Automatic Recognition of Tea Bud Image Based on Support Vector Machine

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Abstract. The existing recognition method of tea shoots is only to judge the single color or shape features, resulting in low recognition accuracy. Therefore, an automatic recognition method of tea shoots image based on support vector machine is designed. In this method, two kinds of image features, color and shape texture, are extracted from the tea bud image for discrimination. The RGB model is used to extract color features, and LBP/C operator is used to extract the shape and texture features of the bud. The extracted features are used as the feature vectors of the training samples, and support vector machine model training is carried out to obtain the support vector machine classifier, and the tea bud image is recognized. The experimental results show that the recognition rate, recall rate and comprehensive evaluation index of the method are higher than those of the traditional method, which proves that the method has high recognition accuracy and improves the recognition efficiency.

Keywords: Support vector machine · Image recognition · Feature extraction

1 Introduction

China is an important tea producing and selling country in the world. Tea culture is deeply loved by people all over the world. Due to the huge production of tea, the use of mechanical picking instead of manual picking can speed up the picking efficiency and alleviate the shortage of labor, but on the one hand, this method is lack of selectivity and will pick the old leaves, young leaves and buds together, but the efficiency of manual picking is low, the cost is high, and the phenomenon of hard work sometimes occurs in the peak period of tea picking. Therefore, it is necessary to develop an efficient and selective method of tea bud recognition to realize the classification production of Longjing tea. One of the key technologies is to study the automatic detection and recognition of Longjing tea buds.

S. Liu and L. Xia (Eds.): ADHIP 2020, LNICST 348, pp. 279–290, 2021.
https://doi.org/10.1007/978-3-030-67874-6_26

Support vector machine (SVM) is a very popular algorithm in the field of artificial intelligence. In 1995, Vapnik et al. Proposed a classification algorithm based on statistical learning theory to realize structural risk minimization [1]. Its main principle is to construct an optimal linear hyperplane in the sample space, to maximize the distance between the two closest samples on both sides of the plane, and to obtain a good generalization ability. The support vector in the algorithm refers to the training points which are closest to the classification decision surface and the most difficult to identify in the training set samples. Whether the distance between these points and the plane has reached the maximum is the standard for SVM to reach the optimal classification. With the rapid development of machine learning methods in the 1990 s, SVM has been widely used in biology, handwriting, text recognition and other fields [2]. Some domestic scholars have carried out multi-agent research on tea image grade recognition technology. The recognition method is simple and fast, but when the image quality is low and the number of pixels is small, it can not accurately identify tea buds. Therefore, this paper proposes an automatic recognition method of tea bud image based on support vector machine.

2 Extracting Image Feature Parameters of Tea Buds

2.1 Tea Shoots Image Collection

Because there are many types of tea, this article selects Longjing tea as the research object. The image of Longjing tea is collected into a computer, and the image is digitized using imaging technology and analog-to-digital conversion technology. With the continuous development of computer technology and microelectronic technology, especially the rapid improvement of the performance of the charge-coupler (CCD), the imaging quality is good, and the performance is stable, which is widely used. The tea images obtained in this article were taken with a digital camera at an angle of approximately 45° to the horizontal ground. When the camera shooting angle is 0° (i.e. horizontal shooting), the contour features of tea shoots obtained are the clearest and the most complete. However, due to the different growth position of tea shoots, this shooting method will appear serious occlusion phenomenon, which is not convenient for the subsequent processing of the shoot image. When 900 is used to shoot vertically and downward, the outline of the tender leaves is clear, but the shape of the tender buds is not easy to identify. In this case, the tender buds tend to converge into a nearly circular area, which can not be distinguished from the young leaves, which is not conducive to subsequent processing. When the shooting angle is 45°, the outline of tea shoots and leaves is clear, and the occlusion phenomenon is less [3], which is easy to distinguish from the background of old leaves, as shown in the following figure:

(1)

(2)

(3)

Fig. 1. Tea sample image

The shooting angle of Fig. (1) in the above figure is 0°, that of Fig. (2) is 45°, and that of Fig. (3) is 90°. When sampling, close shot mode is adopted, flash is turned off, and direct sunlight is avoided. The number of buds in each frame is 1–4. When the number of buds exceeds 4, the occlusion in Longjing tea pictures is serious. At the same time, there are some incomplete tea bud areas, which will bring inconvenience to subsequent processing.

