OPTIMAL CONTROL OF PLANT GROWTH IN HYDROPONICS USING NEURAL NETWORKS AND GENETIC ALGORITHMS

T. Morimoto and Y. Hashimoto
Dept. of Biomechanical Systems
Ehime University, Tarumi 790
Matsuyama, Japan

Abstract

In the cultivation of fruit vegetables, well-balanced growth between vegetative growth and reproductive growth is important to obtain the better quality of fruits. We defined the ratio (TLL/SD) of total leaf length (TLL) to stem diameter (SD) as an indicator for the well-balanced growth only in the seedling stage. In hydroponics, nutrient concentration of the solution is one of the most important manipulating factors for adjusting TLL/SD.

This paper presents the application of genetic algorithms and neural networks to the optimal control of TLL/SD of tomato plants during the seedling stage in hydroponics. The control input is the nutrient concentration of the solution. We first divided the seedling stage into four stages and then tried to obtain the 4-step setpoints of nutrient concentration which maximize TLL/SD. A three layer neural network was markedly effective for identifying the process model of TLL/SD to nutrient concentration. Furthermore, the genetic algorithm ensured that the optimal value was obtained quickly from the neural network model simulation. The optimal 4-step setpoints of nutrient concentration obtained here were useful for the actual control of plant growth. Thus, this intelligent control technique based on neural networks and genetic algorithms was shown to be quite useful for the control of such complex systems as plant growth systems.

1. Introduction

For the cultivation of plants in plant factories, hydroponic culture techniques are essential because those have several potential advantages, e.g. technical easiness for the mechanization of cultivating processes and for the flexible control of root-zone environment, over soil cultures (Van Winden, 1988; Hashimoto, 1991).

In the hydroponic cultivation, nutrient concentration of the solution is one of the most important manipulating factors for controlling the growth of plants (Ehret and Ho, 1986). It is often controlled to well maintain the balance between reproductive growth and vegetative growth or to promote reproductive growth rather than vegetative growth. During the seedling stage, the ratio (TLL/SD) of total leaf length (TLL) to stem diameter (SD) appears to be a good indicator for predicting the future reproductive and vegetative growth (Lou and Kato, 1987). Higher values of TLL/SD result in better reproductive growth. Hence, controls for maximizing TLL/SD may be valuable in the cultivation of fruit vegetables. However, since the dynamics of TLL/SD, as affected by the nutrient concentration, is defined as an ill-defined process, we cannot apply a conventional mathematical optimization technique to this process. In an actual cultivation, therefore, the control of nutrient concentration is dependent upon the intuition and experience of a skilled grower.

Recently, however, intelligent control techniques using neural network or genetic algorithm have extensively developed in the control of the complex system to which conventional mathematical approaches cannot easily apply (Hunt *et al.*, 1992; Nordwik and Render, 1991). Neural networks are effective for identifying the dynamics of complex systems with their own high learning abilities (Chen *et al.*, 1990). On the other hand, genetic algorithms are search techniques of an optimal value. Those simulate the mechanics of genetic operators, such as crossover and mutation, and search for an optimal

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value (Goldberg, 1989). Control techniques based on neural networks and genetic algorithms have been applied to the agricultural production systems in recent years (Morimoto *et al.*, 1995a and 1995b).

The present work is attempt to apply an intelligent control technique combining with genetic algorithms and neural networks to the optimal control of TLL/SD of tomato plants in hydroponics. The control input is the nutrient concentration of the solution.

2. Plant materials and experimental conditions

Plant material is tomato plants (*Lycopersicon esculentum* Mill. cv. Momotarou), from 5 to 50 cm in height, during the seedling stage, which are grown in a deep hydroponic system. Nutrient solution is made by mixing the Otsuka liquid fertilizer No.1 and No.2 at the rate of 3 to 2. The experiment was done in a greenhouse.

For the identification of plant growth, leaf length, stem diameter, plant height, leaf area, etc. of tomato plants are measured every day using an image processing sensor and a ruler. Here, the ratio of total leaf length to stem diameter (TLL/SD) is used for the indicator for the future reproductive and vegetative growth. The total leaf length (TLL) is the sum of all leaf lengths from bottom leaf to top leaf and the stem diameter (SD) is the average stem diameter from bottom to top.

3. Optimal control problem

In the present study, the optimal control of plant growth is done only during the seedling stage. During the seedling stage, TLL/SD can be seen a good indicator for predicting the future balance between vegetative growth and reproductive growth. Higher values of TLL/SD leads to better reproductive growth. For optimal control, here, the seedling stage was divided into four stages. The optimal control problem is to search for the 4-step setpoints of nutrient concentration (NC_1, NC_2, NC_3 and NC_4) which maximize TLL/SD, and then apply this optimal strategy to the real control system.

