Research on a method of fruit tree pruning based on BP neural network

Shiyang Liu\(^1\), Jiaojiao Yao\(^2\), Hui Li*\(^1\), Changpeng Qiu*\(^2\), Ruijun Liu\(^3\)

\(^1\)College of Information and Electrical Engineering, China Agricultural University, Beijing 100083, China; \(^2\)College of Horticulture, China Agricultural University, Beijing 100083, China; \(^3\)Beijing Key Laboratory of Big Data Technology for Food Safety, Beijing Technology and Business University. Beijing 100048, China

Liusy123@foxmail.com

Abstract: The mainstream pruning robots do not have the ability to make decisions independently. The pruning schemes are all artificially generated by experts according to the collected images. In order to improve the intelligence of pruning robots and reduce the labor cost of pruning work, it is necessary to study the robot pruning decision algorithm corresponding to different fruit tree varieties.

In this paper, taking apples in the early fruit period as an example, referring to the technical principle of traditional fruit tree pruning and aiming at two types of interference in the pruning process, the back branches and interfering branches, a pruning decision algorithm based on BP neural network was proposed. The algorithm formed the training set by artificially collecting the accurate data of the spatial characteristics of the fruit tree branches and performed calibration for pruning type, and the neural network model was trained according to the calibrated data set. The model trained in the first stage showed the situation that the competition branches cannot be identified. Based on this, an improved algorithm was proposed to improve the classification performance of the competition branches. The experimental results verified that the F1 score of the method for the back branches was 0.913; the F1 score for the centripetal branches was 0.867; the improved algorithm has an F1 score of 0.755 for the competition branches; the overall conformed to the expectation, which could provide algorithm support for the pruning robot to make artificial intelligence decision.

1. Introduction

China is a big agricultural country, and fruit trees planting is an important part of China's agricultural industry. Fruit tree pruning is a major problem that perplexes many producers during fruit tree production. At present, China's planting industry is still in the state of extensive manual management. Most small and medium-sized growers lack sound planting theory to guide agricultural production, and production personnel often do not have enough knowledge to judge how to prune fruit trees, which brings about a series of problems such as low nutrient utilization rate of fruit trees, increased labor costs, and waste of production resources\(^{[1-3]}\). Therefore, establishing and perfecting the theory of fruit tree pruning method, exploring the relationship between tree shape and yield, and constructing a mathematical model that can be used to guide the pruning of fruit trees, are the major issues in accelerating the promotion and expansion of the national plant industry and the implementation of the sustainable agricultural development strategy. At this stage, China's fruit tree planting still mainly uses manual analysis and judgment method to prune. This method has high requirements for production
personnel's production work experience and is difficult to promote. The fruit tree pruning lacks regularity and is hard to be analyzed quantitatively, so its automation and intelligentization are still weak [4]. At present, how to improve the standardization degree of fruit tree pruning methods to meet the needs of mechanical automation operations has become the focus of agricultural research at home and abroad.

Fruit tree pruning is essentially a random, nonlinear, and complex system. The traditional method of forming a “traditional tree shape” through years of production and planting and moving closer to the shape by pruning is not only difficult to quantify, but also still has large error although the linear membership functions and experimentally measured weight value were artificially constructed to evaluate pruning. Furthermore, this method still cannot solve the nonlinear problem of pruning, with large errors between the analysis results and the actual growth results of the fruit trees, so it fails to be applied to actual production [5,6]. Nowadays, the computer analysis of fruit tree pruning is mostly in the simulation stage. Most of the focus is on the relationship between the growth morphology change and yield of pruning tree, while the decision-making research on pruning method is still blank. Taking the pruning in the winter of apple trees as an example, it is necessary to cut off the branches that interfere with the nutrient transport of the apple tree branches according to the actual situation, to improve the yield of fruit trees in the coming year. Interference branches can be roughly divided into two types according to the situation: absolute interference branches and relative interference branches. Absolute interference branches account for more than 60% of the workload of winter pruning of apple tree, mainly including the back branches, competition branches and centripetal branches [7-9]. This type of branch features is more obvious and easier to be identified. The relative interference branches have different shapes, and different pruning experts have different judgments on the branches, so it is difficult to generalize the unified features. This paper started with the absolute interference branches, collected the key point data of the branches in the field, and trained the model through BP neural network, trying to find a method of using artificial intelligence to make the pruning decision.

