Research on Recognition and Extraction of Peach Tree Branch Trunk Images

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Abstract

Fruit tree pruning is a necessary means to improve yield and longevity. The current pruning means are mostly manual pruning, resulting in low pruning efficiency. The identification and extraction of target branch images is a key technology for automated pruning of fruit trees, which has seriously restricted the development of automated pruning of fruit trees. To this end, this paper proposes a branch image filling and extraction algorithm based on peach tree pruning technology. The algorithm is based on the analysis of peach tree branches, leaves and environment to obtain the intrinsic connection of branch images, so as to segment the branch part of the image with the leaf noise and carry out the obscured branch filling process to achieve the repair of the obscured part of the branches and obtain a more complete peach tree branch model. The algorithm was found to have a minimum correct recognition rate of 82.13%, a maximum of 89.79% and an average of 86.65% through experiments. The key factor in reducing the recognition rate is the total number of recognition hyperpoints, which are new pixel points generated during the image processing. These new points do not affect the shape and number of branches, and therefore do not affect the judgement of pruning and the related pruning process. Therefore, the correct recognition rate of the proposed algorithm can meet the practical needs and can be used as a theoretical basis for branch identification and automated pruning of peach trees.

Keywords: *Image extraction, Pruning, Peach tree branches, Image recognition.*

I. Introduction

For peach trees, it is particularly important to prune their branches in a short time during the growing process [1]. The existing pruning methods are mainly manual, and the huge number of peach trees planted leads to a huge amount of human and material resources being consumed in manual pruning. This is why research into intelligent pruning equipment is an urgent need for peach production.

As a key technology for intelligent pruning, the recognition and extraction of branch images is a technology that needs to be broken through in order to achieve intelligent pruning. At present, there are few studies on branch recognition of fruit trees, but most of them focus on fruit recognition. For example, Feng used Multi-Spectral Dynamic Imaging (MSX) technology to acquire apple fruit images and proposed an effective potential fruit region locking algorithm to obtain better results [2]. Camera-based ripe litchi recognition method for estimating fruit yield, and further improved fruit detection accuracy using the non-maximum suppression Algorithm for multi-scale detection [3]. Zhao proposed a tomato recognition algorithm based on multi-feature images and image fusion [4]. Lv proposed a multi-source image fusion-based method for the recognition of green grapes in orchards. In addition, there are studies on recognition techniques related to pears [5-6], bananas [7], cherries [8,9], and oranges [10,11]. In terms of fruit tree branch recognition, the current focus is on apple branch recognition, for example, Karkee established the 3D skeleton of apple trees through 3D construction and optimised the performance of the algorithm using training samples of 10 trees to reach the pruning level of human labourers[12] .Zhang analysed the tree structure through feature images of apple branches, trunks and leaves[13] . Qian used images to build a model as a

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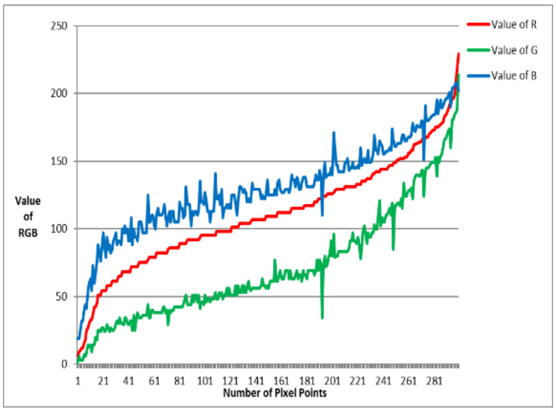
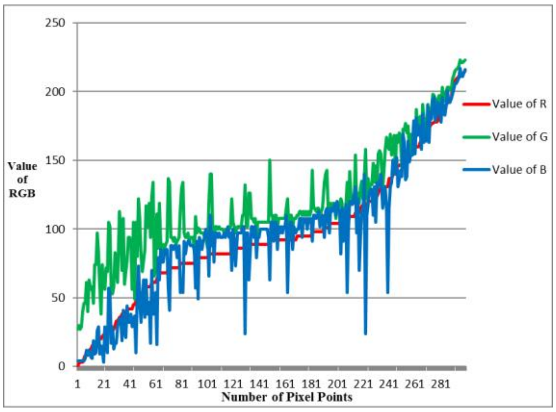
way to assess apple single-tree yield[14]. Hang proposed an improved convolutional neural network model (CNN) to classify apple tree diseases, and the method is highly feasible and effective for apple tree disease identification[15]. Little research has been reported on the pruning of peach trees and the above identification methods are highly specific and difficult to apply to the visual identification of peach trees. Therefore, this paper proposes an image recognition algorithm applicable to peach tree branches. The algorithm proposes a branch nadir filling method based on threshold segmentation, expansion and erosion, noise cancellation and other processing, so as to effectively fill in the occluded branches and ensure the integrity of the three-dimensional model of the branches.

