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Research Article

Study and Simulation on Fuzzy Control Model for Crop Disease

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Abstract: In order to solve the precision medicine problem of crop diseases control, the conventional fuzzy model which applies to crop diseases control was established. Subordinate function, reasoning pattern and domain of discourse of fuzzy model were select. The computational process of the weight of five drug need fuzzy control sub model was mainly introduced and AHP and Neural Networks were adopted. Self-learning fuzzy control model for crop disease control was proposed to make control rules study and better adapt the on-site work environment. The result of MATLAB showed an expected effect of controlling the spray rate of the system. The study provided a new control strategy and method to realize intelligent control of precision spraying for crop.

Keywords: Crops disease stress, fuzzy control, precision spraying, self-learning fuzzy control system

INTRODUCTION

At present, crop diseases are generally evaluated by crop growth symptoms or the environment. The species and extent of crop disease are estimated by metabolism-related morphological characteristics of plant growth and the changes of environmental conditions and many other factors. Physiological information is not taken into consideration when crop suffers diseases. Chemical control (Wang and Hong, 2004) is still one of the major initiatives of controlling pests and eliminating eradication bases. The area of taking chemical prevention takes up 70% of the entire area that prevent pests. Good controlling efforts could be achieved through correct using of agricultural chemicals to make timely prevention on the premise of good forecast. However, application is not precise when preventing through chemical control, which results in chemical harm to crops and decline of the quality of agricultural products, excessive pesticide residues, ecological deterioration of the environment. Thus, making accurate, fast, reliable judgments on the level of crop diseases and making adaption according to the circumstances and cure disease control are particularly important.

Literature (Wang and Hong, 2004; Blodgett *et al*., 1997; Shen *et al*., 1999) studies show that, the frequency of its sound increases with the level of diseases stress to some extent and have a certain statistical regularity in different disease conditions. Acoustic emission signals, used as physiological indicators of Crop disease stress, determine the current crop of disease the current level of crop diseases (Blodgett *et al*., 1997; Shen *et al*., 1999). Based on the theory of acoustic emission technology, analyze the signal obtained from acoustic emission sensors and research the correlation between acoustic emission signals and the extent of crop diseases and the physiological state (Han *et al*., 2006; Kang *et al*., 2004; Zhang *et al*., 2006; Huo and Yang, 2002; Yang and Guo, 2009), combining the characteristics of crop diseases by stress, water stress and other environmental factors, to achieve crop spraying and adjustment according to the situation. However, the relationship among environmental parameters, transpiration, plant acoustic emission signals and the amount of drug required cannot be expressed by precise mathematical model. It is not appropriate to determine the amount of plant spraying simply referring to one factor. Fuzzy Control is a Kind of artificial intelligence control strategy expressed by language rules, which does not need accurate mathematical model while can take full advantage of production experience of On-site staff. In This study ambient temperature, humidity, light intensity, CO_2 concentration and AE are taken as input of the fuzzy control system. And the amount of the current amount of delivery is determined by these factors. In order to facilitate a virtuous cycle of ecological agriculture, sustainable development of agricultural production and protect human health and survival, we design a conventional fuzzy control model which provides accurate disease prevention and treatment and establish a new type of fuzzy control system spraying to improve the effect of spraying.

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CROP DISEASE CONTROL FUZZY CONTROL SYSTEM

Based on the above analysis, the Crop disease control fuzzy control system use four sensors separately detect the ambient temperature T, humidity H, light LI and CO_2 concentration C. considering the correlation between acoustic emission frequency and environmental factors, the frequency of acoustic emission signals detected by A R15 type Acoustic emission sensor AE is taken as input signal of the system along.