BP neural network is a kind of nonlinear dynamic system based on artificial intelligence [10-11] and can better fit the relationship between the spatial characteristics of branches and whether or not to cut off. In addition, BP neural network has powerful self-learning ability and self-adaptive ability, unable to correct the threshold and weight value of the model according to the input calibrated data set, which makes the output of BP neural network more in line with actual needs, with better accuracy and general. Therefore, this paper chose BP neural network method to analyze the fruit tree pruning, trained the model according to the training set calibrated by pruning experts, and analyzed the performance of the model in the test set.

2. Experimental materials and methods

2.1. Experimental location and data collection
The data collection location was the Eight Fruit Tree Experimental Park in Beijing, and the collection time was the winter in 2018-2019. Ten apple trees with relatively distinct shapes in the early fruit period were selected, and the morphological data were collected by the calibration rods. In order to ensure the accuracy of the deep learning model, the collection method was manual collection, and the tools were a tape and a vernier caliper. For each apple tree, 15*2 points on the back branches and centripetal branches with distinctive features were selected, 15*2 points on the retained branches that were not cut off were selected, and 5*4 points on the competition branches and the corresponding retained branches were selected. The data acquisition device for the fruit tree shapes is shown in Figure 1. The typical interference branches are shown in Figure 2 and Figure 3.
2.2. Morphological eigenvalues of branches
BP neural network training for branches requires to set the value of the input layer, which should have the ability to reflect the spatial characteristics of the branches. Taking into account the morphological characteristics of the branches and the actual collection situation, five eigenvalues were set as inputs, and the output was the category of the branches (0, 1, 2, 3), where 0 was supposed to be retained and 0 was supposed to be pruned. 1 represented that the branch was a back branch, 2 represented that the branch was a centripetal branch, and 3 represented that the branch was a competition branch. The morphological eigenvalues of the branches are defined as follows.

The cylindrical coordinate system was established by taking the calibration rod as the Z axis, and it was specified that the meristematic point from the main branch of each branch was the start node of the branch, and the end of the branch growth was the end node of the branch. Before the measurement, one direction was set as a direction of 0°. According to this, the following five eigenvalues are obtained:

1. Longitudinal height of the branch \( \Delta h = h_1 - h_2 \), where \( h_1 \) is the height of the start node of the branch, while \( h_2 \) is the height of the end node of the branch.

2. Radial length of the branch \( \Delta r = r_1 - r_2 \), where \( r_1 \) is the distance from the start node of the branch to the calibration rod, and \( r_2 \) is the distance from the end node of the branch to the calibration rod.

3. Growth angle of the branch \( \Delta \alpha = |\alpha_1 - \alpha_2| \), where \( \alpha_1 \) is the angle formed by the start node of the branch and the direction of 0°, while \( \alpha_2 \) is the angle formed by the end node of the branch and the direction of 0°.
the direction of 0°. According to common sense, the positive and negative of the branch growth angles do not have special meaning, so the absolute value of the angle is taken here.

4 Average diameter of the branches $\bar{d} = 0.25(d_1 + d_2 + d_3 + d_4)$. Four points are selected equidistantly for each branch, and the diameter of the point is measured by a vernier caliper, taking the average value as the average diameter of the branch.

5 Curvature of the branch $\rho = L_T/L_E$, where $L_T$ represents the true length of the branch, while $L_E$ represents the Euclidean distance between the start node and the end node of the branches, and the ratio of the two is the curvature of the branch.

2.3. BP neural network

A neural network is a broadly parallel interconnected network of adaptive simple units, whose organization can simulate the interaction of biological nervous systems with real-world objects. BP neural network is the most widely used one of the current neural networks and its essence is a multi-layer feedforward network trained by error backpropagation. It can realize nonlinear mapping from input to output and obtain reasonable solution rules [12-16]. According to the actual demand, this paper utilized a standard three-layer BP neural network structure, including an input layer, an output layer, and a hidden layer. The input layer had 5 nodes, which were the five morphological eigenvalues of the branches $\Delta h, \Delta r, \Delta \alpha, \bar{d}, \rho$; defined in Section 1.2; the output layer had 1 node, indicating the branch category $N=0, 1, 2, 3$. An empirical formula was selected according to the node in the hidden layer of BP neural network:

$$s = \sqrt{m + n + a}$$

Where $m$ is the number of the nodes in the input layer, $n$ is the number of the nodes in the output layer, and $a$ is a constant parameter between 1-10 selected according to the size of the data set. In this paper, $a=5$ was selected, so $s=8$, that is, the hidden layer had 8 nodes $S_1$-$S_8$. The BP neural network structure was 5-8-1, and the BP neural network model was established accordingly. The model diagram is shown in Figure 4.

