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Target Identification Method of Lingwu dates Based on BP Neural Network

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Abstract: Aim at the identification of Lingwu dates in the natural environment, a method for image segmentation based on BP neural network was put forward. After compressing the collected images, color feature of dates was analyzed in color spaces to select apposite color spaces and their components for recognition. And finally,the BP neural network was used to identify Lingwu dates. Experimental results indicate that, identification of Lingwu dates based on BP neural network with RGB color space and R-G component is higher than using other color spaces' components. Therefore, this method is applied to the identification of Lingwu dates.

Keywords: BP neural network, color spaces, identification, Lingwu dates.

1. INTRODUCTION

Lingwu dates is the main cultivar in Ningxia, with a planting area of nearly 14.2 million mu, and the annual output has been over 100 million kilograms, to achieve an annual turnover of over 300 million yuan [1]. Currently this high yield, short harvest fruit is mainly relied on hand-finished, with an increasing planting area, the way of hand-picked has been restricted by labor costs and food hygiene factors, there are an urgent need to automate the process of sorting after picking. Mature recognition of Lingwu dates is a prerequisite for automated picking.

In the field of picking robot recognition in agroforestry, domestic and foreign scholars have done a lot of research work. Current research can be divided into five categories: Category 1, analysis methods based on the different spectral reflectance characteristics. Scheerta and Brown first put forward the use of fruit and foliage background goal difference among the infrared and visible light and the electromagnetic spectrum reflectance to achieve fruit detection [2]; Safren, getting acquisition visible and near infrared region by using hyperspectral image, use PCA algorithm, ECHO algorithm and morphological operations and watershed algorithm to achieve the identification of green apple [3]. Category 2, recognition methods based on the shape feature. Illingworth detect the contour curvature to locate tomatoes through circular Hough transform [4]; Limsiroratanal, who use the Fourier described, according to the elliptical shape of the object, identify papaya successfully [5]. Category 3, analysis methods based on color features. D'Esnon and Rabatel, who use color vision system to detect apples on trees for the first time, through the color image segmentation to obtain a binary image, and locate the centers of fruit [6]. Harrell and Slaughter study the target detection methods of citrus picking robot, using RGB color characteristics and saturation and hue to classify [7]. Wijethunga put forward three kinds of kiwi counting algorithm based on Lab color image segmentation, and use artificial neural network model of self-organizing map (SOM) in the CIE Lab color model to achieve kiwi identification in different maturity under different shooting conditions [8]. Category 4, detection method based on stereo vision. Jimenez, who use laser range-finder sensor to get rang images, and then analyze the recognition based on shape [9]. Zhao Jun and Tow Joel present a method to position apple in panoramic images. First, they use color and texture features of the fruit to make edge detection, and then use thresholding to separate the region and the background, and ultimately use circle fitting to locate the position of the fruit. This algorithm can also be used to detect images of close-range vision and apple [10]. Category 5, other identification methods. Reid and Searcy propose a Bayesian algorithm segmentation algorithm based on the classic corn image threshold [11]. A.L. Tabb and others locate apples by GMOG [12]. Hetal, who calculated the strength of the different characteristics of the input test image, color, direction and edge, etc. and apply different weights to estimate the position of the target fruit [13].

Although there are quite a lot of studies on agroforestry harvesting robots, some technologies have matured, but because of the huge differences among study objects in terms of variety and study area, resulting in no common software systems and technology products. Thus, on the basis of the full reference to domestic and foreign research results, with a combination of varieties characteristics of the fruits, this paper presents a mature Lingwu dates recognition method which is suitable for hanging branches. First, compress the

Fig. (1). Line profile analysis chart.

collected imagines using the Nearest Neighbor method. Then, extract and analyze color feature of Lingwu dates and the background in 13 color models, you can select a color model and identify the components. Since then, create a sample of Lingwu dates set by a random sampling method. Finally, train BP neural network to identify Lingwu dates based on color features.