II. Materials and Methods

The images of the sample were taken with a 480*640 pixel industrial camera, which was used to capture images of the branches of the peach tree at an angle of 45 degrees upwards. A total of 300 images were acquired to form the image library required for the experiment. After RGB equalisation of the images, 300 pixel points were randomly selected on each of the branches and leaves, and the R-value, G-value and B-value of these 300 pixel points were counted and collated into a line graph as shown in Fig 1(a). In the branch RGB value statistics, 300 pixel points were randomly selected in the branch area and the RGB values of each of these 300 pixel points were counted and sorted into a line graph according to the R value from smallest to largest. The RGB values of 299 of the 300 extracted pixel points are the smallest of the R, G and B values, which satisfies the rule G<R and G<B. Therefore, this RGB value rule can be used to extract the trunk part and complete the image segmentation of the trunk part. Similarly, in the leaf RGB statistics, 300 pixels are randomly selected in the leaf part, and the G value of 284 pixels is the largest of the R, G and B values, which satisfies the law G>R and G>B, as shown in Fig 1(b). Therefore, this RGB value law can be used to separate the leaf parts of the tree.



(a) RGB analysis of the branches



(a) RGB analysis of the leaf blades

Fig 1: RGB analysis diagram of the tree

2.1 Peach tree branch image processing method

2.1.1 Branch image pre-processing

Fig 2(a) shows the image of the branch trunk of a peach tree. Through the image feature analysis of the branch trunk of a peach tree, it was found that there were obvious differences in the brightness of the branch trunk due to the shooting angle and the light intensity. Therefore, RGB equalisation was first applied to the image to increase the contrast, as shown in Fig 2(b).

(a) Original image of peach tree branches (b) Image after equalisation

Fig 2: pre-processing of images

2.1.2 Extraction and restoration of branches and trunks

2.1.2.1 Segmentation of feature images

Based on the RGB value law of the branches, the branches and leaves of the peach tree were segmented using G>R,G>B, as shown in Fig 3(a). In the process of binarisation, the identified image was converted to white by setting the limit threshold, which was set to 0.001 in this program, as shown in Fig 3(b).

(a) Feature image of branches (b) Binary image of branches

Fig 3: extraction of branch images

2.1.2.2 Image processing for noise removal

There is too much noise in the binary image of the segmented image and isolated points need to be removed based on the connected area of each isolated point. By setting different thresholds and taking the optimal result, the threshold value taken in this paper is 500, and the image shown in Fig. 4(a) is obtained after removing the noisy image. By comparing the processed image with the binary image, the noise is removed and the branch is repaired, the branch is more obvious, but there will still be small scattered areas around the branch that are connected to the graph. In order to remove this small area, the image is first eroded to remove the part of the image that is connected to the branch, then the binary image is reversed and a threshold is set to remove the isolated small area image. In this image, there are a few scattered black points in the branch part, as shown in Fig 4(b). On this basis, the inverse binary image is obtained and the small area image is again eliminated to achieve the final denoising of the branch, as shown in Fig 4(c).