4. Design of optimal control system

The controls of physiological processes of plants are usually implemented by environmental factors. Figure 1 shows a block diagram of optimal control system of plant growth using neural networks and genetic algorithms. In the system, neural networks are utilized for the identification of TLL/SD as affected by nutrient concentration. Through identification, we obtain a dynamic model to predict the future behaviors of TLL/SD (Part (a)). On the other hand, genetic algorithms are used for the search of optimal 4-step setpoints of nutrient concentration which maximize TLL/SD through simulation of the identified model (Part (b)). The optimal control is implemented based on these optimal setpoints. These procedures are repeated to follow the time-varying characteristics of the physiological dynamics of plants.

4.1. Neural network for identification

We supposed multi input (nutrient concentration, $u1(t)$, and light intensity, $u2(t)$) and single output (TLL/SD, $y(t)$) system for the identification. Figure 2 shows neural network architecture for the process model identification, which is composed of three layers: input, hidden and output layer. The current output variable $y(k)$, TLL/SD, is estimated from both time series of two input variables, nutrient concentration $\{u_1(k), ..., u_1(k-n)\}$ and light intensity$\{u_2(k), ..., u_2(k-n)\}$, and past time series of the output variable $\{y(k-1), ..., y(k-n)\}$ (k=0, 1, .., N, N: data number, n: system parameter number) like an ARMA model procedure (Chen *et al.*, 1991; Morimoto et al., 1991). Two (n+1)th input time series and one nth output time series are applied to the input layer and the current output to the output layer as training signals. Therefore, neuron numbers in the input and output layers are 3n+2 and 1, respectively. The learning method is error back propagation (Rumelhart *et al.*, 1986). Iteration number for the error back propagation computation is 5000 times.

4.2. Genetic algorithm application for optimal control

The optimal 4-step setpoints of nutrient concentration was searched for through simulation of the identified model using genetic algorithms. The searching process is analogous to a natural evolution process. It is noted that the decision variable to be obtained is the combination of 4-step setpoints of nutrient concentration (NC_1, NC_2, NC_3 and NC_4).

4.2.1. Coding of decision variable

For the first step to effectively use the genetic operators such as crossover and mutation, we usually code the decision variable as finite-length binary strings. Such decision variable as binary strings is called "individual". The set of several individuals is called "population". Figure 3 shows a definition of individuals and the coding patterns. Since we are going to obtain the optimal value of 4-step setpoints of nutrient concentration, one individual is expressed as NC_1, NC_2, NC_3 and NC_4. Each parameter in the individual was coded as a 6-bit binary string which gives 0£NC£63 in decimal.

4.2.2. Procedure of genetic algorithm

Figure 4 shows a flow chart of genetic algorithm. At first, initial population P(0) consists of Ni sorts of individuals (N_i=6) are generated at random. Then, the crossover and mutation operators are applied to those individuals. Through these operations, we obtained N (=N_i+N_c+N_m) sorts of individuals (N_c and N_m: individual numbers newly created by the crossover and the mutation). Next, the fitness of all individuals are calculated using the neural network model. The fitness means the criterion of each individual and it is given by the average value of TLL/SD at the last (=four) stage. Finally, individuals with higher fitness are selected as new individuals for the next generation based on ranking-based selection method and elitist strategy. In elitist strategy, the current best and better individuals are always copied to next generation. This process is continued until an optimal value can be obtained.

A 1-point crossover was implemented. Two individuals are first mated at random from the mating pool (population) and then two new strings are generated by swapping all binary characters from 1-bit to 3-bit position of the two 6-bit binary strings with each other. The crossover is implemented according to a crossover rate P_c. The mutation is based on a 1-point mutation and implemented by inverting one character, which is selected at random, in the 6-bit string from 1 to 0 and vice versa. The position for the mutation is randomly chosen. The mutation is applied according to a mutation rate P_m.

5. Results and discussion

5.1. Actual plant growth response

Figure 5 shows observed daily changes in TLL/SD, plant height, and stem diameter of tomato plants and cumulative light intensity during the seedling stage under three different nutrient concentration. From the figure, there are marked differences in the growth after 5 days and it is found that the response of TLL/SD is markedly affected by the nutrient concentration. The growth becomes larger as the nutrient concentration increases. An extremely low nutrient concentration severely reduces the stem growth. The data number N obtained here is 22. Here, the response of TLL/SD as affected by both nutrient concentration and light intensity is identified by using the neural network shown in Fig.2.