2.2 Extract Color Features of Buds

The RGB color space is the most used color model in color image processing. This is due to the standardization of the three primary colors. Today, almost all colors can be represented by the linear combination of the three components R, G, and B [4, 5]. The original image of tea samples obtained in this experiment is based on RGB color space, so the preferred color feature is RGB. According to the principle of RGB three primary colors, each color can be weighted by red, green and blue primary colors. RGB model is based on Cartesian system, as shown below:

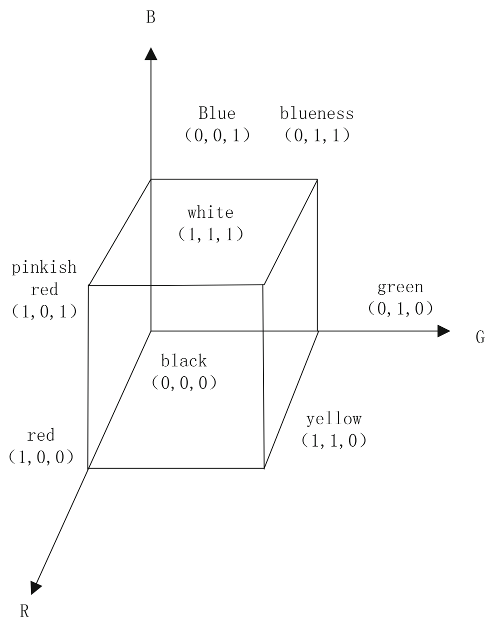

Fig. 2. RGB color model

In the picture above, R, G, and B are located at three corners respectively. Black is at the origin, and white is at the furthest distance from the origin. The gray level is distributed along the line of black and white. Normalize and count the color characteristics of 400 tea bud samples [6]. In view of the space limitation of the article, only part of the data is listed, as shown in the following table (Table 1):

Table 1. Color characteristic data of tea shoots

Serial number	R	G	B
1	167.5	168.7	91.5
2	143	166	67.8
3	88.6	109.7	39
4	118.3	131.8	67.8

(*continued*)

Table 1. (*continued*)

Serial number	R	G	B
5	73.8	84.9	36.7
6	113.8	119.7	70.9
7	135.8	116.8	58.3
8	129.8	133	59
9	68.6	75.9	40.8
10	106.8	113.5	58

Although the RGB color model is widely used and ideal for hardware implementation. However, from the perspective of visual psychology, the human eye's description of colored objects is not based on the RGB primary colors, but on hue, saturation, and brightness (HSI). Hue describes the characteristics of pure color, saturation measures the degree of pure color diluted by white light, brightness is the key parameter to describe color perception. The HSI model is suitable for image processing and explaining the local characteristics of objects, and can effectively separate color information and achromatic information of an image. In addition, with the improvement of hardware level, the conversion of color space can be effectively accelerated by hardware [7, 8], PC and workstations have available modules to convert video or RGB images to HSI images in real time. Based on the above analysis, this paper selects a total of 9 color features R, G, B, H, S, I, L, u, v to train the classifier model. Color feature selection adopts the method of averaging the pixels of the tea bud area. Each tea image is adjusted to the same size (width: 100 pixels, height: 150 pixels), and RGB is converted into HSI, Luv color space, H, S, I, L, u, v6 color feature values are unified in the range of 0−255.

2.3 Texture Feature Extraction of Buds

By observing the image, we can know that the new leaf (including the bud) area is above the upper edge of the old leaf, so we use the edge contour extraction, first extract the upper edge contour of the old leaf. The extraction method is as follows: firstly, the coordinate of the lower left corner of the image is (0,0) Secondly, the upper left corner of the image is scanned line by line until the upper edge of the old leaf blade is detected, and the coordinate value is recorded. The method to determine the edge of old leaves is as follows:

$$B(i) = \begin{cases} j & (T_{bw}(j,i) = 0) \\ 0 & (T_{bw}(j,i) = 1) \end{cases} \tag{1}$$

In the above formula, $B(i)$ is the vertical coordinate value of the edge of column i of the record. If there is no edge pixel in this column, the record is zero; $T_{bw}(j,i)$ represents the pixel value of row j and column i in the figure, 1 represents the white background, 0 Indicates black leaves.

