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# Plant Leaves Recognition and Classification Model Based on Image Features and Neural Network

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**Abstract**

In this paper, on the basis of image processing, plant leaves are respectively extracted 7 HU invariant moment eigenvalues, three shape eigenvalues and eight texture eigenvalues based on gray level co-occurrence matrix. Then the paper adopts BP network, which has been optimized by L-M algorithm to identify the classes of the plant leaves based on 7, 10 and 18 eigenvalues. The experimental results show that the classification effect of 18 eigenvalues is the best, the average recognition rate of which is 100%, providing a fast and effective method for the identification of plant species.

***Keywords:*** *Image processing, Feature extraction, L-M algorithm, BP neural network, Classification*

## 1. Introduction

Plant classification is a basis and premise of plan research and development. Plant classification and identification has a great significance and function to clarify the relationships and classification system between species, further to research on the origin of species, the distribution center and the evolution process and trend. With the continuous development of the technology of the digital image processing and pattern recognition, there are more and more studies on plant classification and recognition based on the image features of plant leaves. In this paper, the researchers selected five kinds of common plant leaves as samples. On the basis of image processing, we extracted the characteristic parameters of leaves and identified the selected leaves with different characteristic parameters using the optimized neural network, so as to get the effective classification model and method.

## 2. Acquisition and Processing of the Plant Leaf Images

### 2.1 Acquisition of the plant leaf images

Firstly, we picked five kinds of common plant leaves (they are respectively euonymus japonicus, honeysuckle flower, populus tomentosa, chenopodium album and dracaena sanderiana), cleaned them, and got their digital images with scanner. Then we leaded the digital images into a computer (completed in MATLAB R2010b environment) and preprocessed the images after reading the data.

### 2.2 Processing of plant leaf images

First of all, normalized processing was conducted on the sizes of the images. Then the processed color images were transferred into gray-scale images by weighted average method. It is the edge information of the blade gray images that is the key factor in the image characteristic values extraction. Therefore, this paper used the median filtering to take the noise for the images. To divide leaf and its background into binary images, the images still needed to do the threshold segmentation to lay a good foundation for the feature extraction. There are many methods of threshold segmentations. In this paper, the maximum entropy threshold method was applied. Shown in Fig.1 and Fig.2.

Fig.1 Gray Image

Fig.2 Binary Image

## 3. The Extraction of the Image Characteristic Parameters

There are a lot of image features for the classification of plant leaves. This paper selected the image of HU moment invariant features, shape features and texture features as the basis of the sample classification.

### 3.1 The extraction of HU moment invariant features

HU invariant moment method is a classic method of image feature extraction. In 1962, on the basis of algebraic invariants, HU introduced the concept of image moment invariant, constructing seven moment invariants of translation, scaling and rotation invariance by using the central moment. Then it was widely used in image recognition.

Its principle is as follows: suppose $f(x,y)$ is image gray value on the spot $(x,y)$, its $(p+q)$ order center distance is:

$$\mu_{pq}=\sum_x\sum_y (x-x_0)^p (y-y_0)^q f(x,y)$$
$$(p,q=0,1,2,\cdots) \tag{1}$$

In this formula: $x_0=m_{10}/m_{00}$, $y_0=m_{01}/m_{00}$ is a whole image centroid coordinates. With the normalization of zero order central moments, we get the $(p+q)$ order normalized central distance of images:

$$\eta_{pq}=\mu_{pq}/\mu_{00}^{r} \quad \text{(in this formula: } r=1+(p+q)/2\text{)} \tag{2}$$

Using the second order and third order normalized central moments as well as the linear combination, HU launched the following seven moment invariants group[1]:

