Classification of Collection Walnut Based on GLCM and SVM

Jun LU, Xian-zhong HAN* and Ke-jian WANG
Agricultural University of Hebei, Baoding 071000, China
*Corresponding author

Keywords: Gray level co-occurrence matrix, Texture feature extraction, Image identification, Support vector machine, Collection walnut.

Abstract. In order to complete the classification and matching of walnut more efficiently, this paper proposes a texture feature extraction and classification method based on gray level co-occurrence matrix and support vector machine (SVM) classifier. The method extracts the characteristic parameters of walnut image, such as energy, contrast, correlation, inverse different moment and so on, and then uses BP neural network and support vector clustering model to train and test the extracted characteristic parameters, in order to check the extraction of matrix parameters. The results of feature extraction and classification test of 300 samples of Mangjian lion head, Guanmao walnut and Jixin walnut by Matlab simulation software show that the recognition rate of feature parameters extracted by gray level co-occurrence matrix can reach 93.3%. The recognition rate of SVM is higher than BP neural network classification, which means SVM clustering method is more suitable for textural classification matching.

Introduction

Since ancient times, the Chinese people on the construction, urban planning, art form, and so pay attention to pairs, and respected symmetry, the natural pair of walnut matching requirements are also very strict. Walnut as a natural product, the more symmetrical, matching the higher the similarity, the higher the value of its collection. In general, the size of the matching walnut measurements in the case of no more than one millimeter, the more similar the better, the surface texture features must also ensure that the three pairs of successful, walnut has a collection value. With the extensive application of computer technology, compared with the manual identification of walnut and paired the way, the use of computer technology to complete the automatic matching walnut will become the most efficient and accurate method. In the process of playing walnut automatic matching process, the biggest problem is the extraction of walnut image texture features. In this paper, we use the mathematic covariance matrix method to calculate the energy parameters, entropy and moment of inertia of the three kinds of walnut images, and then use the training sample set to complete the training of BP neural network and support vector clustering. Classification, so as to test the gray scale co-occurrence matrix applied to the walnut texture feature extraction effect and practicality.

Image Preprocessing

Image Grayscale

The grayscale image contains many levels of color depth between black and white, where the value of each pixel on the grayscale image can be called grayscale, the range is generally 0 to 255, this test uses the weighted average method[1] on the color walnut image gray image processing, the formula is as follows:

\[ \text{Gray} = 0.299R + 0.578G + 0.114B \] (1)
Image Segmentation

The purpose of image segmentation is to separate the walnut background image from the target image. The quality of the segmentation will directly affect the final feature extraction and classification results. In this experiment, the threshold-based segmentation method is adopted and the threshold is selected by iterative selection method. The steps are as follows:

1. Find the maximum gray value of the entire walnut image and minimum gray value, and set the initial grayscale threshold to $T_0 = \frac{G_{\text{max}} + G_{\text{min}}}{2}$.

2. According to the gray threshold, the walnut image is divided into foreground and background, and the average gray scale values $Z_1$ and $Z_2$ of the two parts are obtained respectively, and a new gray threshold $T_k = \frac{Z_1 + Z_2}{2}$.

3. If $T_k = T_{k-1}$, then $T_k$ is the desired gray level threshold, otherwise proceed to step (2) to perform iterative calculations.

Feature Extraction Based on Gray Level Co-occurrence Matrix

The Principle of Gray-Level Co-occurrence Matrix

The gray covariance matrix was proposed by Haralick et al. in 1973 and is a commonly used method for describing texture features by studying the spatial correlation of image grayscale[2].

The gray covariance matrix is a square matrix, and the dimension of the matrix is the gray level of the image. In general, the grayscale image has a gray level of 256, and the gray scale of the image required in the actual application is much smaller than 256 because the dimension of the matrix is too large and the image cannot be described very well Texture features, but if you want to increase the window size, then greatly increase the amount of calculation, and the boundary area of the error rate will increase. Therefore, before generating the gray level co-occurrence matrix, it is necessary to compress the original grayscale image, and the gray scale is usually quantized to 8 or 16[3].