5.2. Identification results using neural network

Let's show the identification result. Figure 6 shows the comparisons between estimated responses (solid lines) and observed responses (dotted lines) of TLL/SD. For identification using the neural network, we have to determine the number of system parameter n and the number of hidden neuron N_h. These values were determined through trials and errors by examining the error between the model output and the observed output. The error decreased with increasing the system parameter number. However, we selected n=1 as a best value for the system parameter number from the viewpoints of computing time saving, effective identification and error minimization. The hidden neuron number N_h was also determined to be 5 from the same viewpoints. Hence, the neuron numbers are 5 (=3n+2) in the input layer, 5 in the hidden layer, and 1 in the output layer. All estimated responses showed a good agreement with observed responses. Thus, we could obtain a computational model for calculating the fitness (=average value of TLL/SD at four stage) as affected by any 4-step setpoints of nutrient concentration.

5.3. Search evolution characteristics

The searching process of an optimal value using the genetic algorithm is analogous to a natural evolution process. Figure 7 shows an evolution curve of the fitness. Horizontal axis indicates the iteration number for genetic operations, which is called "generation". The crossover rate P_c and mutation rate P_m used here are 0.8 and 0.8, respectively. The mutation rate used here is much higher than that in conventional ones (P_m<0.1). This is because recent studies in a molecular biology show a higher mutation rate. From the figure, the fitness dramatically increased with generation number and then reached the maximum value at 9th-generation. An optimal value is given by the individual with maximum fitness. Thus, we could rapidly obtain the optimal value without falling into local optima by using the genetic algorithm. This seems to be caused by the higher crossover and the higher mutation rate (Morimoto *et al.,* 1995b).

5.4. Optimal control performances in the model simulation and the actual experiment

Figure 8 shows the estimated optimal control performance of TLL/SD, which is calculated from the model simulation of neural network (upper figure). Lower figure represents the optimal 4-step setpoints of nutrient concentration obtained from the figure 7. Here, the nutrient concentration was limited in the range of 0.2 to 2.0 (mS/cm). The setpoints of nutrient concentration were recommended to be a little high level (NC_1=1.5 mS/cm) in the 1st-stage, a markedly low level (NC_2=0.3) in the 2nd-stage, a little high level (NC_3=1.6) in the 3rd-stage and a maximum level (NC_4=2.0) in the 4th-stage. The low nutrient concentration in the 2nd stage is thought to be effective to suppress the excessive vegetative growth during the seedling stage. The high nutrient concentration in the 3rd and 4th stages appears to be useful to accelerate the reproductive growth such as the fruit set of 1st truss and the flowering of 2nd truss.

Figure 9 shows an actual optimal control performance of TLL/SD. On the figure, daily changes in stem diameter and total leaf length are also shown. The solid line shows the optimal control performance and the dotted line represents the conventional control performance. The conventional strategy is to simply increase the nutrient concentration in steps along with the plant growth. Comparing both responses, it is apparent that the values of TLL/SD by the optimal control are 10-20% higher than those by the conventional control. We found that this is caused by the significant suppress of the stem growth with no reduction of the leaf growth from the figure.

6. Conclusion

An intelligent control technique combined with neural networks and genetic algorithms was applied to the optimal control of plant growth in hydroponics. The aim is to determine the optimal 4-step setpoints of nutrient concentration which maximize TLL/SD. The use of three-layer neural network made it possible to identify such complex system as the TLL/SD to both nutrient concentration and light intensity, and we obtained successful model to compute TLL/SD as affected by any nutrient concentration. By using the genetic algorithm, furthermore, we could quickly search for an optimal 4-step setpoints of nutrient concentration within 9-generation through simulation of the identified model when both crossover rate and mutation rate take high values, e.g., P_c=0.8 and P_m=0.8. This optimal value was effective for the actual control of plant growth. Thus, an intelligent control technique proposed here seems to be useful for the optimal control of such complex systems as physiological systems of plants.