The 5-input single-output fuzzy control model established by the software of MATLAB is shown in Fig. 1. When precise control spraying, acoustic emission frequencies AE are overwhelmingly dominant and at the same time they reflect the current dosage required and supplied. T values directly reflect the temperature, importance only secondary to AE. H values reflect humidity, which has a comparatively important impact on the amount of administration, slightly less important than T. LI values reflect the light intensity, importance secondary to H. C values reflect the concentration of CO_2, the lowest level of importance. w_i (i = 1, 2, 3, 4, 5) are the weights of the 5 inputs. According to the site analysis, each of the 5 inputs has a varying influence on the amount of administration and they affect each other. Therefore, they also affect the weights of administration amount. Drawing on the weighted average method, every output of the SISO control model is weighted and then averaged, expressed in:

$$U = f\,(w_1AE + w_2T + w_3H + w_4LI + w_5C) \qquad (1)$$

where,
U : The output of the fuzzy control model
F : The relationship between the fuzzy controls

Multi-input power value (Ercument, 2003; Li and Zhang, 1996; Weisong and Chih-Hsin, 2001) plays a dominant role in the design of the control system and the accuracy of each input's weight determines the merits of the whole control system performance. It's confirmed that there is no proper reference having studied to get the degree of influence that the 5 input signals in disease prevention and control system have on the administration. According to the distribution analysis of the five volumes in the preliminary studies, there are many affecting factors to dose required when plants experience disease stress, not just considering AE, but also the temperature, humidity, CO_2, light and other impacts. If the relationship between the 5 inputs and the impact on the input of the regulator are not clear, the current administration amount cannot be synthesized according to the 5 inputs, which means that control system performance cannot be achieved to guarantee disease control systems working properly.

BP algorithm is adopted to learn the network in the study, here is the analysis of the BP algorithm. In neural network the relationship between the input variables and output variables is achieved through the connection weights between the input layer and hidden layer and hidden layer and output layer. Network need to be tested before use. The learning process of network can be divided into two parts-forward propagation and backward propagation. In the process of forward propagation, the state of each neuron only affects the output of the next layer of the neural network. If we cannot get the desired result in the output layer, which means that there is error between actual output and expected output. And we turned back to backward propagation and return the error message along the original communication channel successively to the input layer by modifying the weights and thresholds that connect layers of neurons. Calculate to see the error and if not satisfactory spread the error message through the forward process until the error signal reaches the least or desired requirements after repeated use of the processes. Then networking training process is completed. Networking learning process is as follows:

Assume N samples (x_k, t_k) (k = 1, 2,…, N), O_i representing the output of every node. a_k represents the output from the network corresponding to any possible input x_k. The whole inputs $net_{jk}^{l} = \sum_i w_{ij}^{l} O_{ik}^{l-1}$ put into

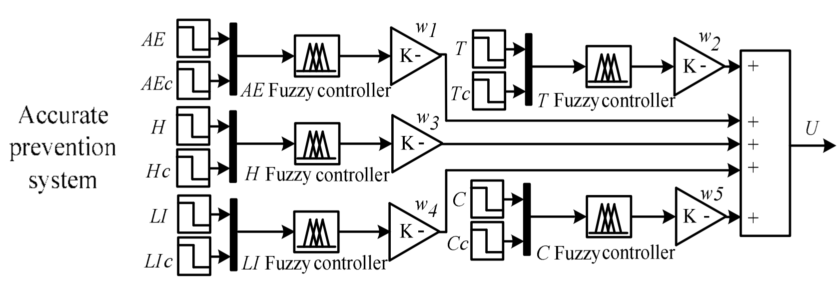


Fig. 1: Fuzzy control system on disease preserve

the node j of the first layer are expressed by, where represents the output of the l-1 layer when the k[th] sample is input and w_{ij}^{l} represents the connection weights between node j of the 1[st] layer and node I of the l-1 layer. The output of node j from the l[th] layer is expressed by $O_{jk}^{l} = O_{jk}^{l} = f(net_{jk}^{l})$. Squared error function is used here: $E_k = \frac{1}{2}\sum_j (t_{jk} - a_{jk})^2$, where a_{jk} represents the actual output of node j. The total error is:

$$E = \frac{1}{2N}\sum_{k=1}^{N} E_k \text{ , } \delta_{jk}^{l} = \frac{\partial E_k}{\partial net_{jk}^{l}} \text{ ,}$$

$$\frac{\partial E_k}{\partial w_{ij}^{l}} = \frac{\partial E_k}{\partial net_{jk}^{l}} \frac{\partial net_{jk}^{l}}{\partial w_{ij}^{l}} = \frac{\partial E_k}{\partial net_{jk}^{l}} O_{ik}^{l-1} \tag{2}$$

Here are two cases caused by whether node j is the output unit to discuss:

