Design and Verification of Fuzzy Neural Network Automatic Control Algorithm in Intelligent Agriculture

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Abstract: Through the analysis and in-depth study of the fuzzy control system model and neural network, the optimal control strategy is obtained by the organic combination of fuzzy reasoning and neural network analysis training, and the automatic control algorithm based on fuzzy neural network is designed. The modified algorithm is applied and verified in Modern Agriculture Demonstration Park of Chengdu Agricultural College. The results show that the designed algorithm can meet the demand of automatic control in the field of intelligent agricultural control, and the control system has good universality and scalability. The application of automatic control algorithm based on fuzzy neural network can accelerate the development of agricultural modernization in China, and lay a solid foundation for the further research on the application of automatic control in other fields.

1. Introduction
Due to the continuous development of information technology, the planting methods of agricultural production and management have been transformed to modern agriculture with mechanization, precision and intelligence. Farm in developed countries, intelligent agricultural production, operation and management systems are common. Intelligent management means using WSN to automatically collect environmental parameter information of crop growth process and automatic methods to realize the monitoring, control, management and storage of crop growth environment, which can not only effectively improve crop yield, but also ensure product quality. In China, intelligent agricultural production management methods have not been well promoted and applied, but with the in-depth application of the Internet of things technology, the state from the policy and economic support and investment in agriculture, many smart agricultural demonstration parks have begun to take shape.

In the automatic control technology of intelligent agriculture, it is difficult to model the environment object accurately due to the continuous changes of environmental data. Based on this, the existing fuzzy control can’t meet the automatic control requirements of intelligent agriculture with dynamic change of agricultural environment, and the adaptability of current application of the analysis of agricultural environment change and the verification of neural network analysis algorithm in the agricultural environment is poor.

2. Model analysis of fuzzy control system
Fuzzy control is a technique based on fuzzy set theory and fuzzy logic reasoning, which is mainly nonlinear control in the field of intelligent control. The conventional control method requires accurate
modeling operation for the project. The more accurate the modeling is, the more accurate the corresponding control information will be. However, in real application scenarios, the dependent variable changes dynamically in real time. If we try to achieve the goal of simplifying the system by controlling the parameters, the corresponding control information is usually not accurate. Therefore, in the agricultural production environment, the fuzzy control algorithm can play the role of automatic control in the practical application scenarios with many variables. The system consists of selecting input variables, fuzzy controller, actuator, controlled object and transmitter. Fuzzy control system model, as shown in Fig 1.

![Fuzzy control system model](image1)

Fig 1. Fuzzy control system model

The formulation of fuzzy control rules is the key part of fuzzy control system. In general, the control system is determined based on the expert experience calculation and the field staff experience acquisition two methods through If...Then determines the fuzzy control rules. Fuzzy control algorithm does not rely on accurate mathematical model in the application site, even if it can achieve intelligent control of the system, it is difficult to quickly adjust the system to the best state, can be based on the operation and experience to obtain membership functions and fuzzy control rules, do not rely on the accurate model of the application site. Therefore, even if the intelligent control of complex system can be realized, it is difficult to make the system adjust to the optimal state relatively quickly.

3. An overview of neural networks

The neural network has shown its extraordinary advantages in pattern recognition and classification, recognition and filtering, automatic control and prediction, and obtains certain regularity from the mass of information through continuous analysis and adaptive training. BP algorithm in the field of automatic control and intelligent use of the most common, the BP network can learn and store a lot of input-output model mapping, is a kind of is obtained by error back propagation algorithm training of the multilayer feedforward network, using the method of gradient descent continuously adjust the threshold and the weights of network, to minimize the sum of square error of network. BP algorithm is composed of two processes: forward propagation of data stream and back propagation of error signal. The topology of neural network includes input layer, hidden layer and output layer, as shown in Fig 2.

![BP neural network structure](image2)

Fig 2. BP neural network structure

In the BP network algorithm, the signal is calculated in the forward direction, and when the threshold and weight are adjusted by error, the error of the previous layer is estimated according to the
corresponding error output of each layer, so as to obtain the corresponding error value of the whole network. Due to its strong self-learning ability and nonlinear mapping ability, it can train for the information in real industrial and agricultural situations and obtain the optimal control strategy.