Assuming that $f(x, y)$ is a two-dimensional digital image with a size of $M \times N$ and a gray level of $N_g$, and satisfying a certain spatial relation, the elements of the gray level co-occurrence matrix are defined as a fixed position relation $(D, \theta)$, the probability that the gray scale is $i$, the probability of the gray level $j$, that is, the gray level co-occurrence matrix is defined as:

$$C_{ij} = \sum_{x=1}^{N} \sum_{y=1}^{N} (P_{x,y} = i) \wedge (P_{x',y'} = j)$$

$$x' = x + d \cos(\theta) \vee \{d\in[1, \max(d)]\} \wedge [\theta \in (0,2\pi)]$$

$$y' = y + d \sin(\theta) \vee \{d\in[1, \max(d)]\} \wedge [\theta \in (0,2\pi)]$$

Where $x, y$ and $x', y'$ are the coordinate values of the two pixels that are associated with each other on the target image, and $d$ is the distance between two pixels, where $C(i, j)$ is defined as $N_g \times N_g$ gray level co-occurrence matrix And $\theta$ is the angle between the two pixels and the horizontal axis of the coordinate[4,5]. In general, $d = \{1, 2, 3, 4\}$, $\theta = \{0^\circ, 45^\circ, 90^\circ, 135^\circ\}$ can be selected as shown in Figure.

Figure 1. The pixel of the gray-level co-occurrence matrix
The Characteristic Parameters of Gray Level Co-occurrence Matrix

Taking into account the practical applicability, this paper selects five commonly used statistical features to intuitively reflect the texture characteristics of walnut images, namely, angular second moment, entropy, contrast, correlation and inverse moment[6-9]. Where the texture characteristic parameters are as follows:

**Angular Second Moment.** The sum of the squares of the elements of the gray-level co-occurrence matrix, which reflects the uniformity of the thickness of the image texture and the grayscale, is as follows:

\[
\text{ASM} = \sum_{i,j} C_{i,j}^2
\]

**Entropy.** The entropy is used to measure the amount of information in the target image, reflecting the complexity or nonuniformity of the texture of the image, as follows:

\[
\text{ENT} = -\sum_{i,j} C_{i,j} \log C_{i,j}
\]

**Contrast.** Contrast, also known as the moment of inertia, used to describe the target image texture clarity and texture of the groove depth, the formula is as follows:

\[
\text{CON} = \sum_{i,j} (i - j)^2 C_{i,j}
\]

**Correlation.** The correlation is used to measure the similarity of the elements in the row or column direction, that is, the uniformity of the image texture in the gray level co-occurrence matrix. The formula is as follows:

\[
\text{COR} = \sum (i,j)(i - t)(j - t)C(i,j)/(\sum (i,j)(i - t)(j - t)m(i)
\]

Where \( t \) is defined as:

\[
t = \sum_{i,j} i \times C_{i,j}
\]

**Inverse Different Moment.** The inverse moment is used to reflect the homogeneity of the image texture and measure the local texture change of the image. The formula is as follows:

\[
\text{IDM} = \sum C(i,j)/1 + (i - j)^2
\]

Texture Feature Extraction Based on Gray Level Co-occurrence Matrix

In this paper, the eigenvalues of grayscale symbiosis matrices were extracted from each of the 100 cultivated walnut samples.

**Extract the Target Grayscale Image**

Using the formula (1), the color image of the extracted pungent lion head, the official cap walnut and the walnut walnut were grayed out, and the background of the target walnut image was separated according to the image segmentation method, and the walnut ash The image is placed in a 160 * 160 pixel sub-image.

**Texture Eigenvalue Extraction**

In the process of obtaining the gray level co-occurrence matrix of three kinds of walnut, the growth step \( d = 1 \) is selected and the energy of the gray level co-occurrence matrix is calculated in the four directions of \( 0 = \{ 0, 45, 90, 135 \} \) Entropy, correlation, contrast and inverse moments of the five texture parameters. The 300 sets of eigenvectors are statistically analyzed to obtain the mean values of the parameters of each species of walnut, as shown in Table 1.
Table 1. Gray-scale co-occurrence matrix feature parameters mean.

| Eigenvalues     | Nausea lion head walnut | Official cap walnut | Chicken Heart Walnut |
|-----------------|-------------------------|---------------------|----------------------|
| Energy          | 0.1591285               | 0.132538            | 0.114177             |
| Entropy         | 2.9347271               | 3.1382418           | 3.2209543            |
| Contrast        | 10.8279949              | 11.6813425          | 15.4182087           |
| Correlation     | 0.046255                | 0.0449669           | 0.0323621            |
| Inverse moment  | 0.1517477               | 0.1246411           | 0.1054938            |