- If node j is the output unit, then $O_{jk}^{l} = a_{jk}$:

$$\delta_{jk}^{l} = \frac{\partial E_k}{\partial net_{jk}^{l}} = \frac{\partial E_k}{\partial a_{jk}} \frac{\partial a_{jk}}{\partial net_{jk}^{l}}$$
$$= -(t_k - a_k) f'(net_{jk}^{l})$$

$$\frac{\partial E_k}{\partial w_{ij}^{l}} = \frac{\partial E_k}{\partial net_{jk}^{l}} O_{ik}^{l-1} = \delta_{jk}^{l} O_{ik}^{l-1}$$
$$= -(t_k - a_k) f'(net_{jk}^{l}) O_{ik}^{l-1} \tag{3}$$

- If node j is the hidden layer unit, then:

$$\delta_{jk}^{l} = \frac{\partial E_k}{\partial net_{jk}^{l}} = \frac{\partial E_k}{\partial O_{jk}^{l}} \frac{\partial O_{jk}^{l}}{\partial net_{jk}^{l}}$$
$$= \frac{\partial E_k}{\partial O_{jk}^{l}} f'(net_{jk}^{l}) \tag{4}$$

where, O_{jk}^{l} is the input sent into the (l+1) level. It needs to be counted back to work out $\frac{\partial E_k}{\partial O_{jk}^{l}}$:

$$\frac{\partial E_k}{\partial O_{jk}^{l}} = \sum_m \frac{\partial E_k}{\partial net_{mk}^{l+1}} \frac{\partial net_{mk}^{l+1}}{\partial O_{jk}^{l}}$$
$$= \sum_m \frac{\partial E_k}{\partial net_{mk}^{l+1}} w_{mj}^{l+1} = \sum_m \delta_{mk}^{l+1} w_{mj}^{l+1} \tag{5}$$

where, m is the neurons from the l+1 layer. We can get from the previous two equations:

$$\delta_{jk}^{l} = \sum \delta_{mk}^{l+1} w_{mj}^{l+1} f'(net_{jk}^{l})$$

Then,

$$\frac{\partial E_k}{\partial w_{ij}^{l}} = \frac{\partial E_k}{\partial net_{jk}^{l}} O_{ik}^{l-1} = \delta_{jk}^{l} O_{ik}^{l-1}$$
$$= \sum \delta_{mk}^{l+1} w_{mj}^{l+1} f'(net_{jk}^{l}) O_{ik}^{l-1} \tag{6}$$

Derived from the above formula we can see that the back-propagation algorithm steps can be summarized as follows:

- Initialize the network and learning parameters
- Repeat the following process until meet the requirement:
  - From k = 1 to N, forward process of computing: calculate O_{jk}^{l}, a_k and net_{jk} $(k = 2, \dots, N)$, every unit from each layer. The reverse calculation process: calculate from the output layer and hidden layer δ_{jk}^{l}
  - Weights correction. $\Delta W_{ij} = -\mu \frac{\partial E}{\partial w_{ij}}, \mu > 0, \mu$ is the step, where $\frac{\partial E}{\partial w_{ij}} = \sum_{k=1}^{N} \frac{\partial E_k}{\partial w_{ij}}$

The process of BP algorithm is as follows:

- **Network initialization:** The system uses a small random number set as the initial values for weights.
- **The input of input vector (forward):** First, enter the input vector to the input layer and subsequently the input vector will spread to the output layer. And then calculate the sum of additional weights. So the output value will be converted to be determined by double bending function. the formula is as follows:

Output value = f (sum of input) (7)

1. The input of teacher signal to the output layer. Provide teacher vector corresponding to the input vector to the output layer.
2. Learning error back-propagation weights. According to:

New Weights = Sum of Used Weights + cons tan ts×Neuron Output (8)

update the weights. Neuron output in the expression refers to the previous of the two neurons that weights connect. δ is calculated by the following expression. When learning weights that connect the output values:

δ = output× [1 - output] × [Teachers Signals - Neuron Output] (9)

Besides when learning weights:

δ = output× [1 - output] × [The Immediately Subsequent Sum of Additional Weights of δ] (10)

3. Return to the 2nd step. Repeat the 2nd to 4th steps to study weights:

$$S_i = \sum_{j=0}^{n} x_j W_{ji} = \sum_{j=1}^{n} x_j W_{ji} - \theta_i = X \cdot W_i \quad (11)$$

