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Approximate Optimal Control-Based Neurocontroller with a State Observation System for Seedlings Growth in Greenhouse

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***Abstract*— In this paper, an approximate optimal control-based neurocontroller for guiding the seedlings growth in greenhouse is presented. The main goal of this approach is to obtain a close-loop operation with a state neurocontroller, whose design is based on approximate optimal control theory. The neurocontroller drives the progress of the crop growth development while minimizing a predefined cost function in terms of operative costs and final state errors under physical constraints on process variables and actuator signals. The aim is to find an approximate optimal control policy to guide the development of tomato seedlings from an initial to a desired state by controlling the greenhouse's microclimate. In this paper we propose an indirect measuring of the seedlings growth state using artificial vision. In order to show the performance and practical feasibility of the proposed approach, an experiment was carried out for the development of tomato seedings.**

I. INTRODUCTION

Several optimal control-based controllers for guiding the crop growth had been designed, such as [14] [12] [13] [15]; [16], among others. The goal of the guidance processes is to obtain a certain output according to a production schedule within a predefined period and with the lowest cost and the greatest profit. In addition, the final product should have certain characteristics as imposed by the market, such as weight, number of nodes, number of leaves, color, size or others.

Since the internal microclimatic variables of the greenhouse, such as temperature, relative humidity, carbon dioxide (CO_2) and solar radiation, affect the growth and development rate of crops [8] [9], these variables can be manipulated to guide such growth development and reach the predefined technical and economical objectives [15] [16]. Another aspect to take into account is that each crop imposes their own particular constraint to the ranges of variation for microclimate conditions. For instance, with temperatures below a minimum level, the seedlings stop growing, and with temperatures above a maximum level they can suffer irreversible damages. Thus, it is very important to reach internal climatic conditions (set points) following an appropriated trajectory, which guides the seedlings growth from an initial state to a desired final state minimizing a costs function, in a predefined time, and considering the climate constraints imposed by the particular crop. The generated trajectory will be optimal with respect to that criterion function defined for each particular case. Therefore, a problem is to obtain an optimal strategy in order to get that optimal trajectory conformed by a set points. In such a sense, the work proposes to use the theory of optimal control to solve said problem. It can be complemented, approached through the neuro-dynamic programming (NDP) technique allows designing a control system that can be implemented by using low cost equipments. This fact results in low investments, which is an important factor to be considered when applications have low profit margins, as does in agriculture business.

In this work, a state observation scheme for guiding the crop growth under greenhouse conditions is proposed. This observer operates with a NDP based optimal controller, whose design procedure is detailed in [12] and [14]. This scheme has the advantage of demanding few computational resources for obtaining the control actions. At the same time, this fact allows that the sophisticated state observer be incorporated, given that it performs an on-line acquisition and image processing. The main difference with regards to others implementations of crop state observer [13], is that in this work a digital camera for images acquisition is incorporated for estimating the plant state.

In order to show the practical feasibility and performance of the proposed neurocontroller, simulation studies were carried out for the tomato-seedling crop development. In addition, some experiments were necessary to model the crop environment, using the scaled-model greenhouse of Fig. 2.

II. PROBLEM STATEMENT

The control scheme based on NDP with state observation and crop image acquisition used in the experimentation has the implementation structure detailed in Fig. 1.

The manipulation of temperature and CO_2 concentration has various objectives, among which we may remark the economy factors —i.e., to obtain the production ready at a pre-established date, with the smallest cost and greatest profit possible. The set of required characteristics that should complete the representative state variables of the crop defines the desired crop practice. Crop features are the average crop' number of leaves and dry weight. Once the final state has been reached, the product is prepared for crop, and then new trays are introduced for a new process to start the process again.

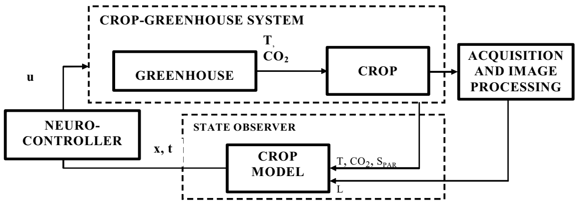

Fig. 1. Control scheme of the crop growth guidance. The feedback of the states uses the measurement of the crop environment variables, the leaf area index, and the crop's dynamic model.