4. Design algorithms based on fuzzy neural network

Fuzzy neural network is the product of the combination of fuzzy control theory and neural network, which combines learning, association, recognition and information processing. Fuzzy control does not depend on the accurate model, so the reasoning speed is slow and the accuracy is low. While the neural network analysis algorithm can learn the scene data and obtain the optimal control strategy, but it cannot process the fuzzy information. Therefore, the combination of fuzzy control and neural network analysis can complement each other, and the processing of fuzzy information in the agricultural field, and the system's optimal fuzzy control rules and strategies can be obtained through training. In addition, the input signal has a great advantage in the processing of fuzzy quantity, and the training of samples can be used to adjust the network weight and deviation, fast convergence speed, and improve the efficiency of the algorithm.

The topology of fuzzy neural network is composed of four layers, as shown in Fig3. The first layer is the input layer, which transmits the input fuzzy parameters to the lower layer. The second layer is the subjection function layer, which describes the subjection degree of the input parameters and is generally expressed by trigonometric functions. The third layer is the control rule layer, which covers the relevant rules of fuzzy control. The fourth layer is the output layer, the neural network processing the output of information.

Fig 3. Structure of fuzzy neural network

The corresponding transmission rules between different layers of the fuzzy neural network algorithm are as follows:

\[ S_i^k = w_{ij}^k \cdot u_j^k \]  \hspace{1cm} (3-1)

In the above formula:
- \( S_i^k \) : Represents the input of the layer k node;
- \( w_{ij}^k \) : Represents the weight value of the i node corresponding to the k layer and the j node corresponding to the k-1 layer;
- \( u_j^k \) : Represents the j input connected to the i node, \( q_i^k \) : Represents the corresponding output of the k layer node;

The first layer is the input layer, where the input of this layer can be passed to the lower output. The input/output relationship is:

\[ S_1^1 = w_{1j}^1 \cdot u_j^1 \] \hspace{1cm} (3-2)
\[ q_1^1 = S_1^1 \] \hspace{1cm} (3-3)

In the above formula, \( q_1^1 \) is the output of the node of layer 1.
The second layer is the membership function layer, which focuses on describing the membership degree of input parameters, which is generally expressed by trigonometric functions. The corresponding input-output relationship is as follows:

\[
S_i^2 = -(u_j^2 - m_{ij})^2 / (\sigma_{ij})^2 \tag{3-4}
\]

\[
\alpha_i^2 = \exp(S_i^2) \tag{3-5}
\]

In the above formula, \(m_{ij}\) represents the j-th input \(u_j^2\) compared to the i-th member function, the corresponding average case;

\(\alpha_{ij}\) : Represents the j-th input \(u_j^2\) compared with the i-th membership function, the corresponding variance;

\(\alpha_i^2\) : Represents the output of the second level node.

The weight of the second layer is \(\alpha_{ij}\), \(m_{ij}\) is the threshold.

The third layer is the control rule layer, which realizes the operation of all the fuzzy control rules. Select the method of multiplication for relevant operation, let \(w_{ij}^2\) be 1, The corresponding input-output relation of the i-th rule is as follows:

\[
S_i^2 = \prod_{j=1}^n w_{ij}^2 \cdot u_i^2 \tag{3-6}
\]

\[
\alpha_i^2 = S_i^2 \tag{3-7}
\]

In the above formula, \(\alpha_i^2\) is the output of the node of layer 3.

The fourth layer is the output layer. The output of this layer is the information processed through the network. The input-output relation corresponding to the i-th output unit is as follows:

\[
S_i^4 = \sum_{j=1}^4 w_{ij}^4 \cdot u_j^4 \tag{3-8}
\]

\[
\alpha_i^4 = S_i^4 \tag{3-9}
\]

In the above formula, \(\alpha_i^4\) represents the output of the fuzzy neural network.