4. Finally, put the sum of weights of each node into the activation function F(•) and we can get the output value Y_i:

$$Y_i = F(S_i) = F(\sum_{j=0}^{n} x_j W_{ji}) = F(X \cdot W_i) \quad (12)$$

As we only get the relationship between the neural networks through the neural network training, we still need to research and analyze weights between various neurons if we want to get the decision-making weights that the input factors have on the output factors. In order to achieve this, we can use the following indicators to describe the relationship between the input factors and the output factors:

- Significant correlation coefficient:

  $\tau_{ij} = \sum_{k=1}^{p} w_{ki(1-e^{-x})\,(1-e^{-x})}$

  where, x = w_{jk}
- Related index:

  $R_{ij}a_k = |(1-e^{-y})/(1+e^{-y})|$

  where, y = τ_{ij}. Absolute impact factor:

  $S_{ij} = R_{ij}/\sum_{i=1}^{m} R_{ij}$

  where,
  i : Neural network input unit and values from 1 to m
  j : Neural network output unit and values from 1 to n
  k : The hidden unit of the neural network and values from 1 to p
  w_{ki} : The weight between i and k
  w_{jk} : The weight between j and k

  In accordance with (13~15), weights of AE, T, H, LI and C were respectively 0.0564, 0.0847, 0.5523, 0.5531 and 0.3066.

Sample once every six seconds and collect 100 sets of data, average the data collected within 2 min. When precise control spraying, set the reference values of AE and four parameters (T, H, LI, C) respectively as 0.8, 0.6, 0.8, 0.7 and 2.5. From the data collection, we can see that AE varies between 0.1 to 1.35 when precise control spraying, based on which the range is defined as 0.1 to 1.5. In the meanwhile calculate the deviation between the actual value and the reference value, resulting in the deviation range of roughly -0.7 to 0.7 and error change rate range of roughly -0.35 to 0.35; T varies between 0.2 to 1.0 and in the meanwhile calculate the deviation between T and the set reference value and we can obtain that the deviation ranges between roughly -0.4 to 0.4 and the error change rate ranges roughly between -0.2 to 0.2; LI varies between 0.1 to 1.5 and meanwhile calculate the deviation between LI and its set reference value and we can get that the deviation ranges between -0.7 to 0.7 and the error change rate ranges roughly between -0.35 and 0.35. Assume that the linguistic variables of input deviation are E1, E2, E3, E4, E5 and their basic discourse settings are E1 = [-│0.7│, │0.7│], E2 = [-│0.4│, │0.4│], E3 = [-│0.7│, │0.7│], E4 = [-│0.4│, │0.4│], E5 = [-│1.5│, │1.5│]. Its corresponding fuzzy sets are $\underset{\sim}{A}_i$, $\underset{\sim}{B}_i$, $\underset{\sim}{C}_i$, $\underset{\sim}{D}_i$, $\underset{\sim}{E}_i$, (i = 0, 1,…. 7) and fuzzy discourses are X, Y, Z, W, M. amongst X, Y, Z are divided into seven levels and their fuzzy language sets are {NB, NM, NS, ZO, PS, PM, PB}. The language values of fuzzy subsets are from {negative and larger, negative with middle, negative and smaller, zero, positive and smaller, positive and middle, positive and larger}. The linguistic variables of output control u_1 are U_1 and its basic domain is u_1 [10, 50]. And its corresponding set is $\underset{\sim}{E}_i$ (i = 1, 2,… 5) and its domain is V divided into nine levels. Its fuzzy language sets are {A, B, C, D, E, F, G, H, I} and language values from {special low, low, lower than in, in large and medium, high, high, rated}.

