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Multiple neural control of a greenhouse

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ABSTRACT

In this paper an ART2 classifier is used to extract local models of a database taken from a greenhouse. Once the clusters are formed, multilayer feed-forward neural networks are then trained to model each cluster (subsystem) in order to achieve a multiple neural control of the greenhouse. The considered control strategy consists of the division of the greenhouse control phase in periods where a suitable controller is selected to drive the internal climate of the greenhouse, which is modeled with an Elman neural network. The same ART2 classifier is then used as a supervisor to select the suitable neural controller corresponding to the appropriate mode.

1. Introduction

Greenhouses are Multi-Input and Multi-Output (MIMO) systems. They are highly nonlinear and strongly coupled systems that are largely influenced by the outside weather (wind velocity, outside temperature and humidity) and by many other practical constraints (actuators and moistening cycle). These classify greenhouses as non-linear dynamic and complex systems. The first and main characteristic of complex systems is that they contain a large number of mutually interacting entities (components, agents, processes, etc.) whose aggregate is a nonlinear activity that cannot be derived from the direct summations of the activity of individual entities and typically exhibit a sort of self-organization. Complex systems also include systems in which many subsystems and constituent elements interact with each other as well as with their environment in the presence of uncertainties and unpredictable phenomena. Traditionally, there are two different approaches to describe the greenhouse climate: one is based on energy and mass flow equations describing the process, and another is based on the analysis of input-output data from the process by using a system identification approach. In control context, it is very difficult to create favorable environment in a greenhouse for the crop in order to reach predetermined results for high yield, high quality and low production cost due to the complexity of greenhouse environments [1–3].

The last decade has shown an increase in the use of local model representations of non-linear and complex systems. The basic structure includes a number of approaches: Takagi and Sugeno (1985) [17] fuzzy systems, local model networks (Johansen and Foss, 1993) [18], gain-scheduled control (Shamma and Athans, 1990) [19], the smooth threshold autoregressive (STAR) models of Tong (1990) [20] and state dependent models of Priestley (1988). Multi-models as well as black box models were also proposed [4–7]. Therefore, the use of neural networks in nonlinear black-box modeling of process systems is a challenging and promising research field. Such neural network models may be derived from measured input/output data (database) of the plant working in open-loop experiments. This database can be used to extract different behaviors of the plant involving clustering methods.

Clustering can be defined as a process of separating a set of objects into several subsets on the basis of their similarity. It is a form of unsupervised learning, that is, the training data comprises a set of example input vectors without any corresponding desired output vectors. The aim is generally to define clusters that minimize intracluster variability while maximizing intercluster distances, i.e. finding clusters, in which members are similar to each other, but distant to members of other clusters.

Clustering using fuzzy logic and neural networks has been successfully applied to classification and pattern recognition [8]. ART systems, especially ART2 can be useful in performing unsupervised classification. The user does not need to decide how many clusters are to be generated; rather, one has to define a vigilance parameter to control the formation of clusters. Higher vigilance levels result in fine clusters, while lower vigilance levels generate coarser clusters. A range of vigilance parameters (from

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low to high) can be used to perform a hierarchical unsupervised classification [9,10].

In our case the ART2 classifier is used to decompose a database of a greenhouse operating in open-loop in order to create clusters (classes). Once the clusters are formed, multilayer feed-forward neural networks can be trained to model each cluster (subsystem) in order to achieve a multiple neural networks to control the considered greenhouse.

This paper is organized as follows: In Section 2, we describe the considered greenhouse. In Section 3, we present the greenhouse clustering using ART system. In Section 4, we describe the greenhouse neural modeling. In Section 5, we demonstrate the principle and the simulation results of the greenhouse multiple neural control. Finally, a conclusion is given in Section 6.

2. Greenhouse description

The considered greenhouse is a classical one. It is made of glass; the surface is 40 m^2 and the volume is 120 m^3. It is equipped with sensors to measure internal and external climates. The internal climate is defined by the internal temperature and the internal hygrometry, which constitute the outputs of the greenhouse, while the external climate is composed of the external temperature, the external hygrometry, the solar radiation and wind speed which act directly on the operation of the greenhouse. The external climate parameters are uncontrollable inputs and they are considered as disturbances. The internal climate control of the greenhouse is insured with a set of actuators, which are: a heater that operates in Boolean mode with a power of 5 KW, a shutter opening between 0 and 35 degrees, a sprayer that works in Boolean mode and a shade with a length varying between 0 and 3 meters.

The greenhouse is equivalent to a non-linear and multi-variable system. It can be represented by the block diagram as shown in Fig. 1.

A database on the greenhouse was taken in a day in March. This database consists of 1440 lines (the sampling time is one minute, 24(h) × 60(min) = 1440) and ten columns corresponding respectively to: $Te(k)$, $Ti(k)$, $He(k)$, $Hi(k)$, $Vv(k)$, $Rg(k)$, $Ch(k)$, $Br(k)$, $Ov(k)$ $Om(k)$. The measurements have been stated at 0 h (0 min) and stopped at 23 h and 59 min (1440 min).