(a) First denoising (b) Second denoising (c)Third denoising

Fig 4: noise removal

2.1.2.3 Branch and stem restoration

The extracted image of the branch trunk shows a broken branch section due to the obscuration of the leafy part of the tree, which divides the whole branch trunk into several pieces. It is necessary to mark the connected area before repairing the branch and remove the largest area, as shown in Fig 5(a). After removing the maximum area of connectivity, what remains is an image of the broken branch that was obscured by the leaves. As you can see, the cracks between the broken branches are not very large, so by continuously expanding the image, the broken branches can be connected, and after the expansion, the connected image can be recovered by using the Erosion command. Because the image is expanded and the parts of the image are connected together, the connection point will not break again after the image has been corroded, thus repairing the obscured part of the branch, and the repair diagram is shown in Fig 5(b).After the repair of the leaf-obscured peach tree branches is completed, there may still be a large gap with the largest area of branches. In order to fill this gap, the coordinates of its white pixel point were first found, and then the coordinate point with the maximum value of the vertical coordinate and its corresponding maximum value of the horizontal coordinate was taken and a rectangular area was created below it to turn it white, as shown in Fig 5(c). The branch was then connected to the white rectangular area by an expansion process, and finally restored using the Erosion command, the result of which is shown in Fig 5 (d).

(a) Removal of connected area (b) Repair of obscured branches (c) Adding rectangular areas (d) Connection of rectangular areas

Fig 5: filling of branches

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The above processing of the captured images not only effectively eliminates noise, but also restores the areas obscured by leaves, thus completing the processing and restoration of the peach tree branches, and the resulting restored peach tree branches are shown in Fig 6.

(a) Original image (b) Restored image

Fig 6: restoration of branch images

2.2 Experimental verification

Three images were randomly selected from the library of 300 images collected and operated according to the above method to test the general applicability of the regular method. Three copies of the randomly selected images, whose original images are shown in Fig 7(a)(b)(c). The images were equalised to obtain the images shown in Fig 7(d)(e)(f). The segmentation was carried out using the law of RGB values in the equalised colour images and a threshold of 0.001 image segmentation was carried out to obtain the binary images shown in Fig 7(g)(h)(i).

From the figure, it is easy to see that the initial binary image obtained has a high level of noise. According to our proposed method, further noise removal processes need to be implemented until the obtained binary image meets the requirements. Therefore, isolated points need to be removed based on the connected area of each isolated point. The optimal result is obtained by setting different thresholds, which in this paper is taken to be 500.

(a) Random original image(1)

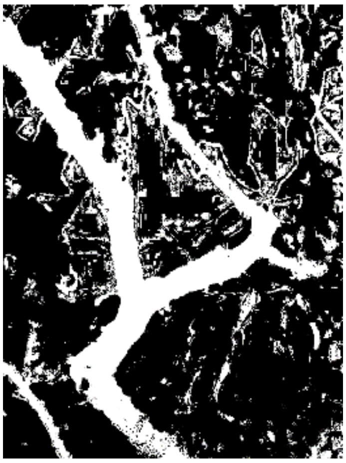
(b) Random original image(2)

(c) Random original image(3)

(d) Image after equalisation(1)

(e) Image after equalisation(2)

(f) Image after equalisation (3)



(g) Binary image after splitting(1)

(h) Binary image after splitting(2)

(i) Binary image after splitting (3)

Fig 7: image pre-processing

Based on the above method, two separate noise removal processes were performed. Finally, the image was obtained by filling the branch section by reversing the binary imag, as shown in Fig. 8 (a)(b)(c). The image of the broken branch was obtained by preserving the maximum connected area, and the branch was repaired by swelling and erosion operations, and the filled repaired branch was obtained by superimposing the images as shown in Fig. 8 (d)(e)(f). The method has been shown to be highly versatile through experimentation.