Triangular, trapezoidal, bell-shaped and Gaussian-type are four common types in fuzzy control system. These membership functions are characterized by being continuous and derivation available at every point and they are more suitable for correction of adaptive membership function with self-learning fuzzy control. The seven fuzzy sets are from {negative and larger, negative with middle, negative and smaller, zero, positive and smaller, positive and middle, positive and larger}. Generally speaking, steeper the shape of membership function is, higher the sensitivity of control is; conversely, if change of the membership function is slow, the characteristics of control are more smooth and the stability of the system is better. The shape and distribution of triangular membership function are expressed by three parameters. As its shape is related to slope of the line, it's suitable for online adjustment. Triangular membership function is adopted in the study. It is described by:

Table 1: The regulator position control rules

(a) AE

E \ Ec	NB	NS	ZO	PS	PB
PB	A	B	C	D	E
PZ	B	C	D	E	F
PS	C	D	E	F	G
ZO	D	E	F	G	H
NS	E	F	G	H	I
NZ	F	G	H	I	I
NB	I	I	I	I	I

(b) T

E \ Ec	PB	PS	ZO	NS	NB
PB	I	I	I	H	H
PZ	I	I	H	H	G
PS	I	I	H	G	F
ZO	I	H	G	F	E
NS	H	G	F	E	D
NZ	G	F	E	D	C
NB	F	E	D	C	B

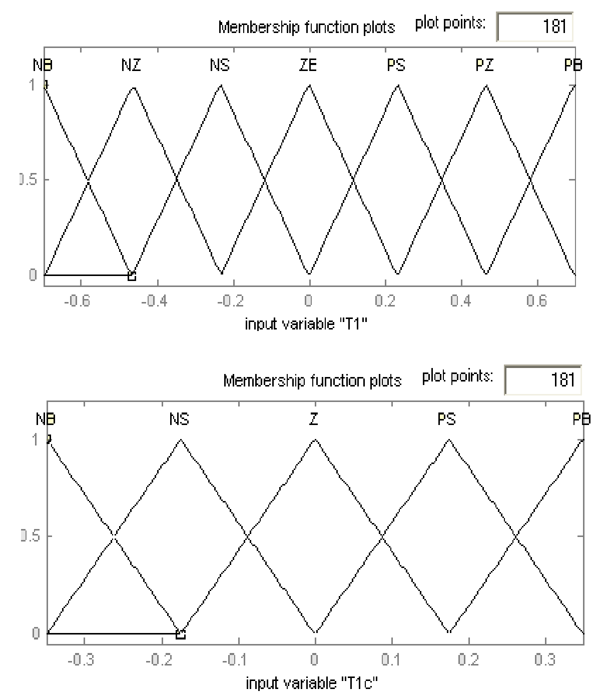


Fig. 2: Sugeno reasoning AE, T

$$\mu(x)\begin{cases}(x-a)/(b-a), a<x<b \\ (x-c0/(b-c), b<x<c\end{cases} \quad (13)$$

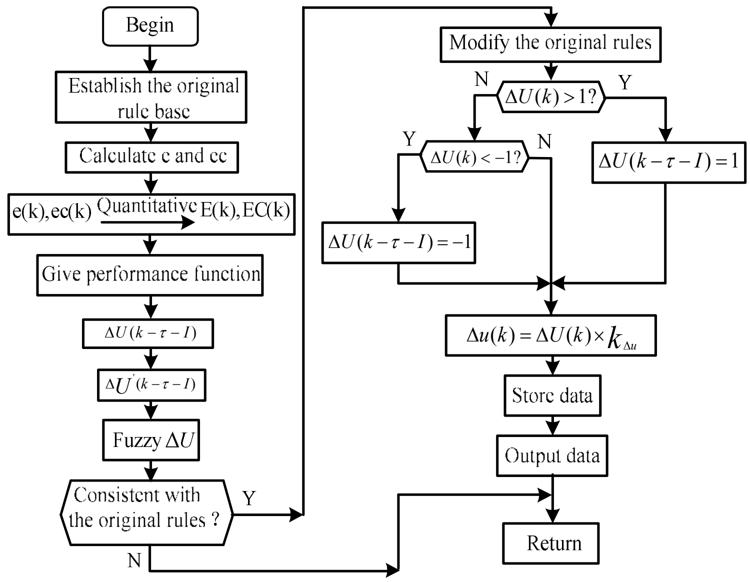
Firstly, E = given value-the actual measured value for the sub-model of AE. If deviation of disease control E is positive, it indicates that the measured value is less than the ideal value and the output value of drug regulator should be increased until to the rated output from the value position; If the error E is zero, it indicates that it's the ideal value and meanwhile the drug regulator can maintain the desired output value; if E is negative, it indicates that the current output of drug regulator is higher than the ideal value. If drugs required of the regions in the field are small, there is no need to provide extra dose of medicine. Savings could be achieved by appropriate decreasing the output value; the output of fuzzy control model is input for the drug regulator and its ideal value can be set to a fixed value. Ec = E (k) - E (k - 1) for deviation of AE's sub-model; and the rate of deviation change is negative, which indicates that the new dose required is smaller than the original. You should decrease the input of regulator by a level to save drug; if the error rate is zero, it indicates that there is no change of the dose required and the regulator could be handled by deviations; if the error rate is positive, it indicates that the new dose required is larger than the original, or it has a larger trend; at this situation the input should be increased by a level to prevent a rather large increase on administration.