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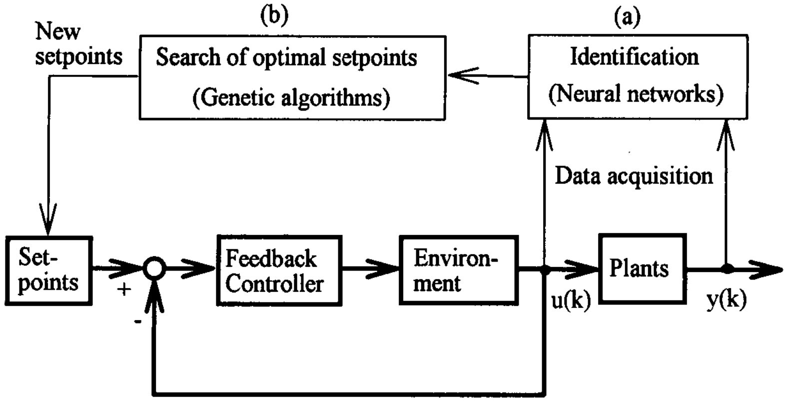

Fig. 1 Block diagram of an optimal control system of plant growth using neural networks and genetic algorithms

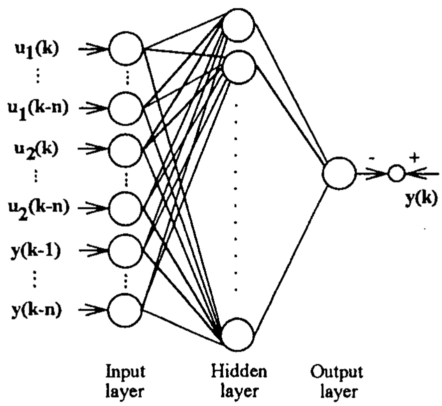

Fig. 2 Neural network architecture for process model identification

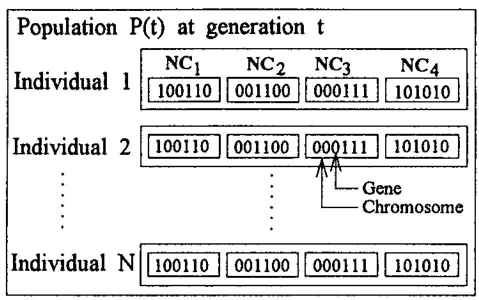

Fig. 3 Definition of individuals and the coding patterns for GA application

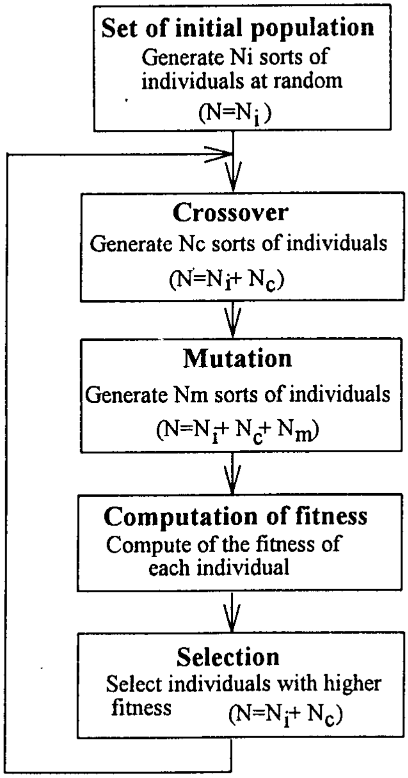

Fig. 4 Flow chart of the genetic algorithm used in the present study.

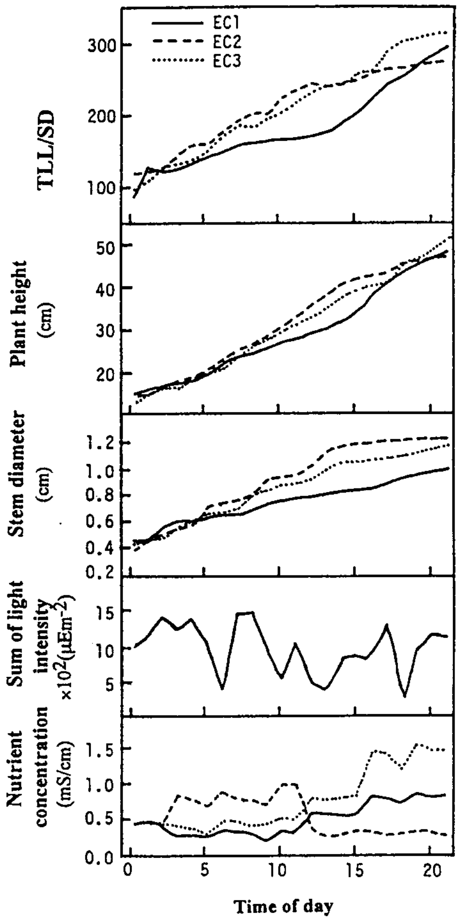

Fig. 5 Observed daily changes in TLL/SD, plant height, stem diameter, light intensity and nutrient concentration.