A. *The control system*

The controller is designed with base on the optimal control theory [14] [12], solving the problem by the NDP technique [4]. The criterion or costs function is

$$J(\mathbf{x}, \mathbf{x}_d, \mathbf{v}) = \int_t^{t_f} I(\mathbf{x}, \mathbf{v}) d\tau + \Gamma \cdot |\mathbf{x}(t_f) - \mathbf{x}_d| \tag{1}$$

where $\mathbf{x}$ is the time-dependant state vector defined as $\mathbf{x}=[W\ N]^T$, W is the dry weight in grams, and N is the number of leaves; I and $\mathbf{v}$ are the performance index and the monetary costs vector associated to the control actions, respectively, detailed in [12]; [13]; $\mathbf{x}_d=[W_d\ N_d]^T$ contains the desired final values for the state variables where W_d is the desired final dry weigh and N_d is the desired number of leaves, and Γ is the weighting matrix. In addition, the closed-loop system can be expressed as follows

$$\begin{cases} \dot{\mathbf{x}} = f(\mathbf{x}, \mathbf{u}, t) & \mathbf{x}(0) = \mathbf{x}_0 \\ \mathbf{u} = \mu(\mathbf{x}, t) & 0 \le t \le t_f \end{cases} \tag{2}$$

where $\mathbf{u}$ is the control vector defined as $\mathbf{u}=[a(t)\ CO_2(t)]^T$, $f(\cdot)$ is the equivalent function of the model which combines the crop dynamic model and the greenhouse algebraic model; finally, $\mathbf{x}_0$ is the initial condition for the nonlinear equation (i.e., initial dry weight and number of leaves). The optimal control law or optimal policy is denoted by μ, which is a function of the state $\mathbf{x}$ and the time t. The modeled experimental greenhouse available in the Instituto de Automática's laboratory is shown in Fig. 2, in which the experiments were carried out.

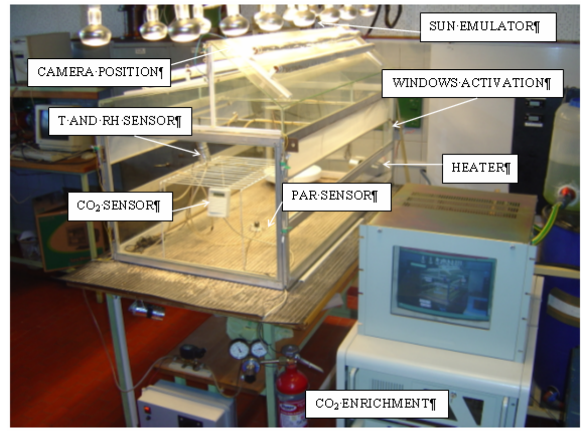

Fig. 2. Scale model of the greenhouse used in the experiments, located at the INAUT's Laboratory.

The optimal control problem of the crop growth guidance can be formulated as follows. By considering the dynamic model of the production system of Eqn. (2), it is desired to obtain an optimal control law (which gives the values of heater use and window opening and CO_2 set points) such that the crop growth goes from an arbitrary initial state condition to a desired final state by minimizing the cost function of Eqn. (1).

B. *Crop state measurement*

The typical procedure to measure the process state is to take a seedling sample, counting its leaves, dehydrating it in an oven at 40°C during 10 hours, and weighing the sample to obtain its dry weight. Then, this weight is divided by the number of sample's seedlings to obtain the values of dry weight and number of leaves of each seedling. If this procedure is would perform on-line, a perturbation will be produced to the cultivation that generates a destructive and irreversible effect. The reason is that the absence of one seedling in a place of the tray cell generates a vacuum between the remaining plants —the well known "border effect"— given that they regulates its biological variables such as evapotranspiration and light catchment in a modified fashion. Therefore, after the extraction of one seedling, the rate patterns of growth and development for the remaining seedlings will not be the same ones. Hence, the direct measurement is a destructive procedure not only for one plant but for several seedlings of the lab tray. This fact makes the direct measurement in the experimentations has to be performed at the end of the guidance process. Thus, by considering the strong perturbation that introduces in the crop growth rate the direct measurement of the state, a state observation system must been carried out.

