Analysis of Spray Uniformity of Sprayers Based on Deep Belief Network

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Abstract. Improving spray quality has an important practical significance for controlling the drift of harmful substances, increasing the effective utilization rate of pesticides and reducing environmental pollution. The influence of factors on spray quality is analyzed, and the nozzle wear is regarded as one of the influencing factors for the first time in this paper. It also constructs the relationship between spray distribution uniformity and influencing factors Model by proposes a soft measurement method based on deep belief network. Besides, when the distribution coefficient of variation and another influencing factors is given, the pressure value corresponding to them can get by neural network inverse modeling method, And the pressure can be used as the controlled variable in the spraying process. Compared to BP, the DBN model has stronger nonlinear mapping capabilities, higher prediction accuracy, and high practical value.

Keywords: Sprayers; Influencing factors; Distribution coefficient of variation; DBN.

1. Introduction

According to statistic of the National Agricultural Technology Extension Service Center In 2018, the amount of pesticides used in the crops was 268,400 tons [1]. Effective control of pests is an essential part of the agricultural production process. The basis for ensuring sustainable agricultural development [2]. At present, the uniformity of spray distribution is used as an important index to measure the quality of sprays. Only by improving the uniformity of spray distribution can pesticide utilization be improved. The influence of different pressures, spray heights, duty cycles, frequencies, speeds, nozzle materials, spray directions, fan speeds, nozzle types and spray angles on spray quality were studied by Scholars [3][4][5][6][7]. Current studies have obtained the relationship between influencing factors and uniformity through experiments, but have not studied how to control the influencing factors to meet the best uniformity.

In order to meet the requirements of uniformity in real-time spraying and the importance of spray uniformity in the spraying process, this paper adds nozzle time as one of the influence factors, and uses a deep belief network and inverse modeling soft measurement, a soft-sensor model between influencing factors and uniformity was established, and the validity of the model was verified by Matlab.

2. Influencing Factors and Evaluation Standard of Distribution Uniformity

There are many factors that affect the spray quality of plant protection machines. In addition to uncontrollable factors, such as wind speed, temperature, relative humidity, and wind direction, the factors of the plant protection machinery itself, including spray pressure, nozzle frequency, nozzle duty cycle, height, speed, spray directions, fan speed, nozzle type, boom vibration and spray angle. In
addition, the nozzle wear caused by liquid flow has an important impact on the uniformity of spray distribution. The factors that affect nozzle wear include working pressure, nozzle model, nozzle material, chemical liquid characteristics, and nozzle usage time. In China, fan nozzles are widely used. Most fan nozzle nozzles are oval, as shown in Fig. 1. Where, $a$ is half length of ellipse short axis, $b$ is half length of ellipse long axis, $h$ is the nozzle thickness. According to experimental findings [8], the wear on the long axis can be ignored. Then we can get the expression of the relationship between the use time of the nozzle and the wear of the nozzle. The wear rate of the nozzle is:

$$\eta = \frac{Q - Q_0}{Q_0} = \sqrt{\left[1 + \left(\frac{b_0}{a_0}\right)^2 \right] e^{-\left(\frac{h_0}{a_0}\right)^2} - \left(\frac{b_0}{a_0}\right)^2 - 1}$$

(1)

Where $Q_0$ is the flow before the nozzle is worn, $Q$ is the flow after the nozzle is worn, $\delta$ is coefficient, $a_0$ and $b_0$ are the initial short axis length and long axis length of the nozzle, $m$ and $K$ depend on the characteristics of the liquid medicine.

Spray distribution uniformity refers to the degree of distribution of the spray droplets falling on the target, usually the spray distribution coefficient of variation $C_y$ is used as a measure of the uniformity of the dynamic spray distribution, the formula for calculating the distribution coefficient of variation is as follows:

$$C_y = \frac{S}{\overline{X}} \times 100\%$$

(2)

$$S = \sqrt{\frac{\sum_{i=1}^{N} (X_i - \overline{X})^2}{N-1}}$$

(3)

Where, $S$ is the standard deviation of the sample data, $N$ is the number of sample data, $\overline{X}$ is the average of the sample data, $mg/cm^2$, $X_i$ is the value of single sample data, $mg/cm^2$.

3. Deep Belief Network and Inverse Modeling

3.1. Deep Belief Network(DBN)

It uses hierarchical abstract thinking, through a hierarchical structure, based on the greedy algorithm proposed by Hinton, performs unsupervised learning from top to bottom, layer by layer [9]. Then does supervised learning from top to bottom to fine-tune the weight of the entire network. A typical DBN model is shown as Fig. 2:

3.1.1. Restricted Boltzmann Machine(RBM). Restricted Boltzmann is the basic model of a Deep Belief Network [10]. Let the visible layer be $v$, and the hidden layer be $h$, and the number of nodes is $n$ and $m$, then the energy function is:
\[ E(v, h \mid \theta) = -\sum_{i=1}^{m} a_i v_i - \sum_{j=1}^{n} b_j h_j - \sum_{i,j}^{m,n} v_i h_j \omega_{ij} \]  

(4)

3.1.2. Contrast Divergence algorithm (CD). The idea of the contrast divergence algorithm is: set the training sample to the state of visible layer nodes, then perform the state transition of the visible layer and the hidden layer, after \( k \) times of transition and parameters’ update, the visible layer and hidden layer are reconstructed. The RBM sampling iterative process is shown in Fig. 3. Generally, \( k \) can be taken as 1 to meet the requirements.