3. Experiment and result analysis

3.1. Data collection and processing

3.1.1. Original data collection
To reflect the morphological characteristics of a branch, at least the spatial coordinate positions of the meristematic point (start point) and the end node of the branch were required. Therefore, 6 coordinate values of 2 points needed to be measured for a branch. In order to ensure that the average diameter of the branches was representative, the diameter values of four point at different positions were collected. To reflect the curvature of branches, two additional length data were required, so the morphological data group of a branch in the original data contained 12 data, which are respectively: cylindrical coordinate of the start point \((h_1, r_1, \alpha_1)\), cylindrical coordinate of the end node \((h_2, r_2, \alpha_2)\), diameters of the four points \((d_1, d_2, d_3, d_4)\), the Euclidean distance \(L_E\) of the start and the end nodes, and the true length of the branch \(L_T\). As described in Section 1.1, 10 apple trees with suitable shapes were selected. For each apple tree, 15 branches and centripetal branches were selected, and 15 retained branches were selected, and 5 pairs (10) of competition branches and the corresponding retained branches were selected. 40 sets of data were collected from each tree and a total of 400 sets of data were used for model training and evaluation.

### 3.1.2. Data Expansion

Since the branches have a certain geometric invariance, a small amount of translation or scaling of the branches in space had no effect on whether the branches should be cut. Therefore, in order to expand the training data set, the data expansion was carried out by means of scaling. For each group of data, when the growth angle \(\Delta \alpha\) and the curvature \(\rho\) remain unchanged, the other data were scaled by 0.8 times, 0.9 times, 1 time, 1.1 times, and 1.2 times, respectively, that is, there were 5 groups of expansion data. The extra data obtained by the data expansion had the same true value as the original data, and an extended data set with total 2000 groups of data could be obtained after processing. Each group of data in the extended data set were processed according to the definition in Section 1.2, and the 12 original data were converted into five morphological eigenvalues. Among them, 1500 groups were selected as the training set and 500 groups were selected as the test set. Some processed eigenvalue data are shown in Table 1.

| No. | \(\Delta h\)(cm) | \(\Delta r\)(cm) | \(\Delta \alpha\)(°) | \(\bar{d}\)(mm) | \(\rho\) | Type |
|-----|----------------|----------------|-------------------|---------------|-------|------|
| 1   | 75             | 38             | 33                | 7.1           | 1.21  | 0    |
| 2   | 91             | 5              | 7                 | 5.7           | 1.09  | 1    |
| 3   | 74             | 12             | 1                 | 5.1           | 1.13  | 1    |
| 4   | 109            | -22            | 5                 | 5.9           | 1.42  | 2    |
| 5   | 87             | -16            | 4                 | 6.4           | 1.11  | 2    |
| 6   | 60             | 56             | 60                | 7.1           | 1.51  | 3    |
| 7   | 87             | 68             | 45                | 7.4           | 1.34  | 3    |

### 3.1.3. Data normalization

In order to eliminate the influence of the input and output dimensions, speed up the iteration, and prevent the input value from being too large to cause the output to saturate, data normalization was required for the training data set. For each data type \(T_i\), its normalization processing interval was set as \((a, b)\), and then the normalization processing formula was:

\[
T_i' = a + \frac{b - a}{T_{\max} - T_{\min}} \left( T_i - T_{\min} \right)
\]

Where \(T_i\) is the \(i\)th input of the neural network \((i = 1, 2, 3, 4, 5)\), \(T_i'\) is the normalized input data, and \(T_{\min}\) and \(T_{\max}\) are the maximum and minimum values among all \(T_i\).

