and sets) relative to the learning process. These characteristics represent an important differential when compared with existing intelligent **agents** learning systems, because in applications involving continuous environments and/or environments considered to be highly dimensional, the use of traditional **Reinforcement Learning** methods based on lookup tables (a table that stores value functions for a small or discrete state space) is no longer possible, since the state space becomes too large.

This second part of **hierarchical neuro-fuzzy systems** focus on the use of **reinforcement learning** process. The first part presented HNFB models based on supervised learning methods. The RL-HNFB and RL-HNFP models were evaluated in a benchmark **control application** and a simulated Khepera robot environment with multiple obstacles.

BACKGROUND

The model described in this paper was developed based on an analysis of the limitations in existing models and of the desirable characteristics for RL-based learning systems, particularly in applications involving continuous and/or high dimensional environments [Jouffe,1998][Sutton,1998][Barto,2003][**Satoh**,2006]. Thus, the *Reinforcement Learning Hierarchical Neuro-Fuzzy Systems* have been devised to overcome these basic limitations. Two different models of this class of **neuro-fuzzy systems** have been developed, based on **reinforcement learning** techniques.

HIERARCHICAL NEURO-FUZZY SYSTEMS

This section presents the new class of **neuro-fuzzy systems** that are based on hierarchical partitioning. As mentioned in the first part, two sub-sets of **hierarchical neuro-fuzzy systems** have been developed, according to the learning process used: supervised learning models (HNFB [Souza,2002][Vellasco,2004], HNFB[-1] [Gonçalves,2006], HNFB-Mamdani [Bezerra,2005]);

and **reinforcement learning** models (RL-HNFB [Figueiredo,2005a], RL-HNFP [Figueiredo,2005b]). The focus of this article is on the second sub-set of models. These models are described in the following sections.

REINFORCEMENT LEARNING HIERARCHICAL NEURO-FUZZY MODELS

The RL-HNFB and RL-HNFP models are composed of one or various standard cells, called RL-neuro-fuzzy-BSP (RL-NFB) and RL-neuro-fuzzy-Politree (RLNFP), respectively. The following sub-sections describe the basic cells, the hierarchical structures and the learning algorithm.

Reinforcement Learning Neuro-Fuzzy BSP and Politree Cells

An RL-NFB cell is a mini-neuro-fuzzy system that performs **binary partitioning** of a given space in accordance with ρ and μ membership functions. In the same way, an RL-NFP cell is a mini-neuro-fuzzy system that performs 2^n partitioning of a given input space, also using complementary membership functions in each input dimension. The RL-NFB and RL-NFP cells generate a precise (crisp) output after the defuzzification process [Figueiredo,2005a][Figueiredo,2005b].

The RL-NFB cell has only one input (x) associated with it. The RL-NFP cell receives all the inputs that are being considered in the problem. For illustration purpose, figure 1(a) depicts a cell with two inputs – x_1 and x_2 - (**Quadtree partitioning**), providing a simpler representation than the n-dimensional form of Politree. In figure 1(a) each partitioning is generated by the combination of two membership functions - ρ (*low*) and μ (*high*) of each input variable.

The consequents of the cell's poli-partitions may be of the *singleton* type or the output of a stage of a previous level. Although the *singleton* consequent is simple, this consequent is not previously known because each *singleton* consequent is associated with an action that has not been defined a priori. Each poli-partition has a set of possible actions (a_1, a_2, ... a_n), as shown in figure 1(a), and each action is associated with a Q-value function. The *Q*-value is defined as being the sum of the expected values of the rewards obtained by the execution of action *a* in state *s*, in accordance with a policy π. For further details about RL theory, see [Sutton,1998].

The linguistic interpretation of the mapping implemented by the RL-NFP cell depicted in Figure 1(a) is given by the following set of rules:

rule_1: If $x_1 \in \rho_1$ and $x_2 \in \rho_2$ then $y = a_i$
rule_2: If $x_1 \in \rho_1$ and $x_2 \in \mu_2$ then $y = a_j$
rule_3: If $x_1 \in \mu_1$ and $x_2 \in \rho_2$ then $y = a_p$
rule_4: If $x_1 \in \mu_1$ and $x_2 \in \mu_2$ then $y = a_q$

where consequent a_i corresponds to one of the two possible consequents below:

a singleton (fuzzy singleton consequent, or zero-order Sugeno): the case where a_i=constant;
the output of a stage of a previous level: the case where $a_i = y_m$, where y_m represents the output of a generic cell 'm'.

RL-HNFB and RL-HNFP Architectures

RL-HNFB and RL-HNFP models can be created based on the interconnection of the basic cells. The cells form a hierarchical structure that results in the rules that compose the **agent**'s reasoning.

In the example of an architecture presented in figure 1(b), the poli-partitions *1, 3, 4, ..., m-1* have not been subdivided, having as consequents of its rules the values $a_1, a_3, a_4, ..., a_{m-1}$, respectively. On the other hand, poli-partitions 2 and m have been subdivided; so the consequents of its rules are the outputs (y_2 and y_m) of subsystems *2* and *m*, respectively. On its turn, these subsystems have, as consequent, the values $a_{21}, a_{22}, ..., a_{2m}$, and $a_{m1}, a_{m2}, ..., a_{mm}$, respectively. Each '$a_i$' corresponds to a consequent of zero-order Sugeno (singleton), representing the action that will be identified (between the possible actions), through **reinforcement learning**, as being the most favorable for a certain state of the environment. It must be stressed that the definition of which partition must be subdivided or not is defined automatically by the learning algorithm.

The output of the system depicted in figure 1(b) (defuzzification) is given by equation (1). In these equations, α_i corresponds to the firing level of partition *i* and a_i is the singleton consequent of the rule associated with partition *i*.

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