3.2. A Spray Uniformity Soft Model Based on DBN

The input and output of the \( o \)th neuron in the output layer is:

\[ x^l_s = \sum_{k=1}^{c} \omega_{ks} x^{l-1}_k + b_{ks} \]  

(5)

\[ y^l_o = f(x^l_o) = \sum_{k=1}^{c} \omega_{ko} x^{l-1}_k + b_{ko} \]  

(6)

Let the objective function be:

\[ E = \frac{1}{2} \|y - y^f\|^2 \]  

(7)

Where, \( y \) is actual output; \( y^f \) is Network output. Make:

\[ \omega^* = \omega - \lambda \frac{\partial E}{\partial \omega} \]  

(8)

\[ \frac{\partial E}{\partial \omega_{js}} = \sum_{o=1}^{m} (y^o_o - y^f_o) \cdot f'(x^l_o) \cdot y^{l-1}_k \]  

(9)

\[ \frac{\partial E}{\partial b^l_k} = \frac{\partial E}{\partial x^l_k} \frac{\partial x^l_k}{\partial b^l_k} = \sum_{o=1}^{m} \delta_{l+1}^o \cdot \omega_{ko} \cdot f(x^l_k) \]  

(10)

Based on the positive modeling, keeping the weights and biases obtained by the positive modeling unchanged, the gradient descent method is used to minimize the error between the actual output and the target output of the network by updating the value of the input parameters. In this paper, the four-layer DBN as an example:

\[ x^*_{i} = x_{i} + \eta \frac{\partial E}{\partial x_{i}} \]  

(11)

\[ \frac{\partial E}{\partial x_{i}} = \frac{\partial E}{\partial y_{j}} \frac{\partial y_{j}^2}{\partial x_{i}} = \frac{\partial E}{\partial y_{j}} \frac{\partial y_{j}'}{\partial x_{i}} = \frac{\partial y_{j}'}{\partial x_{i}} (y - y_{j}^f) \sum_{j=1}^{m} \omega_{j} \sum_{j=1}^{m} f'(y_{j}^{l-2}) \omega_{j} \cdots \sum_{j=1}^{m} f'(y_{j}^{l-2}) \omega_{j} \]  

(12)

3.3. Simulation Verification

Based on the actual situation of this machine and the above-mentioned influencing factors, the main factors affecting the spray quality in this experiment are working pressure, nozzle height, running speed, and nozzle usage time, weighing method is used to measure and evaluate the uniformity of distribution. The plant protection machine device is shown in Fig. 4.
The devise is divided into 50cm×50 cm. Put a disposable paper cup in each square, before each measurement, use the electronic balance with the accuracy of± 0.1g to weigh each small paper cup and records the initial mass. The pressure of the nozzles is 0.1Mpa-0.4Mpa, the spray height is 30cm-65cm, the simulated travel speed is 10m/s-30m/s, the cumulative spray time is 2h-20h, the spray time of each experiment is 1min, each group of experiments is performed three times. The average value is used as final test data. The experimental data is divided into two groups, 100 groups of data are used as training samples, and 10 groups of data are used as test samples. After repeated tests, the structure is 4-6-6-1; the learning rate of the RBM is set to 1.5 and 0.5; The learning rate for supervised learning is set to 0.1. Simulation training is performed by Matlab. The simulation training results are shown in Fig. 5:

According to the simulation results, it can be seen that there is a higher prediction advantages of Deep Belief Network in terms of prediction accuracy than traditional Back Propagation(BP). DBN has lower error than BP network. Besides, it takes less time in training than BP network. Therefore, the accuracy of the DBN can meet the requirements and lay a good foundation for the next steps. The simulation training results of inverse modeling are shown in Fig. 7:
The pressure prediction results are shown in Fig. 8:

According to the simulation results, the inverse modeling predicts that the sample error is within 0.1%, which can meet the accuracy requirements of the spray system for uniformity. When the spray distribution variation coefficient is set to a certain value, the travel speed and spray height and the nozzle usage time given, spray pressure can be changed within the specified range, which can meet the corresponding spray uniformity requirements.

4. Conclusion

This paper uses the DBN algorithm to specifically analyze the relationship between the factors and the uniformity. For the first time, the nozzle wear time is used as one of the factors affecting the uniformity, and the DBN network algorithm is used to positively model the uniformity. To obtain the model of the relationship between influencing factors and uniformity, keeping the weights and biases unchanged on the basis of positive modeling, then the unique pressure value corresponding to the given coefficient of variation and other influencing factors is obtained by inverse modeling method. Finally, the simulation is verified by Matlab. The results show that the DBN network has better data fitting ability and higher prediction accuracy.

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