The texture of tea belongs to natural texture, which is analyzed by statistical method. Among the methods of texture analysis based on statistics, LBP (local binary patterns) is widely concerned because of its simple calculation and strong applicability. LBP can describe the spatial structure of local texture, but does not emphasize the contrast information of texture, so it often combines the contrast information (LBP/C) as the texture feature descriptor [9]. The calculation of C descriptor only needs a part of LBP template, and the specific calculation method of LBP/C operator is shown in the figure below:

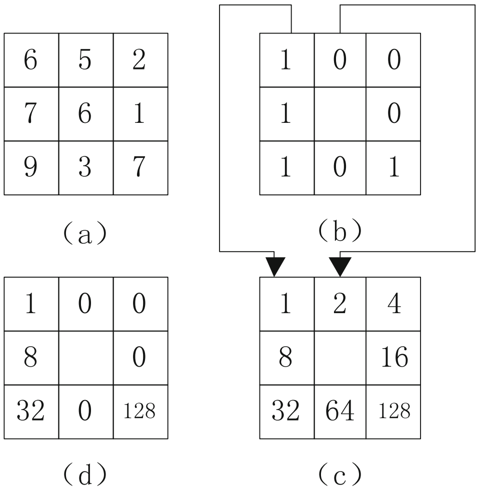

Fig. 3. Calculation method of LBP/C

In the 3 × 3 neighborhood with gray level 6 as the center, binarize the neighborhood pixels with the center of the neighborhood as the min value to obtain (b) in the above figure, and then compare the above figure with (a). The corresponding binary template in (b) can be used to find the mean difference. Each pixel of the original image will get an image of the same size after LBP operation, as shown in the following figure:

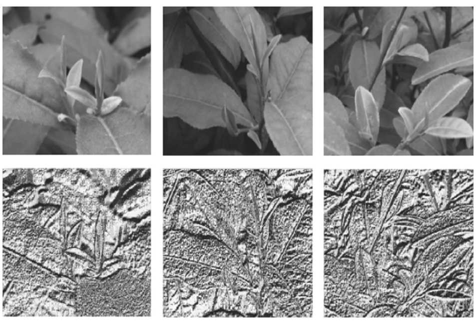

Fig. 4. Obtained texture image

The first row is the original tea shoot image, and the second row is the corresponding texture image. Four mutually uncorrelated and easy-to-calculate features were extracted from it, namely energy, entropy, moment of inertia and correlation, which were counted by LBP/C. At this point, the extraction of image feature parameters of tea buds is completed.

3 Research on Automatic Recognition of Tea Bud Image Based on Support Vector Machine

Support vector machine is a machine learning method based on statistical learning theory, which adopts the principle of structural risk minimization, and has the advantages of small sample, non-linear and "avoiding digital disaster" [10]. Support vector machine can be used to solve linear and nonlinear problems. Its main principle is to find the optimal classification surface for classification. The nonlinear problem can be solved by introducing kernel function into high dimensional space. The linear support vector classifier used in this paper is based on the maximum interval method. The maximum interval method transforms the problem of finding the optimal classification surface into the problem of finding the maximum classification interval. By using Lagrange multiplier method and introducing dual function, the optimization problem is transformed into a quadratic linear programming problem, and the characteristics of training samples are extracted. The training SVM model is used as the feature vector of the training samples, and the training model, i.e. the classification device, is obtained. First determine the number of classifiers, using the SVM algorithm, the goal is to divide the sample into 2 categories, this experiment only needs to train a classifier; determine the feature vector of the training sample, after extracting the image features above, obtain the training sample, and obtain the color feature $C_{i,j}$ With the texture feature $T_{i,j}$, as the training sample feature vector $F\left(C_{i,j}, T_{i,j}\right)$, j represents the category, i represents the i th pixel in the j th category. The color features of each pixel in the R, G, and B channels are extracted as:

$$C_{i,j} = \left(C_{i,j}^{R}, C_{i,j}^{G}, C_{i,j}^{B}\right) \tag{2}$$

The texture characteristics of pixels at energy $E(n)$, entropy $H(n)$, moment of inertia $I(n)$ and correlation $C(n)$ are:

$$T_{i,j} = \left(T_{i,j}^{E}, T_{i,j}^{H}, T_{i,j}^{I}, T_{i,j}^{C}\right) \tag{3}$$

In the training process, use the SVM toolkit that comes with Matlab and use the following model model = svmtrain (TrainLabel, TrainData) to complete the training. Among them: TrainLabel is the category label, TrainData is the training sample data, and the extracted feature vector $F\left(C_{i,j}, T_{i,j}\right)$ Import and conduct model training, that is, build a classifier.