### 3.2. Results and analysis

According to the BP neural network structure designed in Section 1.3, the neural network construction and training was carried out by using the Windows 10 system and the artificial intelligent open source framework Tensorflow released by Google. The structure of the model was of 5-8-1 three-layer network structure with a normalized interval of \((0,1)\) and an initial learning rate of 0.8. The
The classification performance evaluation of the model after training in the test set is shown in Table 2.

| Type | ACC  | PPV  | TPR  | F1-Score |
|------|------|------|------|----------|
| 0    | 0.828| 0.796| 0.765| 0.781    |
| 1    | 0.950| 0.956| 0.873| 0.913    |
| 2    | 0.948| 0.885| 0.850| 0.867    |
| 3    | 0.798| 0.160| 0.240| 0.192    |

The meanings of the data in the table are as follows:

- **Type**: Referring to 1.2, 0 presents reserved branches, 1 presents back branches, 2 presents centripetal branches, and 3 presents competitive branches.
- **Accuracy rate (ACC)**: The ratio of all correct judgment results to the total sample. \( \text{ACC} = \frac{TP + TN}{TP + TN + FP + FN} \)
- **Precision rate (PPV)**: The proportion of correct judgement in the samples where the predicted value of the model is true. \( \text{PPV} = \frac{TP}{TP + FP} \)
- **Recall rate (TPR)**: The proportion of correct judgement in the samples where the true value is true. \( \text{TPR} = \frac{TP}{TP + FN} \)
- **F1-Score**: An index that evaluates the performance of the classifier. \( \text{F1} = \frac{2PR}{P + R} \). \( P \) is the accuracy rate and \( R \) is the recall rate.

It can be seen that this model had a good distinctiveness for the back branches and the centripetal branches, with an accuracy rate of about 95%, and the F1 score was about 0.9. However, the classification error rate for the competition branches was very high, and the F1 score was only 0.192. Considering that there were some differences between the competition branches and the other two types of branches, that was, the back branches and the centripetal branches were not interfered by other branches, it could be judged an independent interference branch once the spatial morphological features were met. However, the judgement of the competition branch needs comparison with the corresponding retained branch, and one of them was selected to prune, that was, the judgement of the competition branch required the help of the retained branch on the main branch, not belonging to the independent interference branch. This difference made it difficult to accurately judge the competition branches only by the morphological features of the branches themselves. In view of these features of the competition branch, this paper proposed an improved method to classify and judge.

### 3.3. Improved algorithm

The competition branch and the corresponding retained branch were simultaneously input, that was, the input layer had 10 data inputs, which were respectively 5 morphological eigenvalues of the competition branch and 5 morphological eigenvalues of the retained branch. The output of (0,1) meant which one of the branches was pruned, 0 presenting to prune the former, and 1 presenting to prune the latter. During training, 250 groups of data of the competition branches and the corresponding retained branches were separately taken out from the data processed in Section 2.1, and the input order of the two was changed. They were expanded to 500 groups of data according to the rules that the output of (competition branch, retained branch) was 0 and the output of (retained branch, competition branch) was 1. 400 groups of them were selected for training and 100 groups were used to test. After the appropriate change of the neural network in Section 2.2, the model was increased significantly in the performance evaluation on the test set. The accuracy rate was 74%, the accuracy rate was 71.4%, the recall rate was 80%, and the F1 score was 0.755. Compared with the original algorithm, the effect is shown in Figure 5. The results compared with the original algorithm are shown in Figure 5.
As can be seen, the improved algorithm greatly increased the recognition rate for the competition branch and had basically met the expected accuracy. Because of quite large sample of the original method, only 10% of them belonged to competition branches, and 90% belonged to the non-competition branches. Therefore, the true negative value in the original method was higher, and although the overall accuracy was higher than the improved method, effective data were few, so simply relying on accuracy was not enough to explain the performance of the algorithm.

4. Conclusions

(1) A fruit tree pruning method based on BP neural network was proposed, which could be used in pruning robots to make intelligent pruning decision. The method utilized the manually collected precise branch nodes to train the model through the BP neural network, to find out the relationship between the spatial morphological features of the branches and the branch categories, and thus decided whether the branches should be pruned. The method had generalization performance and could be used in various species of tree pruning. It also had mobility and helped pruning decisions, meeting the actual needs of fruit tree planting and production.