Controlling the temperature and the hygrometry (internal climate $Y(k) = [T_i(k),\ H_i(k)]^T$) is therefore of utmost importance. For tomato crops, the recommended temperature and hygrometry references are respectively 11 °C and 70%.

3. Greenhouse clustering using ART system

Our purpose is to use the ART2 classifier to extract local models from the greenhouse database and achieve a multiple neural control in order to improve the greenhouse performances.

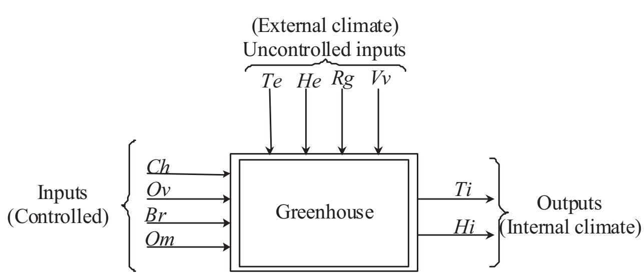

Fig. 1. Block diagram of the greenhouse. where, *Te* : External temperature (°C), *He* : External hygrometry (%), *Rg* : Solar radiation (W/m²), *Vv* : Speed of the wind (Km/h), *Ch* : Heating (thermal power 5 Kw) (Boolean), *Ov* : Opening (degrees), *Br* : Sprayer (Boolean), *Om* : Shade (m), *Ti* : Internal temperature (°C), and *Hi* : Internal hygrometry (%).

3.1. ART2 system

The Adaptive Resonance Theory (ART) was originated by Carpenter and Grossberg (1987a) [9] for the purpose of developing artificial neural networks. The ART performs not only in pattern recognition but also in classification tasks. One of their main goals was to come up with neural networks that can preserve the biological network's plasticity in learning or in recognizing new patterns, namely, in learning without having to erase (forget) or to substantially erase earlier learned patterns. ART architectures are neural networks that carry out stable self-organization of recognition codes for arbitrary sequences of input patterns. ART1 version deals with binary inputs and ART2 version deals with analog patterns. The basic features of the ART2 architecture are shown in Fig. 2.

Patterns of activity that develop over the nodes in two layers F_1 and F_2 of the attentional subsystem are called short-term memory (STM) traces because they exist only in association with a single application of an input vector. The weights associated with the bottom-up $z_{j,i}$ and top-down $z_{i,j}$ connections between F_1 and F_2 are called long-term memory (LTM) traces because they encode information that remains a part of the network for an extended period.

The F_1 layer has been divided into six sublayers: w, x, u,v,p, and q. Each node labeled ***G*** is a gain-control unit that sends a nonspecific inhibitory signal to each unit on the layer it feeds. All sublayers on F_1, as well as the r layer of the orienting subsystem, have the same number of units. Individual sublayers on F_1 are connected unit to unit; that is, layers are not fully interconnected, with the exception of the bottom-up $z_{j,i}$ connections to F_2 and the top-down $z_{i,j}$ connections from F_2.

In the F_2 layer each node represents a cluster. A resonant state can be attained in one of the two ways in favor of the sublayer r in the orienting subsystem. If the network has learned previously to recognize an input vector, then a resonant state will be achieved quickly when that input vector is presented. If the input vector is not immediately recognized, the network will rapidly search through its stored patterns (clusters) looking for a match. During resonance, the adaptation process will reinforce the memory (LTM) of the stored pattern.

If no match is found, the network will enter a resonant state whereupon the new pattern will be stored for the first time, in this case a new node (class) will be automatically created in the F_2

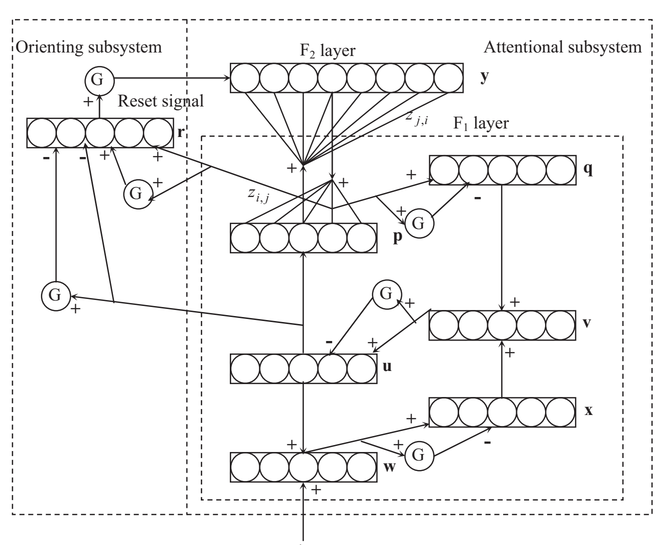

Fig. 2. ART2 neural network architecture.