Texture Eigenvalue Analysis

According to the feature values obtained by the gray level co-occurrence matrix, the five commonly used characteristic parameter values of energy, entropy, moment of inertia, correlation and inverse moment are different for different walnut texture. The results show that the larger the energy parameter value is, the more concentrated the distribution of the matrix elements, the thicker the texture, that is, the texture of the lion's head than the official hat walnut texture, the official cap walnut than the heart of the walnut; the entropy value represents the walnut texture. The more complex the parameters, the more complex the texture, that is, the heart of the walnut than the official cap walnut texture complex, the official cap walnut than the nausea lion head texture complex; inertia on behalf of walnut texture clarity and groove depth, The texture of the heart of the walnut than the official cap walnut texture clear, the official cap walnut than the nausea lion head texture clear; the same reason, the characteristic parameter correlation and the inverse moment also reflect different texture features.

The Walnut Classification Experiment

Neural Network Classification Method

BP neural network is a multilayer feed forward network trained by error back propagation algorithm, which is one of the most widely used neural network models. It uses the gradient descent method of learning rules, through the reverse propagation constantly adjust the network weights and thresholds. The three-layer BP neural network is used for the feature parameters extracted by the gray-level co-occurrence matrix, among which five nodes of the input layer, five corresponding characteristic parameters, four nodes of the hidden layer and three nodes of the output layer.

Support Vector Machine Classification Method

Support Vector Machine Technology. Support vector machine (SVM) is a machine learning method based on statistical learning theory and structural risk minimization principle, which can solve the problem of small sample, nonlinear, local minimum and high dimension. Support vector machine not only can construct closed interface to complete unsupervised data clustering analysis, but also construct non-closed interface to solve the problem of supervised data classification. However, when the training sample set is large, the dimension is high, the categories are more and there are noise points, the traditional support vector machine clustering model will have the problems of slow training speed and low accuracy.

Support Vector Clustering. The support vector clustering method is the expansion of support vector machine by Tax et al. The basic idea is to find out the minimum super span sphere that can enclose all the training classification in the feature parameter space, and then map the resulting hypersphere back into the input space, Get the area boundaries that can classify the data samples.

Assuming that there are N sample sets \{x_1, x_2, \cdots, x_N\}, x_i \in \mathbb{R}^d, the hypersphere center \(\alpha = (\alpha_1, \alpha_2, \cdots, \alpha_d)^T\), the objective function of the support vector clustering method is:

\[
\begin{align}
\min_{\alpha, \xi} & \quad \xi R^2 + C \sum_{i=1}^{N} \xi_i \\
\text{s.t.} & \quad \|\phi(x_i) - \alpha\|^2 \leq R^2 + \xi_i, \xi_i \geq 0, \text{for } i = 1, \ldots, N
\end{align}
\]  

(11)
\[ \xi = (\xi_1, \ldots, \xi_N)^T \] is the relaxation variable, \( \| \cdot \| \) is Euclidean distance, \( C \) is the penalty factor, usually in the range of \([0, 1]\), and a certain number of samples are allowed in the training process. The standard radius appears outside the hypersphere, and the penalty factor \( C \) is used to balance the weight of the slack variable and the radius, and to suppress the noise point and control the effect of the extracorporeal sample size. Introducing Lagrange multipliers \( \beta = (\beta_1, \beta_2, \cdots, \beta_N)^T \) and \( y = (y_1, y_2, \cdots, y_N)^T \) yields:

\[
\begin{align*}
\text{max}_\beta & \sum_{i=1}^{N} K(x_i, x_j)\beta_j - \sum_{i=1}^{N} \beta_i K(x_i, x_i) \\
\text{s.t.} & \sum_{i=1}^{N} \beta_i = 1, \quad 0 \leq \beta_i \leq C
\end{align*}
\]

(12)

Where \( K \) is the kernel function and \( q \) is the kernel function width. The distance between the training set sample \( x \) and the hypersphere center \( a \) is expressed as:

\[
R^2(x) = \| \phi(x) - \alpha \|^2 = K(x, x) - 2 \sum_{i=1}^{N} \beta_i K(x_i, x) + \sum_{i=1}^{N} \beta_i \beta_j K(x_i, x_j) = 1 - 2 \sum_{i=1}^{N} \beta_i K(x_i, x) + \sum_{i=1}^{N} \beta_i \beta_j K(x_i, x_j)
\]

(13)

The form consists of a support vector corresponding to the coefficient \( \beta_i > 0 \) and directly determines the distance between the sample and the center of the hypersphere and the distance from the hypersphere radius. In addition, the formula (13) must satisfy the KKT condition:

\[
y_i \xi_i = 0 \quad \text{for} \quad i = 1, \ldots, N
\]