$$I_1=\eta_{20}+\eta_{02}$$
$$I_2=(\eta_{20}-\eta_{02})^2+4\eta_{11}^2$$
$$I_3=(\eta_{30}-3\eta_{12})^2+(3\eta_{21}-\eta_{03})^2$$
$$I_4=(\eta_{30}+\eta_{12})^2+(\eta_{21}+\eta_{03})^2$$
$$I_5=(\eta_{30}-3\eta_{12})(\eta_{30}+\eta_{12})[(\eta_{30}+\eta_{12})^2-3(\eta_{21}+\eta_{03})^2]$$
$$+(3\eta_{21}-\eta_{03})(\eta_{21}+\eta_{03})[3(\eta_{30}+\eta_{12})^2-(\eta_{21}+\eta_{03})^2]$$
$$I_6=(\eta_{20}-\eta_{02})[(\eta_{30}+\eta_{12})^2-(\eta_{21}+\eta_{03})^2]$$
$$+4\eta_{11}(\eta_{30}+\eta_{12})(\eta_{21}+\eta_{03})$$
$$I_7=(3\eta_{21}-\eta_{03})(\eta_{30}+\eta_{12})[(\eta_{30}+\eta_{12})^2-3(\eta_{21}+\eta_{03})^2]$$
$$+(3\eta_{12}-\eta_{30})(\eta_{21}+\eta_{03})[3(\eta_{30}+\eta_{12})^2-(\eta_{21}+\eta_{03})^2] \tag{3}$$

The groups of seven moment invariants are image translation, rotation and scaling invariance, but because its range is bigger, they may be negative. Therefore, this paper adopts $\Phi_k=\log|I_k|$ $(k=1,2,\cdots 7)$ as characteristic parameters of invariant moment, and the blade invariant moment extracted through MATLAB programming is shown in table 1.

### 3.2 The extraction of shape features

According to the theory of plant classification, the shape characteristic parameters of plant leaves are one of the most important and effective basis for its classification, among which the most useful one is the two-dimensional shape parameter of the leaves. Through comparing and analyzing the collected leaves, this paper selects the three characteristic parameters including the circularity, rectangularity and elongation [2][3] with good classifying effect as the basis of classification.

Boundary track the binary image in the first place to obtain the direction information of the image boundary pixels and their coordinate values. The boundary pixel information is expressed in the pixel location and direction of the chain code.

According to the eight direction chain code calculation, even number chain code number is $N_o$, odd number chain code number is $N_j$, perimeter is $L=\sqrt{2}N_j+N_o$, area $A$ is expressed in the number of target in the whole image pixels.

Circularity: $C=4\pi A/L^2$ (4)

Rectangularity: $R=A/A_w$ (5)

($A_w$ is area of the minimum circumscribed rectangle)

Elongation: $E=R_{\min}/R_{\max}$ (6)

($R_{\min}, R_{\max}$ is minimum and maximum distance for the center of mass of the border respectively)

The above three eigenvalues of the leaves extracted by MATLAB programming are shown in table 1.

Table 1 shows that the absolute difference of the different leaves in three characteristic values is small, which will produce larger error for classification and recognition of leaves. Thus further considerate the texture characteristics of the leaves as the samples of the classification identification.

### 3.3 Texture feature extraction based on gray level co-occurrence matrix

Texture feature is a basic attribute of the object surface, so different plant leaves have different texture characteristics. This paper adopts the method based on gray level co-occurrence matrix to extract the texture characteristics of the leaves.

Gray level co-occurrence matrix reflects the comprehensive information of image gray scale distribution in terms of change amplitude, direction and local areas. Its definition is the joint probability distribution with two grayscale pixels in the image with the distance $d = (\Delta x, \Delta y)$ appearing at the same time. In order to obtain the gray level co-occurrence matrix of the leaves, first of all, gray the collected leaf images. Because the gray scale of a grayscale image is generally 256, it takes a long time to calculate the spatial gray level co-occurrence matrix. Therefore, under the premise that the texture feature is not affected, the original gray scale of the images is compressed to 16. In order to increase the overall image contrast, before the compression, the images are through the process of histogram equalization, which increases the dynamic changes of the grayscale range. Through the experiment and comparison, the distance between the pixel is 1, and calculate the gray level co-occurrence matrix in $0^0, 45^0, 90^0, 135^0$ four directions.