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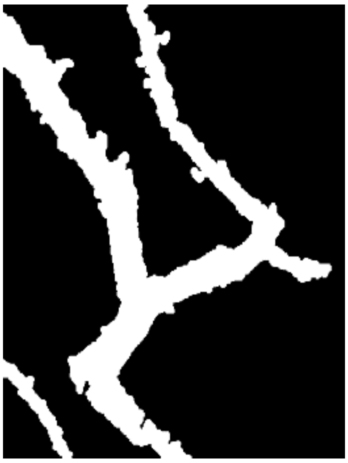
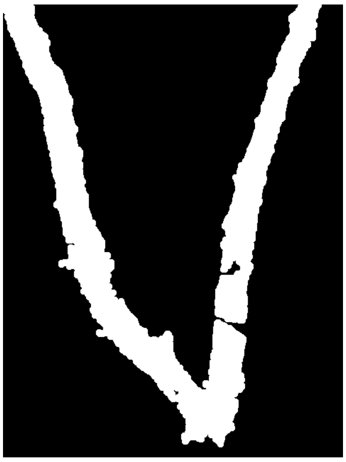
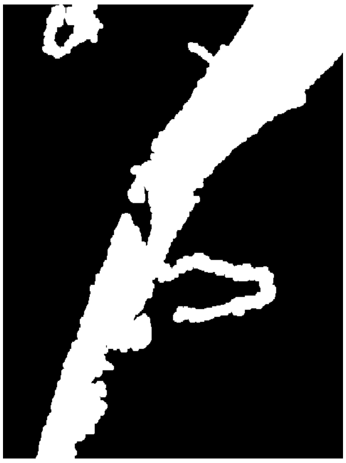
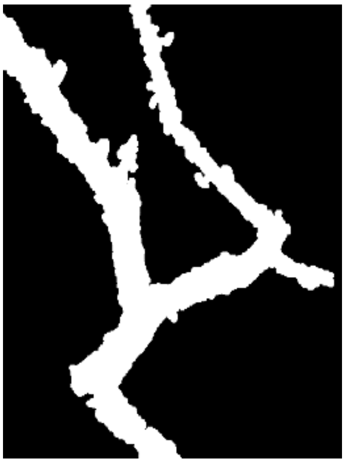




(a) Image of branch after noise removal(1)

(b) Image image after noise removal(2)

(c)Image of branch after noise removal(3)



(d) Image of the restored branch (1)

(d) Image of the restored branch(3)

(f) Image of the restored branch(3)

Fig 8: extraction and restoration of branch images

2.3 Analysis of the correct recognition rate of the algorithm

To further determine the accuracy of this algorithm for peach tree branch recognition, we used two methods for image recognition, manual recognition and image processing based on this algorithm, respectively. The image model obtained from the manual recognition was used as a benchmark to obtain the correct recognition rate of the algorithm. Pixel points in the manual recognition image are defined as actual pixel points, which are compared with the recognition pixel points in the computer intelligent recognition image, and the matching pixel points are regarded as the correct pixel points. The correct recognition rate is obtained by calculating the number of correct pixel points compared with the number of recognition pixel points. Fig 9(a) shows one of the original recognition image and Fig 9(b) shows the corresponding manually recognised branch image. Fig 9(c) shows the branch image model obtained by this algorithm.

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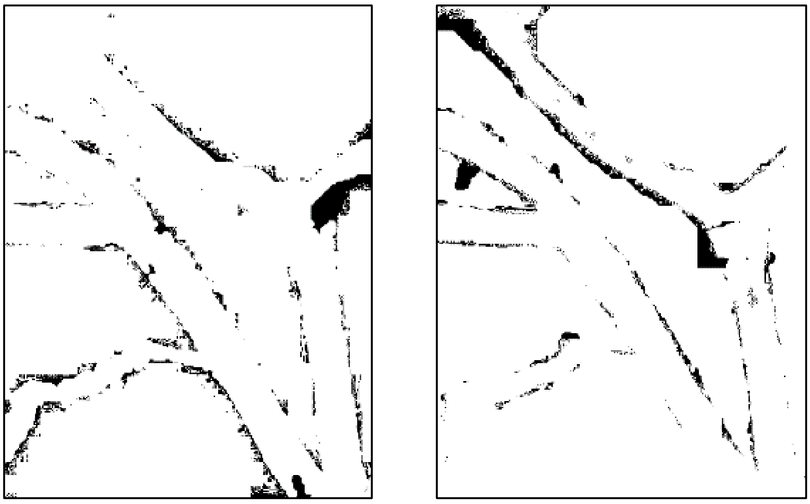
(a) Original image (b) Manually recognised image (c) Image recognized by this algorithm