2. COLLECTION AND COMPRESSION

2.1. Collection

In this paper, study imagines are collected in Lingwu Daquan Forest. Lingwu Daquan Forest is located at 106.34 degrees east and 38.1 degrees north. Study images are collected on September 19, 2012, size of the collected images is:1152×864 pixels. To make the recognition algorithm have a good adaptability for complex natural environment, the paper fully considered the fruit skin color differences, shadows and reflective effect on fruit adhesion and blocking when collecting images, as well as branches, leaves, sky, etc. First, collect images of different Lingwu dates of different maturity, including fruit surface color which is all red, all green and red and green; secondly, collect images both in the shade and a strong light. Furthermore, considering the fruit adhesion and blocking, collect images of two or more adjacent fruits and fruit exist partially obscured. Finally, collect images with different disturbances, such as branches, leaves and sky.

2.2. Compression

The information of Lingwu dates after collecting is huge, which is inconvenient for transmission, storage and handling, there is a need to compress the image information. For images of 1152×684, use wavelet compression method, nearest neighbor interpolation method, bilinear interpolation method and bicubic interpolation method for compression, the comparing results showed that: the color compressed by wavelet image compression method lost more serious, which will affect the color feature extraction and analysis results. Compression results using neighbor interpolation, bilinear interpolation and bicubic interpolation method is similar to the recent better. Thus randomly select nearest neighbor interpolation method to compress image, size after compression comes to be 288×216.

3. FEATURE ANALYSIS AND EXTRACTION

3.1. Color Model

Analysis of color image can not be separated with quantitative color representation, the color model refers to the color of the visible subset in a three-dimensional color space, which contains all colors to a color domain. Any model is only a subset of the visible color, any color model can not contain all the visible information. There are many models for the quantitative description of color, some are discussed in this paper: RGB model, CMYK model, xyz model, Lab model, HSV model, HSL model, YUV model, YCbCr model, YIQ model, YPbPr model, LUV model, YDbDr model and Lch model, totally 13 pieces.

3.2. Line Profile Analysis in each Color Model

Line profile analysis means to select a row of pixels on the image for analysis, compare and select the color characteristics which has large differences from the background component or color components as the recognition components of the classifier.

As shown in Fig. (**1**), select the image of the 400 row of pixels as the hatch lines to be analyzed in 13 color models.

Use RGB color model as an example to analyze a single channel. As shown in Fig. (**2**), RGB channel analysis show that R component values have big differences between mature Lingwu dates and leaves, but for the branches, there is a great fluctuation in R component values, so it's unsuitable to be used as identification component.

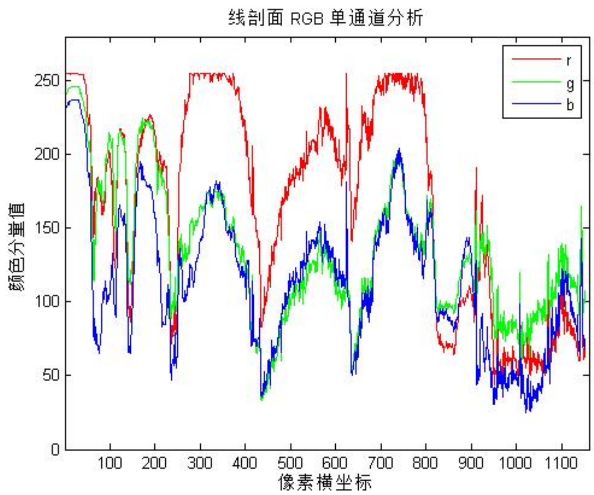

Fig. (2). RGB single-channel analysis.

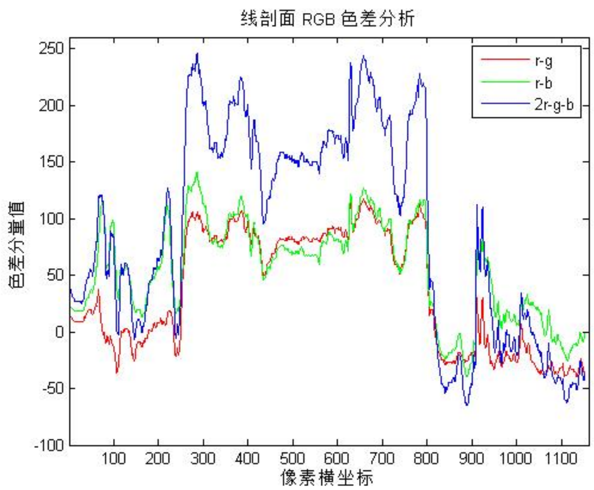

Fig. (3). RGB,2R-G-B,R-B differential analysis.