After subtracting the pixels of R = B = G = 0 (background color), the color features and texture feature values of the remaining pixels are used as test samples, and imported into the classifier trained in the previous step for recognition, and the data is divided into the following on the basis of minimizing the error function. According to the predetermined number of classes, each sample in the image is classified according to its distance from the center of each class, and the two sets of pixel points identified and output are respectively marked. According to the test result of the previous step, the pixel set of the same mark is output again to the image, and the area of the pixel set RGB feature value of the tea shoots in the output image is:

$$\begin{cases} R_{\text{tender}} \in [75, 116] \\ G_{\text{tender}} \in [54, 133] \\ B_{\text{tender}} \in [39, 128] \end{cases} \tag{4}$$

Through RGB discrimination of the tea in the image, the tea shoots identified and output are as follows:

Fig. 5. Tea shoots output

So far, the automatic identification of tea buds has been completed

4 Experiment

In order to verify the effectiveness of the method in this paper, a comparative experiment needs to be designed, using the K-Means method, Grabcut method and the method in this paper to conduct experiments.

4.1 Experimental Design

Under the operating environment of the Windows7 operating system with a CPU of 3.2 GHz, 4 G memory, and 500 G hard disk, the method proposed in this article was tested using MATLAB_R2013b software. In order to avoid the accidentalness of the experimental process as much as possible, and to better verify the effectiveness and practicability of the experimental method in this article, the same equipment was used to shoot under different light sources, different angles and different environments. Six of them are selected as samples, as shown in Fig. 6:

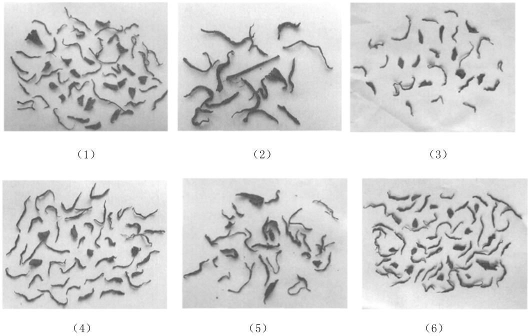

Fig. 6. Test image in the experiment

The above picture, Fig. (1) It is collected under indoor incandescent lamps at night, Fig. (2) is collected under natural light during the day, Fig. (3) is collected under indoor incandescent lamps during the day, Fig. (4) (5) is collected under indoor natural light during the day, and Fig. (6) is night For flash collection. Before the experimental detection, the image is pre-processed (enhanced). The total number of tea particles in each figure is 49, 16, 31, 51, 34, and 59 respectively, and the corresponding number of tender tea particles is 21, 2, 9, 12, 5, 18 grains, the experiment is to deal with the selected 6 images (image enhancement and unified background color (R = B = G = 0) processing, to obtain the color features and texture feature values of the image as a test sample), and then use the method proposed in this article to identify, you can get two types of pixel sets of sprouts and non-sprouts, and finally output the sprout image for the sprout pixel set according to the results as shown below (Fig. 7):

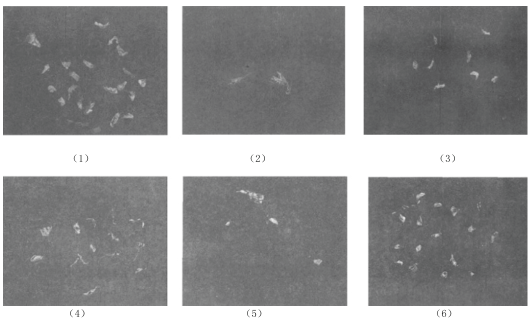

Fig. 7. The results of this method for the identification of tea buds

In order to better illustrate the effectiveness and feasibility of the experimental method, the recognition rate P, recall rate R, and comprehensive evaluation index F_1 are used to evaluate. The formula of recognition rate P is as follows:

$$P = \frac{\text{Identify the correct number of buds in the number of buds}}{\text{Total number of buds identified}} \tag{5}$$