III. PROPOSED SOLUTION

A. Neurocontroller's architecture

Generally the solution for the optimal control problem, considering a nonlinear system and an arbitrary cost function is the Hamilton-Jacobi-Bellman equation [10], which results - in most cases- impossible to solve analytically in a closed form. The majority of these differential equations, with time variants and stochastic systems, and properly quantified on its state and control variables, can be computed with the algorithm of Dynamic Programming (DP) [1] [5]; [3]. Thus, the continuous space of the problem can be replaced by a discrete space with a finite number of elements involving a finite number of states, decisions, and stages of system's temporal evolution. However, it is well known that in many engineering problems, the computational requirements of DP are overwhelming, because the number of states and control actions is very large (Bellman's curse of dimensionality). In such instances, it is more suitable to consider approximate or suboptimal control schemes, such as

$$J(i) = I(i, \mathbf{u}) + \tilde{J}(j, \mathbf{r}) \tag{3}$$

Where, i is the quantified state, $\tilde{J}(\cdot)$ is a function that approximates $J(\cdot)$ and $\mathbf{r}$ is the parameter vector of the approximator. Thus, by the approximate policy iteration algorithm can be found a table μ containing the optimal control policy [4]. Furthermore, this table with the optimal control law μ can be approximated by another device through a parameter vector **s**. Therefore, given that the approximator devices are neural networks (NNs), the DP comes into Neuro-Dynamic Programming (NDP) sphere. Then, the NNs that approximates the costs function of Eqn. (1) is called the Critic, and the NNs that approximates the tabulated version of the control law of Eqn. (3) is called the Actor. Here, the three networks (one for Critic and two for Action) are all implemented by using multilayer feedforward NNs featuring two layers of 10 neurons in the hidden layer. The Actor has two NNs with 3 inputs, dry weight of the tomato seedling, number of leaves, and stage, and two outputs: heater use-opening windows a(t) and CO_2 concentration. The approximation cost-to-go function is the Critic, which has same inputs with one output. The Critic network output $\tilde{J}$, and the Actor network output **u** are trained according to the procedure presented in [12] [14]. The NNs structures are shown in Fig. 3.

B. Crop image processing

With the aim of measure the system state in an on-line fashion there exists, in general, indirect methods that measure variables associated to the crop. Then, once the dynamic model has been obtained, the real time state value is estimated. The methods can be based on several techniques: artificial vision, [6], photosynthesis sensors [11], measurements of the environment variables [13], etc. Note that the availability of the crop model and the temporal evolution of the associated variables are needed. Here, a system was designed for measuring the on-line state, which uses direct information of the crop, more exactly the superficial appearance of the vegetal canopy for the state feedback.

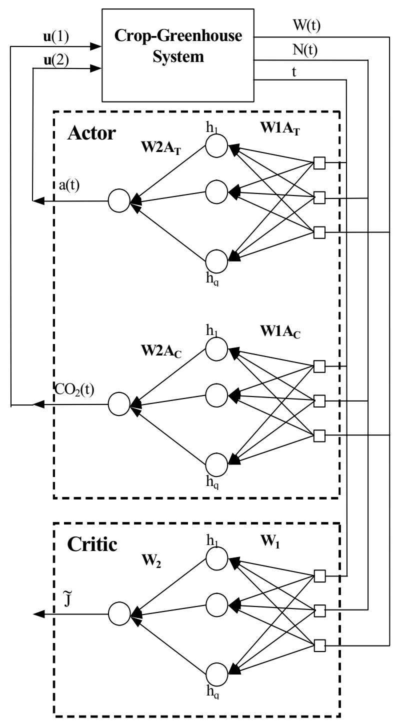

Fig. 3. Actor/Critic scheme of the neurocontroller.

The leaf area index L used by the crop's dynamic model [9] can be correlated with a crop image, which is obtained in real time by a camera installed in a fixed position with reference to the crop, as is shown in Fig. 2. The real time state value is obtained by using the value of L altogether with the environment variables. For the case of the tomato seedling crop, the index L ranges from 0 to 2, index L varies from 0 to 2, a range where it is possible to find values to correlate with desired image characteristics.