Additional analysis of the difference in RGB, As shown in Fig. (**3**), color values of R-G, R-B and 2R-G-B in the maturity jujubes are significantly greater than the values of the background color, which can be used as identification components for further identification. Other color models have a similar analysis methods with RGB color model.

3.3. The Method of Random Sampling

According to line profile analysis, sample randomly in RGB, Lab, YUV, YCbCr, YIQ, YPbPr, LUV, YDbDr and Lch color model for BP neural network training. Specific sampling process is as follows:

(1) Intercept artificially 10 ripe jujube images,10 immature jujube images, 20 leaves images, 20 branches images and 10 sky images from 20 sample images by Photoshop,and make samples intercepted contain light, shadow, dust cover and so on in this process.

(2) Read all the pixel values of the five types of images in (1) by MATLAB. After excluding white image pixel values (all the clipped image background color),according to random algorithm, choose 200 pixel values in each type of picture.

(3) Convert the selected 1000 pixel values from RGB color space to the Lab, YUV, YCbCr, YIQ, YPbPr, LUV, YDbDr and Lch color models by MATLAB. And calculate the pixel values that can be divided or components in each color model.

4. BP NEURAL NETWORK STRUCTURE

4.1. Input and Output Selection

4.1.1. Nodes of Input Layer

One method to use BP neural network: select each pixel of the R, G, B component values of the entire RGB images directly as inputs of the neural network, this method does not require any pre-operation, it is relatively simple, but untreated information will increase the difficulty of network identi-

Table 1. Selection of the number of BP neural network hidden layer neurons.

Number of Nodes	7	8	9	10	11	12
MSE	0.0350	0.0349	0.0355	0.0339	0.0356	0.0352

Table 2. Selection of learning algorithm for BP neural network.

Algorithm	L-M Algorithm	BFGS Algorithm	BP Algorithm
MSE	0.0339	0.0360	0.0362

fication, resulting in slow training. Another approach: extract features of the identification target, use the characteristic values as inputs of the neural network, this method of inputting data to remove redundant part of the original data, which will help reduce the size and complexity of the neural network. In this paper, the second method are used to determine the BP neural network input data, extract color features as the inputs of the neural network, the identification component in each color model by line profile analysis can be used as inputs of neural network, so the number of nodes in the input layer of neural network is one.

4.1.2. Nodes of Output Layer

The number of output nodes of neural network is equal to the number of types of image recognition target. Target species to be identified in this article have one kind, that is mature Lingwu dates, so the output node is one. Meanwhile, the target species to be identified are very few, output values can be expressed by vectors containing only 0 and 1. The output of Lingwu dates to be identified is 1, the rest of the output is 0.

4.1.3. The Number of Hidden Layers, Number of Nodes and Activation Function

After conforming the input and output nodes of BP neural network, the number of hidden layers and nodes and also the specific form of the excitation function need to be confirmed. For most practical problems, three-layer BP neural network can be able to meet the requirements, so we design a three-layer BP network, using the S-type excitation function in hidden layer. Nodes of hidden layer is determined by the empirical formula $l = \sqrt{n+m} + a$, in which l is the optimal number of hidden layer nodes, n is the number of input nodes, m is the number of output nodes, a is a constant of 1 to 10. By this formula, the number of hidden layer nodes of the designed BP neural network in this article is 3 to 12. Then select the number of hidden layer nodes when the training error is minimum by trial and error for the final number of hidden layer nodes. The experimental data is shown in Table **1**, take an example of (R-G) / (R +G) component, set the number of neurons in the hidden layer 3 to 12 layers, the excitation functions of hidden layer and output layer are S-type function, the maximum number of cycles are 5000 and training target accuracy is 0.01. Record training accuracy of each network structure.