The formula for calculating the recall rate is as follows:

$$R = \frac{\text{Identify the correct number of buds in the number of buds}}{\text{The actual total number of buds in the sample}} \tag{6}$$

The calculation formula of comprehensive evaluation index is as follows:

$$F_1 = \frac{2}{\frac{1}{P} + \frac{1}{R}} = \frac{2 \times P \times R}{P + R} \tag{7}$$

According to the above experimental indexes, the experiment was carried out, and the results were analyzed.

4.2 Statistical Results Analysis

Carry out the experiment according to the above process, and the statistical results of this article are shown in the following table (Table 2):

Table 2. Experimental results in this paper

Image	Total grain number of tea	Number of buds of tea	Identify the number of tea bud particles	Correctly identify the number of tea bud particles
1	49	20	21	18
2	16	2	1	1
3	31	10	9	9
4	51	13	14	13
5	34	4	3	3
6	59	17	17	16

According to formulas (5)−(7), the three-phase index of the experiment in this paper can be calculated. According to this method, the experiments using K-Means method and Grabcut method are used respectively, and the results of the three experiments are counted. The results are shown in the following table:

Table 3. Comparison of experimental results of three methods

Methods	Recognition rate P/%	Recall rate R/%	F_1/%
K-Means	73.4	81.4	78.6
Grabcut	88.9	77.4	83.9
Method in this paper	95.5	84.7	88.3

According to the data in Table 3, the recognition rate of K-means method is the lowest among the three methods, and the recall rate of grabcut method is the lowest among the three methods. However, the recognition rate of this method can reach 95.5%, the recall rate can reach 84.7%, and the highest comprehensive evaluation rate is 88.3%. It shows that the recognition rate, recall rate and comprehensive evaluation of the method in this paper are high.

In order to further verify the effectiveness of the method in this paper, k-means method and grabcut method for tea bud image recognition time were compared and analyzed. The comparison results are shown in Fig. 8.

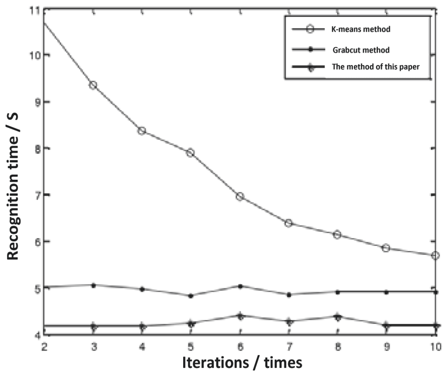

Fig. 8. Comparison results of tea bud image recognition time

According to Fig. 8, the recognition time of tea bud image in this method is within 4.5 s, which is shorter than that of K-means method and grabcut method, which indicates that the recognition efficiency of tea bud image can be improved by using this method.

5 Conclusion

In view of the color difference of tea shoots in Longjing tea image, combining digital image processing technology and application machine learning, this paper proposes an automatic recognition method of tea shoots image based on support vector machine, which makes full use of the characteristics of buds to improve the image recognition rate, and the automatic selection of training samples also provides good features for support vector machine to avoid the subjective selection by hand Sex. The experimental results show that the method selected in this paper is feasible for the recognition of tea shoots in the tea image, and the recognition effect is better than the two traditional methods, achieving the expected experimental effect. However, there are still some shortcomings in this method. When collecting tea images, there are differences in the orientation of tea particles and the shooting light, so the clustering features that affect the selection of the experimental process are not perfect. The next step is to consider the corresponding reflective features in combination with the next research. In addition, this experiment is only conducted on the limited image categories, and the recognition accuracy also needs to be further improved Raise.

Fund Projects. Youth science and technology talent growth project of Guizhou Provincial Education Department (Qian Education KY [2019]181, Qian Education KY [2016]298), Science and technology cooperation project of Guizhou Provincial Science and Technology Department (Qian Science LH [2016] 7288).

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