As there are three cases of error and its change rate, the inputs of regulator could be divided into nine levels according to the control strategy and they are A, B, C, D, E, F, G and H, I, respectively representing value degrees of 5, 10, 15, 20, 25, 30, 35, 40 and 45. The ideal frequency is set to 30. The principles of control for other sub-models and sub-models of AE are similar and they won't be repeated here. In summary, the definitions of administration of AE, T, H, LI, C sub-models and relationship between value position control are shown in children a, b of Table 1.

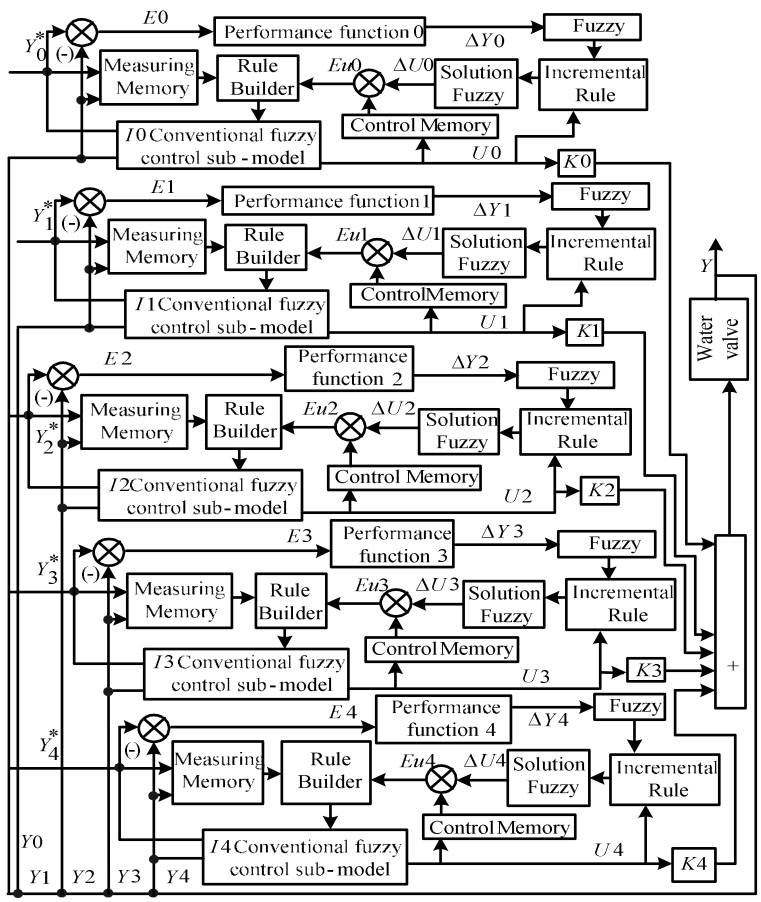
The fuzzy reasoning is conducted while fuzzy rules are confirmed. Fuzzy reasoning sometimes is known as likelihood reasoning. Ma Danni minimal algorithm and Sugeno algorithm are the basic ways of reasoning and Sugeno algorithm is suitable for the case of monotonic membership function. Because the express of Sugeno system is simple and the calculation is easy and fuzzy systems can be constructed using adaptive technology, which makes the fuzzy system more practical. The system will automatically adapt to membership functions and rules of the regulator according to the actual disease situation of crop growth environment and the operation of regulator, so Sugeno reasoning is more effective. In this study Sugeno reasoning method is adopted and trigonometric functions are used as membership functions of the inputs shown in Fig. 2.