Comparing 14 characteristic values of grayscale co-occurrence matrix with each other, this paper selects the four characteristic parameters reflecting texture uniformity, complexity, definition and linear correlation, as follows[4]:

Angular second moment: $ASM = \sum\sum[p(i, j)]^2$ (7)

Entropy: $ENT = -\sum\sum p(i, j)\log p(i, j)$ (8)

Contrast: $CONT = \sum\sum p(i, j)(i-j)^2$ (9)

Correlation: $COR = \frac{\sum\sum(ij)p(i, j) - \mu_1\mu_2}{\sigma_1\sigma_2}$ (10)

(Defines: $\mu_1 = \sum_i i \sum_j p(i, j)$

$\mu_2 = \sum_j j \sum_i p(i, j)$

$\sigma_1^2 = \sum_i (i-\mu_1)^2 \sum_j p(i, j)$

$\sigma_2^2 = \sum_j (j-\mu_2)^2 \sum_i p(i, j)$)

Extract the texture feature vector of leaf in the four directions ( $0^0, 45^0, 90^0, 135^0$ ) by the normalization of gray level co-occurrence matrix. In order to get the texture feature nothing to direction, this paper take the mean and mean square error of each feature vector in four directions as the texture characteristic parameters, which is used as the basis of sample classification. The eight texture feature values extracted by MATLAB programming are shown in table 1.

# 4. The BP Neural Network Classification Model Based on L-M Optimization Algorithm

## 4.1 The structure and learning rules of BP neural network

BP network is one of the most widely used neural network models. It is a kind of the multilayer feed forward network according to the error back propagation algorithm training, consisting of positive information dissemination and error back propagation. The topology structure of BP network includes input layer, hidden layer and output layer [5][6][7].

The structure is shown in Fig. 3.

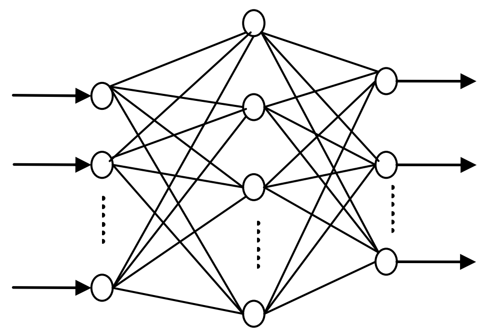


Fig.3 The structure of BP neural network.

The basic idea of BP learning algorithm is to solve the minimum of error function. It uses the steepest gradient descent method in nonlinear programming. Through the back propagation of the network output error, BP learning algorithm constantly adjusts and modifies the network weights and threshold to minimize the network error, whose learning process includes the forward calculation and error back propagation. Because the BP network has problems in practice such as low learning efficiency, slow convergence speed and easy to fall into local minimum point, the L-M optimization algorithm is used to improve BP neural network in this paper.

## 4.2 Basic idea of L-M optimization algorithm

L-M optimization algorithm is actually the combination of the gradient descent method and Newton's method. It has not only the local convergence of Newton's method, but also the global properties of gradient descent method [8][9]. L-M optimization algorithm is mainly calculated in the error square and minimization. It adjusts the weight threshold of Newton's method to

$$\Delta W = -(J^{\mathrm{T}} J + \mu I)^{-1} J^{\mathrm{T}} E$$

In this formula, $\mu$ means adaptive factor and $E$ means matrix for the unit. When $\mu$ is very small, L-M optimization algorithm is close to the Newton algorithm; when $\mu$ tends to infinity, it is the gradient descent method. It can be seen that L-M optimization algorithm can make the error correction smooth between the two algorithms, so that the network has effectively convergence, finishing the iteration of the network in a shorter time.

## 5. Experiment Results and Analysis

The characteristic parameters and classification mode extracted by the above method are applied to the classification and recognition of the five kinds of plant leaves, to test the classification model.

### 5.1 The collection of the training sample data

Table 1 lists 18 characteristic parameters of a group of euonymus japonicas and populous tomentosa. In this table, $\Phi_1 \sim \Phi_7, C, R, E$, $T_1 \sim T_8$ respectively indicate eigenvalues of leaves, including 7 HU invariant moment values, circularity, rectangularity, elongation and the mean and mean square error of the leaf angular second moment, entropy, contrast, correlation.