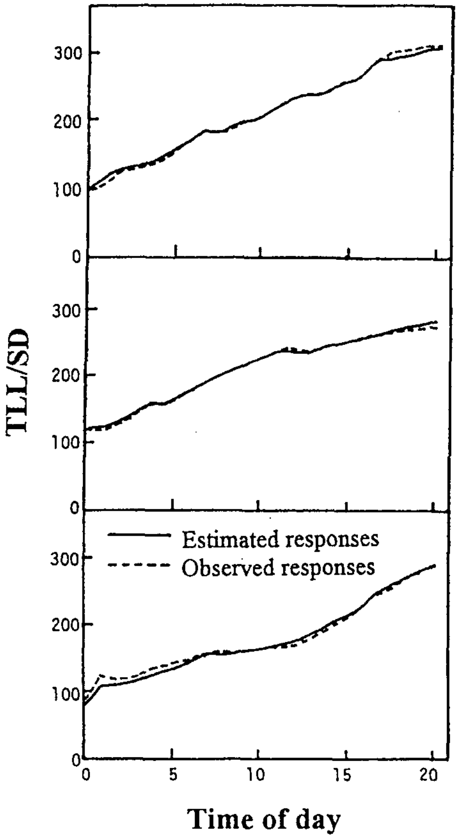

Fig. 6 Comparison of estimated response and observed response of TLL/SD.

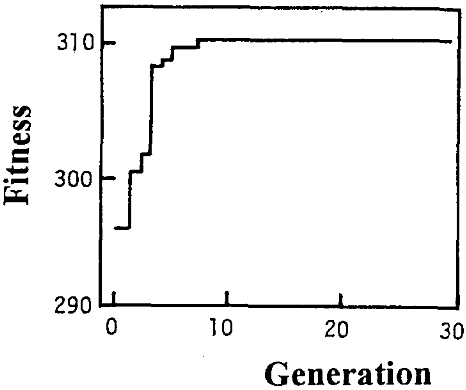

Fig. 7 Evolution curve of the fitness (P_c=0.8, P_m=0.8)

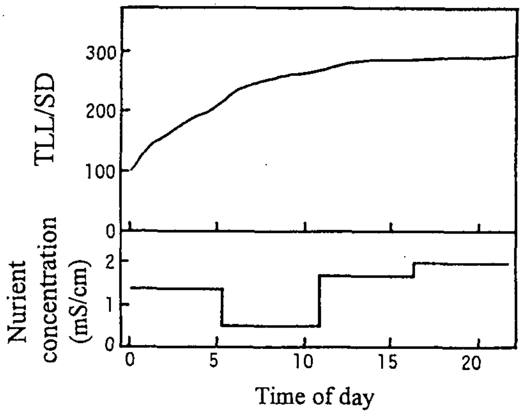

Fig. 8 Estimated optimal control performance of the TLL/SD as affected by 4-step nutrient concentrations.

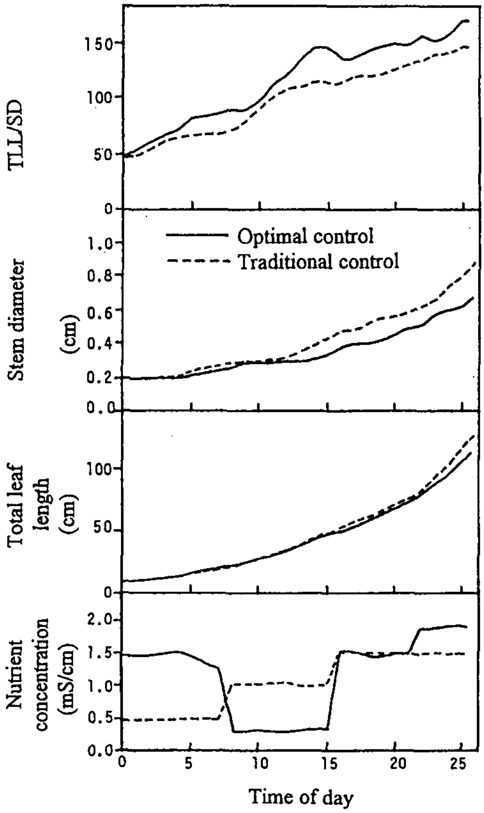

Fig. 9 Actual control performance of the TLL/SD as affected by 4-step nutrient concentrations.