Before the neural network training, the weights and output thresholds were initialized by random numbers, and then the samples were trained by gradient descent method. The objective function is:

\[
E = \frac{1}{2} \sum (d_i^4 - \alpha_i^4)^2 + \frac{1}{2} \sum (d_i^4 - f^4(S_i^4))^2 \tag{3-10}
\]

In the above formula, \(d_i^4\) represents the expectation of the output.

After several times of learning and adaptive training with neural network, the relevant membership functions and the corresponding optimal fuzzy control rules can be obtained.

5. Verification and application of fuzzy neural network control algorithm

Automatic control algorithm of fuzzy neural network to solve the intelligent agricultural irrigation control and in the aspects of intelligent temperature control problem, the algorithm was applied to Modern Agriculture Demonstration Park of Chengdu Agricultural College intelligent control system for irrigation and temperature verification, through the selection of input parameters and corresponding membership function for optimization of automatic control and the corresponding control rules.

5.1 Application and test of automatic irrigation system algorithm based on fuzzy neural network

As water resources are increasingly scarce today, the problem of how to control crop irrigation accurately and efficiently remains to be solved. In the daily irrigation process, farmers judge and determine the irrigation amount of crops artificially according to their experience, and cannot scientifically determine the irrigation amount according to the specific situation of each region and each crop.

In the intelligent irrigation system based on fuzzy neural network, the topology of the algorithm of
fuzzy neural network consists of four layers. The first layer is the input layer, which selects precipitation and soil moisture as inputs to the system. The input is passed directly to the lower output. Rainfall is divided into five fuzzy thresholds: S (small), M (medium), L (large), VL (very large) and QL (extremely large). Soil moisture is divided into five fuzzy thresholds: QL (extremely low), VL (very low), RL (slightly lower), RM (more appropriate), and M (appropriate).

The second layer is the membership function layer. This layer determines the membership function of precipitation and soil moisture and the fuzzy threshold range of the two variables, as shown in Fig4(a) and Fig4(b).

The third layer is the control rule layer, in which the operation of all fuzzy control rules is completed.

The fourth layer is the output layer. This layer selects the irrigation time or irrigation quantity as the output. The irrigation amount is divided into five fuzzy thresholds: VS, LS, M, L and VL.

Now we verify and debug the function of automatic irrigation control in the modern agricultural application system in the agricultural information database of water and dry land sampling in Modern Agriculture Demonstration Park of Chengdu Agricultural College. Two thousand groups of soil moisture, irrigation amount and other information were selected as network-related training samples, train these models with Matlab, and another 1,000 groups of information were used as verification samples. In the training, the error is set to 0.01 and the frequency is 2000. The final result is shown in figure 5. In the training, the error is set to 0.01 and the frequency is 2000. The final result is shown in figure 5.

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Fig 6(a). Function of rainfall after training
Fig 6(b). Function of soil moisture after training

Table 1 optimal fuzzy control rules

| Soil Moisture | QL | VL | RL | RM | M |
|---------------|----|----|----|----|---|
| Rainfall      |    |    |    |    |   |
| S             | VL | VL | L  | LS | VS|
| M             | L  | L  | M  | VS | VS|
| L             | M  | LS | LS | VS | VS|
| VL            | VS | VS | VS | VS | VS|
| QL            | VS | VS | VS | VS | VS|

Through analyzing the membership function diagram before the training, the empirical initial membership functions are not optimal. After repeated analysis and multiple neural network training to continuously adjust the weights and thresholds for the input membership function after the training is continuously adjusted after repeated analysis and multiple neural network training to get the optimal fuzzy control rules based on fuzzy neural network. The optimal fuzzy control rules can be applied to the automatic irrigation control system of agriculture, by writing program to ensure that individual monitoring-station precise irrigation automatic control algorithm, so as to save the water.

5.2 Application and test of temperature automatic control system algorithm based on fuzzy neural network

In the application of intelligent agricultural system, automatic temperature control system in facility agricultural environment is also an important part. The automatic temperature control system can calculate the temperature difference and temperature change rate according to the set temperature, obtain the optimal air supply time through the neural network analysis, and maintain the set constant temperature in the agricultural environment of the facility through the control system, so as to make the crops grow in the optimal environment.