Table 1: The extraction result of the 18 leaf characteristic parameters

| Image | $\Phi_1$ | $\Phi_2$ | $\Phi_3$ | $\Phi_4$ | $\Phi_5$ | $\Phi_6$ | $\Phi_7$ | $C$ | $R$ |
|---|---|---|---|---|---|---|---|---|---|
| **euonymus japonicus** | 1.2736 | 2.9990 | 2.5896 | 2.0948 | 24.4372 | 13.5944 | 28.2367 | 0.3225 | 0.9915 |
| **populus tomentosa** | 1.2482 | 2.9661 | 9.5359 | 9.0199 | 18.2997 | 10.5030 | 21.2756 | 0.2630 | 0.9582 |
| **Image** | $E$ | $T_1$ | $T_2$ | $T_3$ | $T_4$ | $T_5$ | $T_6$ | $T_7$ | $T_8$ |
| **euonymus japonicus** | 0.3341 | 0.9424 | 0.0004 | 0.2110 | 0.0036 | 0.0834 | 0.0303 | 0.4540 | 0.0034 |
| **populus tomentosa** | 0.3333 | 0.9123 | 0.0003 | 0.2038 | 0.0056 | 0.0044 | 0.0018 | 22.593 | 0.1090 |

Experiments are divided into three ways: (1) selecting 7 HU moment invariant feature values of the leaves as the training sample; (2) selecting10 eigenvalues including 7 HU invariant moments invariant feature values and the circularity, rectangularity, and elongation of the leaves as the training sample; (3) selecting 18 characteristic values (from Table 1) as the training sample, in order to study the influence of different leaf eigenvalues on the classification accuracy.

### 5.2 The structure of neural network

This neural network adopts the three-tier network structure including the input layer, hidden layer and output layer. And the input layer respectively includes 7, 10 and 18 neurons, corresponding to 7, 10 and 18 characteristic parameters of the leaves. Research has shown that for three layers of neural network, the number of hidden layer neurons is at least 2n/3 (in which $n$ is the number of neurons in the input layer). So the number of hidden layer neurons is 20. There are 5 neurons in the output layer to distinguish 5 different types of plant leaves. In 50 samples, we select randomly 70% are used for training, 15% for validation and 15% for forecast.

### 5.3 The results of the neural network training

Table 2: Comparing the classification results of different training sample datum

| The number of input neurons | Classification accuracy | $R$ | $MSE$ |
|---|---|---|---|
| 7 | 76 | 0.78649 | 6.4737e-002 |
| 10 | 90 | 0.88982 | 5.014e-002 |
| 18 | 100 | 0.99877 | 6.8029e-005 |

The table shows that with the increase of the selected plant leaf eigenvalues, the correlation of actual values and the predicted values become higher and the classification accuracy is getting better. It infers that, for the plant leaves, using the HU invariant moment is not a complete description of the types of leaf features, because different kinds of plants have huge different attributive characteristics. At the same time, the shape feature and texture feature have a great influence on the classification.

Table 3: Leaf classification confusion matrix (18 eigenvalues)

| Leaf type | | Predicted value (%) | | | | | |
|---|---|---|---|---|---|---|---|
| | | A | B | C | D | E | total |
| Actual Value | A | 22 | 0 | 0 | 0 | 0 | 100 |
| | B | 0 | 16 | 0 | 0 | 0 | 100 |
| | C | 0 | 0 | 22 | 0 | 0 | 100 |
| | D | 0 | 0 | 0 | 22 | 0 | 100 |
| | E | 0 | 0 | 0 | 0 | 18 | 100 |

(in Table 3: A---euonymus japonicus, B---honeysuckle flower, C---populus tomentosa, D---chenopodium album, E---dracaena sanderiana)

Table 2 and Table 3 show that taking 18 characteristic values as the classification training sample of plant leaves can make classification effect better and make the precision reach to 100%.

By learning 50 samples of neural network, we choose 10 samples from euonymus japonicus and dracaena sanderiana which have not participated the training to simulate the maturely trained neural network (18 neurons). The result is that the detection accuracy of dracaena sanderiana and euonymus japonicusis is 100% and 90.9% respectively. There is one piece which is recognized as populus tomentosa.

## 6. Conclusions

In this paper, analyzing the characteristics of plant leaves, the researchers present the extraction method of different eigenvalues based on the images of leaves, and select the different number of characteristic parameters of the same type of leaves to do the classification by using L-M algorithm, the optimized BP neural network. The experimental results show that selecting 18 characteristic parameters of the leaves as the training sample data has the best classification effect. This paper illustrates that the characteristics of the selected parameters and the neural network are feasible and practical in the classification of plant leaves.

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