Fig 9: comparison chart for branch identification

The manually identified image is subjected to a binarisation operation, at which points the manually identified branches are black, and they are overlaid with the binary images (b the branch is white) identified by this algorithm. This is shown in Fig 10(a). Since the binary image of the branch identified manually is black and the branch identified by this algorithm is white, the manually identified branch is still black if it is not identified by this algorithm after the superposition of the two images, which can be called the identification leakage points(ILP) of this algorithm. Therefore, Fig 10(a) can be referred to as the identification leakage points image(ILPI). By superimposing the manually identified binary image(the branch is white) and the binary image identified by this algorithm (the branch is black) in the opposite way, the pixel points that do not appear in the manually identified image will be displayed on the image as black points, as shown in Fig. 10(b), which can be called the identification hyperpoints (IH), so Fig. 10(b) can be called the identification hyperpoints image(IHI).



(a) ILPI of branches (b) IHI of branches

Fig 10: comparative images for recognition

We consider the points corresponding to the manual recognition image and the computer image processing recognition image to be the correct pixel points. For comparison purposes, we consider the number of correct pixel points/total number of manually recognized pixel points as the correct recognition rate; the number of leakage pixel points/total number of manually recognized pixel points as the unrecognized rate; and the number of hyperpoints/total number of manually recognized pixel points as the over-recognized rate. Based on this, we arrive at the following equation.

$$\eta_r = \frac{N_\mathrm{c} - N_e}{N_\mathrm{a}} \times 100\% \tag{1}$$

$$\eta_e = \frac{N_e}{N_\mathrm{a}} \times 100\% \tag{2}$$

$$\eta_n = \frac{N_o}{N_\mathrm{a}} \times 100\% \tag{3}$$

In the above equation, the symbols are interpreted as follows.

η_r: Correct recognition rate
η_e: Over-recognized rate
η_n: Unrecognized rate
N_o: Total number of identified leakage points
N_e: Identify the total number of hyperpoints
N_a: Manual recognition of branch pixel points
N_c: Intelligent computer recognition of branch pixel points

Comparative experiments on 300 captured images found unrecognized rate(η_n), over-recognized rate (η_e) and correct recognition rates (η_r) were 13.35%, 13.32% and 86.65% respectively. The lowest value of correct recognition rate was 82.13% and the highest value was 89.79%. This is shown in Table 1. Therefore, the algorithm can not only fill in the obscured branches of peach trees, but also achieve better recognition results.

TABLE I. Experimental results for relevant parameters

Parameter symbol	Average	Highest value	Minimum value
N_a	74525.6	103358	58641
N_c	73961.8	102062	59538
N_o	9849.4	12780	5987
N_e	9285.6	12754	3373
η_n	13.35%	17.87%	10.21%
η_e	13.32%	20.20%	3.93%
η_r	86.65%	89.79%	82.13%

III. Conclusion

From the statistics of the recognition results of randomly selected collected images, the method used in this paper obtained a high correct recognition rate of eighty-five percent on average. Although the average Unrecognized rate was over thirteen percent, the main reason for this was due to the image changing the thickness of the peach tree branches during swelling and erosion, while the overall shape of the branches was hardly different, so it did not affect the branch pruning decision. The method described in this paper has a high degree of recognition of peach tree branches, and through the image equalisation process can well solve the problem of light when shooting, to achieve a more complete branch filling, so that the overall model of the branch can be obtained, so the method has strong practicality and feasibility.

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