The automatic temperature control system with fuzzy neural network includes four layers: input, membership function, control rule and output.

The first layer is the input layer, which selects two single input fuzzy control variables, temperature difference and temperature change rate of the input variable, and transfers the input of this layer to the output of the lower layer. The temperature difference and temperature change rate are divided into N, Z and other fuzzy thresholds. P stands for positive and N stands for negative. B, M, S and Z represent large, medium, small and zero respectively.

The second layer is the membership function layer, in which the membership function of temperature difference and temperature change rate and their fuzzy threshold range are determined, as shown in Fig 7 (a) and Fig 7 (b)
Fig 7(a). Membership function of Temp difference
Fig 7(b). Membership function of Temp change rate

The third layer is the control rule layer, which performs the processing of all the fuzzy control rules.

The fourth layer is the output layer, which selects the ventilation time as the output. The ventilation time can be divided into such fuzzy thresholds as S (small), M (medium), L (large) and VL (very large).

We use Information database in Modern Agriculture Demonstration Park of Chengdu Agricultural College as the sample data, to debug and verify the function of intelligent agricultural automatic temperature control system. Using Matlab to train 2000 groups of temperature difference, temperature change rate and ventilation time information, as the training sample information of neural network algorithm, and then 1000 groups of the data were selected as verification samples. In the training, the error is 0.01 and the frequency is 2000. The results are shown in Fig 8.

After 2000 trainings, it can be seen from the training results that the training function converges and the principal squared error is less than 0.1. After training, the membership function of temperature and temperature change rate and the optimal fuzzy control rule can be obtained. Membership function (as shown in Fig 9(a) and Fig 9(b), as shown in Table 2 Temperature optimal fuzzy control rules).

Fig. 8 Training results

Fig 9(a). Membership function of Temp after training
Fig 9(b). Function of Temp change rate after training
Table 2 Temperature optimal fuzzy control rules

| Temperature change rate | PB | PM | PS | Z  | N  |
|-------------------------|----|----|----|----|----|
| Temperature Different    |    |    |    |    |    |
| PB                      | VL | VL | VL | VL | L  |
| PM                      | VL | VL | VL | L  | L  |
| PS                      | M  | M  | M  | S  | S  |
| Z                       | M  | M  | M  | S  | S  |
| N                       | S  | S  | S  | S  | S  |

By comparing the membership function before and after training, it can be seen that by adjusting the initial membership function through neural network training, the input membership function and the optimal fuzzy control rule after training can be obtained. In the software program of automatic temperature control system based on fuzzy neural network, the optimal fuzzy control rules after training automatically maintain a scientific constant temperature at the temperature, reduce human error and save energy, so as to make greenhouse crops grow in the best environment, and achieve the goal of improving the yield and quality of crops.

6. Conclusion
Through the analysis and design of fuzzy control principle and neural network, the automatic control algorithm based on fuzzy neural network is designed by combining the fuzzy control algorithm and neural network analysis. Based on the fuzzy neural network to build the topology of the concrete covers four layers, fuzzy control variable input layer is selected as the input variables, directly to the next layer, membership function layer set the scope of the membership function and fuzzy threshold division control rule layer for all the processing of fuzzy control rules, the output layer select output variables. The algorithm was verified in Modern Agriculture Demonstration Park of Chengdu Agricultural College, and an intelligent irrigation control system based on fuzzy neural network was developed based on irrigation control. Through the test and verification of the agricultural information data collected from the greenhouse of Chengdu Agricultural College, the intelligent temperature control algorithm based on fuzzy neural network can meet the requirements of automatic control in the agricultural system. So, validated by practical application, the intelligent control algorithm based on fuzzy neural network can be implemented in the intelligent agriculture intelligent irrigation and the intelligent functions such as automatic temperature control. The system has good generality and good scalability, which lays the foundation for the next research in other fields. After the improvement, the system can also be applied in the control fields such as industry and animal husbandry.

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