The observer scheme is shown in Fig. 1, where the acquisition and image processing is performed for estimating the value L. Note that the observer still uses the dynamic model, although in this case the information related to the crop physical appearance is directly used, which describes with more precision the system state. The sample period of the index L is of one hour. Historical sequences of crop images were used for designing the estimator of L. The images were captured from the same spot respecting the crop. The procedure we chose consisted in the summation of green pixels detected by the camera, divided by the total number of image pixels. The procedure applied to images corresponding to various development stages allowed obtaining a curve similar to that of Fig. 7, although with another scale factor. This scale factor was computed using a seedling taken for measuring. The processed image is shown below in Fig. 4.

Fig. 4. Negative of the crop's processed image used for computing the leaf area index.

The original image was captured by using as background a standard grid sheet, which allows perform the leaf area compute corresponding to the cultivation at its final stage. The procedure was to find the correlation from mm^2 to pixels, where it was obtained that $25mm^2$ are equivalent to 324 pixels. Thus, the detected pixels quantity that belongs to the seedling is 34349 pixels, which belongs to $2650mm^2$ as well. This value, expressed in the MKS system is $0.00265\ m^2$ [leaf]. This procedure was performed for a ten-seedlings sample at the final stage during a laboratory experimentation, obtaining a mean value of the leaf area equal to $0.00245m^2$ [leaf]. In order to meet the value of L in m^2[leaf]m^{-2}[soil], it is necessary to set the plant's density in [plant]m^{-2}. In this case, the used trays size was $0.1917m^2$ with a storage capacity of 160 plants. Finally, the value of the leaf area index is $2.05m^2$[leaf]m^{-2}[soil]. The evolution of the leaf area index estimated by means of this procedure for three experiments, which is based on the acquisition and image processing is shown in the Fig. 7.

IV. EXPERIMENTATION DESCRIPTION AND RESULTS

Based on the proposed methodology, the neurocontroller for guiding the development of the tomato seedling crop in greenhouse under laboratory's climatic conditions is designed. The greenhouse scale model is shown in Fig. 2, where the used sensors and actuators are detailed. The on-line measurement of the system's state is crucial with regards to the neurocontroller implementation. The state of the system is described by the dry weight and the number of leaves, as defines Eqns. (1)-(2).

A. Computing the neurocontroller

In order to design the controller for the crop-greenhouse system, the methodology detailed in [12] and [14] was used. The greenhouse environment conditions were modeled with the same criterion that the used in other experimentations [7]; [13]. Each NNs have 10 neurons at the hidden layer of hyperbolic tangent activation and one output neuron with linear activation. Namely, the approximated control law denoted by $\tilde{\mu}(\cdot,\mathbf{s})$ has the parameter vector **s** composed by W_{aT} and W_{aC}. The computation of the control law and the approximated cost-to-go function is performed by using the algorithm "approximate policy iteration" [4] [12] [14]. This algorithm tunes the coefficients of vector **s** and **r**, in the direction of minimizes the costs function of Eqn. (1). Once the calculation procedure have completed, the actions that are obtained by means of control law $\tilde{\mu}(\cdot,\mathbf{s})$ are shown in Fig. 5, where the internal and external greenhouse temperatures are also shown. Note that the CO_2(t) action remains in 350ppm for all time. This can be explained by the disadvantageous fact that the windows are opened in such a way that the enrichment cost becomes inadequate, according to the criterion proposed by the cost function in the optimal control problem formulation [12] [14].

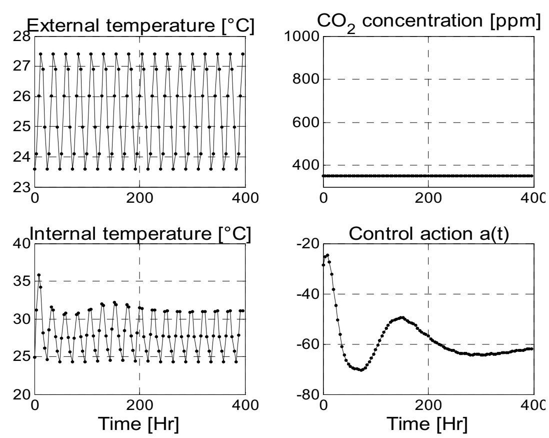

Fig. 5. Left, top: external greenhouse temperature; bottom: resultant evolution of the internal greenhouse temperature. Right: CO_2 enrichment value and evolution of the control actions a(t) (if a(t)>0, then the action is the heater use and, if a(t)<0 then the action is the percentage of window opening).