As is shown in Table **1**, when the number of neurons in the hidden layer is 3 to 12, BP neural network can not reach the objective accuracy after 5000 cycles, less training sample quantities is the main reasons after analysis. But when the number of neurons in the hidden layer is 10, the BP neural network training error reaches the minimum of 0.0339, so the number of neurons in the hidden layer is identified as 10.

4.2. Learning Function Confirmation

Learning functions of BP neural network have standard gradient descent algorithm, momentum BP algorithm, variable learning rate BP algorithm, resilient BP algorithm, variable gradient BP algorithm, BFGS quasi-Newton method and Levenberg-Marquardt algorithm. Levenberg-Marquardt algorithm, which applies to medium-scale neural network training has fast convergence and can reach the goals set by the error in a very short time; BFGS quasi-Newton method is suitable for small and medium size neural network training; Flexible BP algorithm is a training algorithm as excitation function only for Sigmoid function.In this article, Levenberg-Marquardt algorithm, BFGS quasi-Newton method and flexibility BP algorithm are compared, the experimental data is shown in Table **2**, take an example of (R-G) / (R +G) component, set the number of neurons in the hidden layer 10, the maximum number of cycles are 5000 and training target accuracy is 0.01.

The experimental results show that, using Levenberg-Marquardt algorithmcan get a higher training accuracy after a very short period of time, thus we finally adopted Levenberg-Marquardt algorithm as the BP neural network learning algorithm.

5. EXPERIMENTAL RESULTS AND ANALYSIS

5.1. Comparison of the Results of Each Color Model

The design of the BP neural network in this article is: BP neural network of three layers, the input layer node 1, the hidden layer node 10 and the output layer node 1, use the S-function excitation function in hidden layer and output layer, select the Levenberg-Marquardt algorithm as the learning algorithm of BP neural network. Test this BP neural network in different color models,to determine the optimal color model when using the BP neural network classifier, the experimental data is shown in Table **3**.

Table 3. Selection of color space with BP neural network.

Color Space and Segmentation Feature	Training Error	Testing Error Rate	Training Time
RGB(2R-G-B)	0.0689	0.0910	5000
RGB(R-G)/(R+G)	0.0339	0.0460	5000
RGB(R-G)	0.0313	0.0390	5000
Lab(a)	0.0330	0.0410	5000
YCbCr(Cr)	0.0379	0.2370	5000
YIQ(I)	0.0744	0.0490	5000
YIQ(Q)	0.0393	0.0420	5000
YIQ(QI)	0.0320	0.0400	5000
YIQ (2QI)	0.0321	0.0400	5000
YPbPr(Pr)	0.0396	0.0490	5000
YUV(V)	0.0374	0.0480	5000
LUV(U)	0.0460	0.0630	1500

Fig. (4). The result of recognition with BP neural network.

As is shown in Table **3**, input test error and measurement error are both the smallest when using the R-G component in RGB as classification, thus, choose R-G component in RGB as the best color component of BP neural network.

5.2. Image Recognition of Lingwu Dates Based on R-G Component

Set the maximum cycles 5000, the target error is 0.01, based on the test results shown in Fig. (**4**)

As is shown in Fig. (**4**), use the R-G component in RGB color model as input feature of BP neural network can be able to achieve the recognition of Lingwu dates.

CONCLUSION

In this paper, after the compression of collected images, analyze color features of Lingwu dates in many color models, extract color models and components as recognition, compare and select the best color model and components,use BP neural network to recognize Lingwu dates. Experimental results show that using BP neural network as classifier can achieve recognition of Lingwu dates, and the R-G component in RGB color model has a higher accuracy than other color model components,and it is more suitable for the identification of Lingwu dates. However, there are a small amount of recognition errors in this method, and the results are affected by surface spot, which needs a further research.

CONFLICT OF INTEREST

The author confirms that this article content has no conflict of interest.

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