(2) The apple trees in the early fruit period were selected as the experimental objects, and the fruit tree branch classifier was successfully trained. The experimental results showed that the F1 score of the method for the back branches was 0.913; the F1 score for the centripetal branches was 0.867; the improved algorithm has an F1score of 0.755 for the competition branches. Therefore, the algorithm could better reflect the qualitative relationship of whether the branches are pruned, which provided algorithm support for the automated pruning robot in pruning decisions.

(3) The algorithm was applicable to the three main interference branches, namely the back branches, the centripetal branches and the competition branches. For some less typical ones, it could not provide an ideal decision reference for the branches that still have some controversy in manual analysis, which will be the research content of the next phase of the project.

Acknowledgments

This work was financially supported by the Opening Project of Key Laboratories in Beijing(BUBD-2017KF-09)

References

[1] LI Shougen KANG Feng LI Wenbin ZHOU Sanzhang HAN Xuemei . Progress advance on pruning mechanization and automation of fruit trees [J]. Journal of Northeast Agricultural University,2017,48(08):88-96.(in Chinese)
[2] Li Yongzhi, Li Bingzhi, Wang Xiaobin, Key Techniques of Apple Tree Shaping and Pruning [J]. Fruit Growers' Friend, 2018(11):4-5. (in Chinese)

[3] Wang Fengmei. Effective shaping and pruning of apple trees [J]. Agricultural technology and equipment, 2016 (09): 65-67. (in Chinese)

[4] Guo Minzhu. Technical details of apple tree pruning during growing period [J]. Northwest Horticulture (Fruit Tree), 2016 (03): 19-20 (in Chinese)

[5] Yang Lili, Chen Jiafeng, Xie Rui, Hua Jing, Kang Mengzhen, Dong Qiaoxue. Simulation Research for Individual Young Apple Tree Pruning [J]. Transactions of the Chinese Society for Agricultural Machinery, 2015, 46(S1):41-44. (in Chinese)

[6] YANG Lili, ZHANG Dawei, XIE Rui, LUO Jun, WU Caicong. Study on Pruning Simulation of Apple Trees at Initial Fruit Stage [J]. Transactions of the Chinese Society for Agricultural Machinery, 2017, 48(S1):98-102+333. (in Chinese)

[7] Wang Fei, Zhang Sheqi, Li Bingzhi, et al. Three-dimensional reconstruction and evaluation of illumination characteristics of high spindle apple trees [J]. Northern Horticulture, 2012 (06): 10-13. (in Chinese)

[8] Meng Fanjia, Liu Taiyang. Design of Raspberry Pruning Robot [J]. Research on Agricultural Mechanization, 2019, 41 (01): 138-142+147. (in Chinese)

[9] Mayla Aladan. Key Points of Management Techniques for Apple Dwarfing and Close Planting [J]. Jiangxi Agriculture, 2018 (12): 20. (in Chinese)

[10] Nielsen M, Slaughter D C, Gliever C. Vision-based 3D peach tree reconstruction for automated blossom thinning [J]. IEEE Transactions on Industrial Informatics, 2012, 8(1): 188-196.

[11] Liu Xue, Li Yamei, Liu Jiao, Zhong Mengmeng, Chen Yu and Li Xingmin. Shelf life prediction model of fresh eggs based on BP neural network [J]. Transactions of the Chinese Society for Agricultural Machinery, 2015, 46 (10): 328-334.

[12] Widdicombe W D, Thelen K D. Row width and plant density effects on corn grain production in the Northern corn belt [J]. Agronomy Journal, 2002, 94(5): 1020-1023

[13] Cox W J, Hanchar J J, Knoblauch W A, et al. Growth, yield, quality and economics of corn silage under different row spacing [J]. Agronomy Journal, 2006, 98(1): 163-167

[14] Kunwar P Singh, Ankita Basant, Amrita Malik, et al. Artificial neural network modeling of the river water quality: A case study [J]. Ecological Modelling, 2009, 220: 888-895

[15] Wang Jiquan, The Theory of BP Neural Network and Its Application in Agricultural Mechanization[D]. Shenyang: Shenyang Agricultural University, 2011.

[16] Xiao Yong, Shao Jingli, Gu Xiaomin, Characteristics of Groundwater Pollution in Changping Plain, Beijing [J]. South-to-North Water Transfers and Water Science & Technology, 2015, 13(2): 252-256, 338.