If the environment conditions shown in Fig. 5 are applied to the crop, its evolution will be the one that appears in Fig. 6. This one is an evolution in the state space, and is the expected system's evolution for the experimentation. The aim of the experiment is that the evolution of the observed state variables of the cultivation be equal to that shown in Fig. 6, mainly with regard to the final values. The observed variables are values a attainable by means of the states observation system.

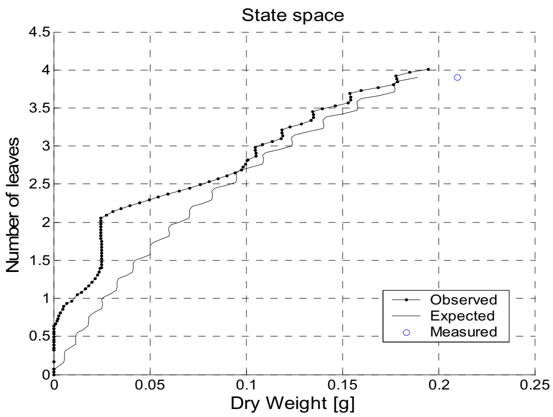

Fig. 6. Evolution of the state variables in the system's state space

B. *Obtained results*

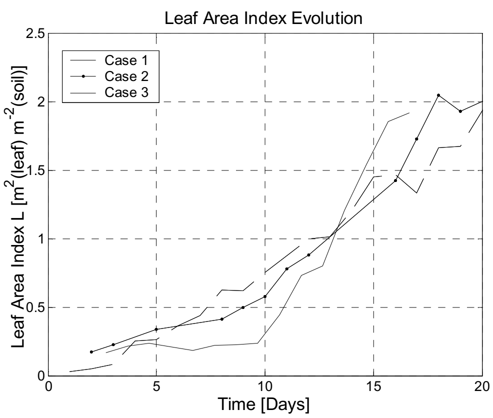

Fig. 7. Evolution of the leaf area index for the experiments. Case1 and 2 were taken from experimentations detailed in ([13Pucheta *et al.,* 2006a).

When the guidance process has finished, the leaf area index evolution of the vegetal canopy is available. This data was measured by the system based on acquisition and image processing. Fig. 7 shows the time evolution of this variable, where —with intention of facilitate the comparison— are superposed the trajectories obtained by three experimentations. Note that it is very different to the obtained by previous experimentations. In Fig. 8 is the evolution of the crop's appearance, whose images were processed by the system to obtain the values of the corresponding L. The relative position of the camera with respect to the cultivation is fixed, and the hour of the day is the same one for each image.

The first characteristic that arises is the different slopes that exhibit the trajectories for each experiment. In the first case, indicated by the label "Case 1", the slope of evolution is constant for all time. The cause is that the control actions were also constant and did not change during its evolution.