SELF-LEARNING FUZZY CONTROL MODEL FOR CROP DISEASE CONTROL

In order to enhance the ability to learn the system to the environment, this study found a field environment for self-learning fuzzy model precision spraying, its



(a)



(b)

Fig. 3: Algorithm flowchart of self-training fuzzy control in disease preserve, and self-learning fuzzy control model in precise preserve

structure consisted with the conventional fuzzy control model, only to each fuzzy model for self-learning training.

As mentioned above, accurate control spraying MISO fuzzy control model according to the decoupling theorem of SISO sub-divided into five fuzzy control model, were set five single-input single-output sub-fuzzy control model and then each self-learning fuzzy control model according to the weighted average method to form a model. Were established five inputs and demand dose relationship between the input and output, to express the characteristics of the controlled object? Precise control on spraying systems, system administration depends primarily on AE, but also taking into account the temperature and other environmental factors. In order to facilitate the establishment of expression, make the following assumptions. Regulator to a certain rotation speed and stability, the resulting flow and speed is proportional to dose. And liquid flow rate regulator output proportional relationship exists between. That the role of the solenoid valve flow area same as the export A_0, the flow rate unchanged at v_0. Administration of the export pipeline to reach the initial velocity, assuming this process through the time $t = l_0/v_0$, where l_0 is the distance from plant to the export pipeline. Assuming the export pipeline basal area is A. y (k + 1) and y (k), respectively and k times the amount of time the pesticide. Set delay time t of 10s. Selected time step 1s, then the sampling time k, AE self-learning fuzzy control, said:

$$Y(k) = (l_0/v_0)\, y(k-1) + A_0/Au\,(k-10) \tag{14}$$

Similarly, the establishment of T, H, LI sampling time k self-learning fuzzy control:

$$Y(k) = (l_0/v_0)\, y(k-1) + A_0/Au\,(k-160) \tag{15}$$

$$Y(k) = (l_0/v_0)\, y(k-1) + A_0/Au\,(k-330) \tag{16}$$

$$Y(k) = (l_0/v_0)\, y(k-1) + A_0/Au\,(k-400) \tag{17}$$

The fuzzy self-learning control algorithm to calculate the precise control after spraying were obtained when the AE, T, H, LI relationship between the new fuzzy control, respectively:

$$\underset{\sim}{R}_{D1} = \begin{array}{cccccc} \underset{\sim}{A}_i{:}\underset{\sim}{B}_j: & NB & NS & ZO & PS & PB \\ PB & -1 & -0.7 & -0.5 & -0.2 & 0 \\ PZ & -0.8 & -0.6 & -0.4 & -0.1 & 0.1 \\ PS & -0.5 & -0.3 & -0.1 & 0.2 & 0.4 \\ ZO & -0.2 & 0 & 0.2 & 0.4 & 0.7 \\ NS & 0 & 0.2 & 0.5 & 0.7 & 0.9 \\ NZ & 0.4 & 0.6 & 0.8 & 1 & 1 \\ NB & 1 & 1 & 1 & 1 & 1 \end{array}$$

$$\underset{\sim}{R}_{D2} = \begin{array}{cccccc} \underset{\sim}{A}_i{:}\underset{\sim}{B}_j: & PB & PS & ZO & NS & NB \\ PB & 1 & 1 & 1 & 0.8 & 0.6 \\ PZ & 1 & 1 & 0.8 & 0.5 & 0.3 \\ PS & 1 & 0.7 & 0.6 & 0.4 & 0.1 \\ ZO & 0.8 & 0.6 & 0.3 & 0.1 & -0.1 \\ NS & 0.5 & 0.3 & 0 & -0.2 & -0.4 \\ NZ & 0 & -0.2 & -0.4 & -0.6 & -0.8 \\ NB & -0.1 & -0.3 & -0.5 & -0.8 & -1 \end{array} \tag{18}$$

Self-learning fuzzy control fuzzy control in the conventional model is based on the model, the output response of the deviation between the ideal responses for processing, modify or create new rules to produce better online control performance. Achieve disease control model for self-learning fuzzy control algorithm flow shown in Fig. 3a.

In the above algorithm, based on the establishment of precise control pesticide self-learning fuzzy control model shown in Fig. 3b. In practical applications by detecting the AE to select the appropriate fuzzy model to determine the job done.