(14)

\[
\beta_i = C - y_i
\]

(15)

\[
(R^2 + \xi_i - \| \phi(x_i) - \alpha \|^2)\beta_i = 0 \quad \text{for} \quad i = 1, \ldots, N
\]

(16)

Therefore, if \( \xi_i > 0 \), and \( \beta_i > 0 \), then \( y_i > 0 \), and \( \| \phi(x_i) - \alpha \|^2 = R^2 + \xi_i \), then \( x_i \) is located outside the superspace of the feature space point. At the same time because \( \beta_i = C \), so \( x_i \) also known as the limited support vector; If \( \xi_i = 0 \), and \( \beta_i > 0 \), then \( y_i > 0 \), and \( \| \phi(x_i) - \alpha \|^2 = R^2 \), then the sample \( x_i \) is located on the surface of the superspace of the feature space, and the sample \( x_i \) is called the support vector. If \( \beta_i = 0 \), then the corresponding sample point \( x_i \) is inside the hypersphere, so it is called the inner point.

**Clustering Results and Analysis**

In this experiment, BP neural network and extended support vector clustering method were used to input the samples of 300 patterns of walnut signatures by using Matlab simulation software. Among them, there were 100 samples of three kinds of walnut, each of which was 80 The samples were used for cluster model training and the last 20 samples were used for sample testing. After the BP neural network test, the correct recognition rate of the muffled walnut is 80%, the correct recognition rate of the official cap walnut is 85%, the correct recognition rate of the walnut is 90%, and the overall recognition rate is 85%. The correct recognition rate of the nuted walnut is 90%, the correct recognition rate of the walnut is 90%, the correct recognition rate of the walnut is 100%, the overall recognition rate is 93.3%, compared with the use of BP Neural network recognition rate is high, and the actual situation with the sample close to a better response to the text of the walnut texture features.

**Summary**

In this paper, a hierarchical classification method based on gray level co-occurrence matrix and support vector machine is proposed. The experimental results show that the extracted energy, entropy and inertia moments have good classification and recognition ability and reflect different And the correct recognition rate of walnut samples obtained by support vector clustering was 93.3%. The results show that the method can be applied to the texture feature extraction and classification of walnut. However, the feature extraction method of walnut texture based on gray-level co-occurrence matrix is also shortcomings. The extraction of characteristic parameters requires a lot
of calculation, and the number of characteristic parameters is large, and the statistical results of data are also very time-consuming. Reduce the gray level of the image to reduce the amount of computation, but to improve the implementation of the algorithm to establish a more perfect and practical play walnut matching system.

References

[1] Tianjuan Zhou, Tiezhong Zhang, Li Yang, et al. Study on Segmentation and Comparison of Strawberry Fruits Based on Mathematical Morphology. Journal of Agricultural Engineering, 23, 9 (2007)164-168.

[2] Haralick R M, Shanmugam K. Texture features for image classification. IEEE Trans. on Sys, Man, and CYB, 1973, SMC-3(6):610-621.

[3] Xiuguo Zou, et al. Breeding of Rice Planthoppers Based on Improved Gray Level Co-occurrence Matrix and Particle Swarm Optimization. Journal of Agricultural Engineering, 2014, 30 (10): 138-144.

[4] Liping Yu, Ming Li, Xiaoqin Yang. Fracture Image Recognition Based on Gray Level Co-occurrence Matrix. Computer Simulation, 2010, 27 (4): 224-227.

[5] Chengcheng Gao, Xiaowei Hui. Texture Feature Extraction Based on Gray Level Co-occurrence Matrix. Journal of Computer Applications, 2010, 19 (6): 195: 198.

[6] Choi J Y, Ro Y M, Plataniotis K N. Color local texture features for color face recognition. IEEE Transactions on Image Processing, 2012, 21(3):1366-1380.

[7] Hossain K, Parekh R. Extending GLCM to include color information for texture recognition. Paruya S. International conference on modeling, optimization and computing. America: American Institute of Physics, 2010:583-588.

[8] Jae Young Choi, Yong Man Ro, Konstantinos N Plantaniotis. Color local texture feature for color face recognition. IEEE Transactions on Image Processing, 2012, 21(3):1366-1380.

[9] Lihong Yuan, Li Fu, Yong Yang. Experimental analysis of texture feature extraction by gray-level co-occurrence matrix. Journal of Computer Applications, 2009, 29 (4): 1018-1021.