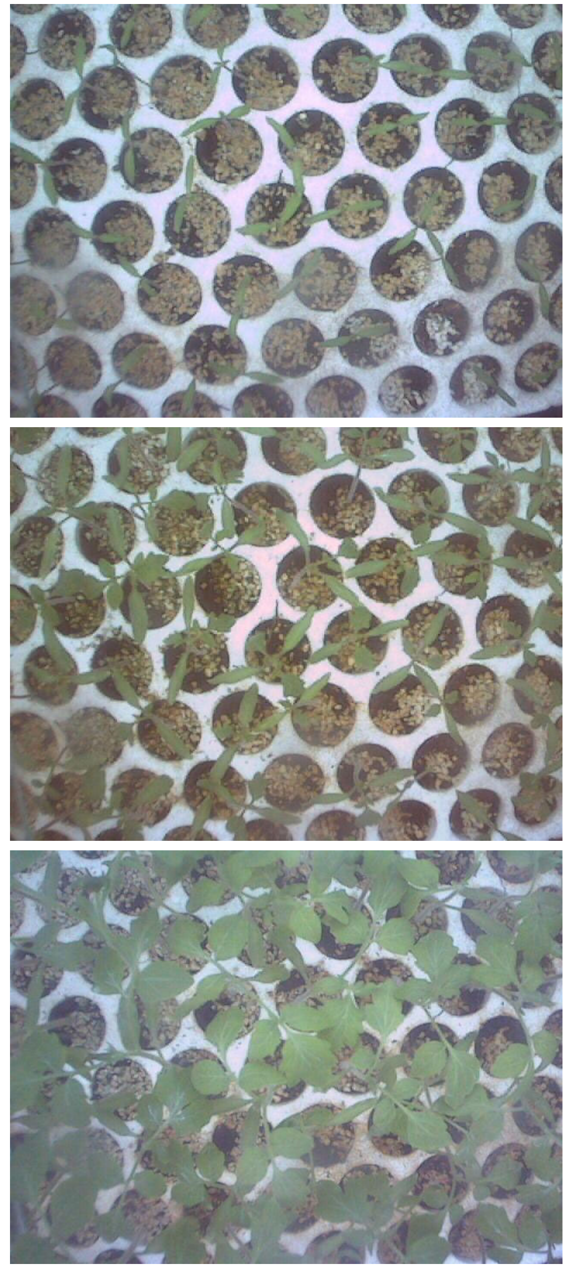

Fig. 8. Sequence of the appearance of the cultivation during the evolution of the guidance process. Top to bottom: days 5, 15 and 20.

In the second case, labeled "Case 2" in Fig. 8, the slope shows a change in variable evolution; given that initially it is one, and from approximately t=240Hr its slope decreases little, compared with the rate of the control action. As regards "Case 3" –the one presented here- the evolution slope of leaf area index changes permanently for each sampling time. In the first part of the process, the slope is small. Along the process evolution the controller increases it until arriving to the desired corresponding value. This behavior for the leaf area index can be explained by analyzing the greenhouse environment conditions, with external temperatures lower than expected ones, according to the model, as shown in Figure 5. This factor depends only on the conditions set in the laboratory. Physically speaking, it is essentially the action of turning on or off the conditioned air system that will regulate such conditions, depending on the decisions made by the personnel. Therefore, the controller tends towards correcting the control actions in the sense that the observed trajectories of the state variables tend to be match the expected trajectories, as in Fig. 6.

CO_2 concentration was maintained in low levels, but readings grater that 350 ppm were mainly caused in the periods when the laboratory air was not cooled. Besides, CO_2 concentration increased because of human consumption of oxygen. By observing the used control scheme in Fig. 1, it can be noted that the control actions, by means of the control law, depend on the present state of the crop; and the controller generates control actions to the greenhouse actuators by mean of the variable a(t) of Eqn. (2).

Note that for t=80Hr approximately, there exists a small disturbance in the observation, since the variables W and N diminish. The cause is that a power shutdown in the system was caused intentionally, and remained in open-loop during hours. Thus, the states observation system generated values considering the same conditions of surroundings previous to the cut until it was arrived at the new value corresponding to the present time. Thus, from t=90Hr in ahead, did not exist significant cuts in the electrical provision and the system was operated normally.

V. CONCLUSIONS

In this paper an approximate optimal control policy was presented to guide the development of tomato seedlings from an initial to a desired state by controlling the greenhouse's microclimate. In addition an indirect measuring of the seedlings growth state using artificial vision was presented. The good operation of the state observer was a fundamental factor to make the system really evolve in feedback operation. In experimentations where indirect information of the crop was used, —as the environment variables CO_2 temperature, concentration and PAR radiation— there is a vulnerability of lose information of the states. A situation is when a strong disturbance arises, as it is the cut of long electrical provision, event that existed in the present experimentation. The observer in this work was introduced to supply for the lack of it noted in previous experiences [13]. This fact allows concluding that, when the information handled by the observer system is obtained more directly from the crop, more accurare is the state estimation and, consequently, the crop development guidance is greatly improved. Predictive control [2] could be a better candidate for designing the controller, which can then be updated by the suggested ADP technique to handle modeling uncertainties.

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