EXPERIMENTS AND RESULT ANALYSIS

In order to verify the effectiveness of the fuzzy control model of accurate control system based on crop diseases, the experiment was carried through. Figure 4 is experiment platform and AE installation diagram. Precision irrigation and precise control when spraying 100 sets of data were collected. For five different input parameters, the fuzzy rules are put into application to control the output. Part of the simulation data in Table 2. As the speed changes more subtle, so only a representative list of simulation results. Precise control of crop spraying in the five fuzzy control system changes required input fuzzy control model gives the corresponding speed for a given value, through the system to automatically adjust the speed of the solenoid valve is controlled to achieve the desired given value, so as to achieve a given dose.

As can be seen from Table 2, even five different inputs, the output speed may be the same, because the amount of five weights each according to the result. From Table 2, the speed trend can be seen in

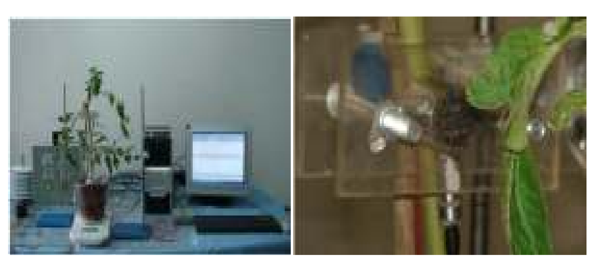


Fig. 4: MISO model of fuzzy control on disease preserve

Table 2: Simulation data of spraying dose

AE	AEC	T	TC	H	HC	LI	LIC	C	CC	Charge (l)
-1.40	-0.3	-0.4	-0.2	-0.6	-0.4	-1.50	0.5	-1.50	0.5	3.0
2.40	0.0	1.0	0.0	1.4	0.0	0.10	0.0	0.10	0.0	4.5
	0.3		0.2		0.4		-0.5		-0.5	6.9
1.05	-0.3	-0.2	-0.2	-0.3	-0.4	-0.75	0.5	-0.75	0.5	5.1
2.05	0.0	0.8	0.0	1.1	0.0	0.85	0.0	0.85	0.0	6.0
	0.3		0.2		0.4		-0.5		-0.5	6.3
-0.70	-0.3	0.0	-0.2	0.0	-0.4	0.00	0.5	0.00	0.5	5.7
1.70	0.0	0.6	0.0	0.8	0.0	1.60	0.0	1.60	0.0	6.3
	0.3		0.2		0.4		-0.5		-0.5	7.8
0.35	-0.3	0.2	-0.2	0.3	-0.4	0.75	0.5	0.75	0.5	6.9
1.35	0.0	0.4	0.0	0.5	0.0	2.35	0.0	2.35	0.0	8.4
	0.3		0.2		0.4		-0.5		-0.5	9.9
0.00	-0.3	0.4	-0.2	0.6	-0.4	1.50	0.5	1.50	0.5	9.9
1.00	0.0	0.2	0.0	0.2	0.0	3.10	0.0	3.10	0.0	11.4
	0.3		0.2		0.4		-0.5		-0.5	12.0

conventional combat, when the five inputs are less than the value, the output speed is relatively small, but with different degrees of deviation changes increase or decrease; when five set near the input value changes, the output speed set near the ideal value fluctuate with changes in deviation; when five input exceeds a set value, the output speed higher, even up to the maximum speed solenoid valve.

CONCLUSION

The theoretical basis of acoustic emission technology, according to acoustic emission signal and the degree of crop diseases, the relationship between the physiological state, crop diseases by stress, water stress and other environmental factors affect characteristics, design of irrigation and precision crop disease control precision of conventional dual-mode fuzzy control model. In order to overcome the subjective rule-making impact on the quality control system, in the structural design of fuzzy control model introduced self-learning function, proposed a crop for self-learning fuzzy control algorithm and the establishment of a crop disease control precision irrigation and accurate self-learning fuzzy control model, the fuzzy control system with self-perfection. The system is running with the revised work rules to adapt to changes in the actual situation. Simulation results show that the control strategy to overcome the existence of other control methods inefficient, excessive fertilization problems of pesticides, precision for the use of pesticides and new plant protection machinery lay the foundation for the design of information technology, crop physiological signal detection will be integrated with the precise control of the disease a new way.

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