Automatic Classification of Chestnuts Based on Decision Fusion

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Abstract—Image acquisition system of chestnuts has been designed in this study. After the preprocessing on the images, including image de-noising, image enhancement, image segmentation, edge extraction and edge linking, the parameters of the shape features of chestnuts such as the areas, the perimeter, the circularity, the eccentricity and the degree of circularity have been extracted. This study proposes a decision fusion strategy using L-M neural network for automatic classification of chestnuts. The simulation results present that the classification accuracy has been improved using the method based on decision fusion compared with the traditional methods.

Keywords-decision fusion; image processing; L-M neural network; automatic classification; chestnut

1. Introduction

Agricultural products are important export products in china. But the grading of the agricultural productions accounts for a large proportion of costs. In recent years, some researchers have done a lot of work using the computer vision technology on automatic classification of agricultural products in foreign country. Some of their research has already been commercialized, and has achieved real-time speed [1]. The research on the classification of agricultural products in our country began later than other country, but it has been the focus of agricultural research in recent decades. [2]-[3] Chestnut is one of the major agricultural products in China. The automatic classification of chestnuts can greatly reduce the cost during production. Jian-Jun Fang et al [4] have studied the real-time classification system of chestnut based on the machine vision technology. But the research was only done to grade the size of the chestnuts. According to "GB/T 22346-2008", there is a precise definition of the sense organ index on the quality of chestnuts [5]. This study uses the machine vision and image processing technology to preprocess the image of the chestnuts, including defect detection, and the shape characteristics of the chestnut were extracted. We designed a decision fusion strategy using L-M Neural network. The simulation results present the classification using the decision fusion strategy based on the shape characteristics of chestnut achieves a more accuracy rating.

2. Image acquisition

In this study, the constructional drawing of our experimental system is shown in Figure 1. In order to reduce the shadow of the chestnut as much as possible, we use four exposure lights located in four different positions. Chestnut images captured are shown in Figure 2, 3.

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Fig.1. Detection system based on computer vision





Fig.2. The image of original defective chestnut

Fig.3. The image of original normal chestnut

3. Image preprocessing and extraction of features

The procedures of the image preprocessing and features extraction about the chestnuts include image noise elimination, image enhancement, image segmentation, edge extraction, edge link, shape features extraction.

3.1. Image processing

1) Image segmentation: In order to reduce the error of the extracted parameters of the chestnuts' external attributes, we filter the image noise with smoothing filter. Taking into consideration of the advantage of the smoothing filter that it is easy to remove the noise of isolating dots and lines, but also it preserves the edges in the image, we adopt the smoothing filter to get rid of the image noise [6].

We can segment the chestnut using the original image with chestnut subtract the background image without chestnut. This study uses the sobel operator to detect the chestnuts' edge. The edge detection results are shown in figure 4, 5. The defective area can also be detected with this the method of edge detection.



Fig.4. The result of edge detection on defective chestnut Fig.5. The result of edge detection on normal chestnut

2) Edge linking: The boundary lines are considered one of the most important features of an object in an image. Many computer vision systems rely on the uses of boundary line information to derive the object shape, to measure the object's parameters and to perform the object recognition task. However, Edges produced by existing edge detection algorithms often contain discontinuities. In order to obtain a precise description and accurate analysis of an object, edge linking is necessary.

In this study, we use the local processing method to link the object edge. The principle of the local processing can simply be depicted that the two pixels which have the similar magnitude and direction of gradient vector belong to one edge [7].

Principal properties used for establishing similarity:

(1) $|\nabla f(x, y)|$: magnitude of the gradient vector;

(2) $\alpha(x, y)$: direction of the gradient vector.

Edge pixel with coordinates (x', y') in neighborhood of (x, y) is similar in magnitude to the pixel at (x, y) if

$$\left|\nabla f(x, y) - \nabla f(x', y')\right| \le T$$

Edge pixel with coordinates (x', y') in neighborhood of (x, y) has a similar angle to the pixel at (x, y) if $|\alpha(x, y) - \alpha(x', y')| < A$

Where T and A is a nonnegative threshold. $\alpha(x, y) = \arctan\left(\frac{G_y}{G_x}\right)$, supposed that the gradient of the pixel (x, y) is (G_x, G_y) . Edge pixel (x', y') is linked with (x', y') if both of the above two criteria are

In this study we define T and A according to the results of experimentation. We find the results are well when we give values of T and A respectively 12 and 8° . The results of the edge link on the chestnuts images are shown in figure 6 and 7.



Fig.6. The result of edge linking on defective chestnut

satisfied.

Fig.7. The result of edge linking on normal chestnut

3.2. Extraction of external features of chestnuts

According to "GB/T 22346-2008", there is a precise definition of the sense organ index on the quality of chestnuts. The external features of the chestnuts include areas, perimeter, circularity, eccentricity and the degree of circularity [5]. In this study, the unit of the area of chestnut is pixel. In the same way, the defect area uses the unit of pixel.

The calculating formula of the degree of the chestnut's circularity can be depicted as:

$$c = \mu / \sigma, \mu = 1 / k (\sum_{k=0}^{k-1} \left\| (xk, yk) - (\overline{x}, \overline{y}) \right\|), \sigma^2 = 1 / k \sum_{k=0}^{k-1} \left\| (x_k, y_k) - (\overline{x} - \overline{y}) \right\| - \mu \right\|^2$$

In which the parameter μ stands for average distance of the edge pixels to the regional centre, while σ^2 is the standard deviation of the edge pixels to the regional centre.

The chestnut's degree of circularity reflects the extensibility, and the calculating formula is $R = 4A/\pi L^2$. In which the parameter A is the area of the object, L is the length of the major axis. In this study we acquire the L with the method of line scanning.

The method of line scanning can be depicted that scan the image from the top to the bottom, from the left to the right. When find the pixel p which is the object pixel, we put the value of corresponding y-coordinate down into array C[i], Where i stands for the value of x-coordinate. So the data in C[i] are the y-coordinates in the same line. Using the maximum value subtracts the minimum in the same line, and put it into the array D[i]. We can get the length L of major axis with the follow formula:

$$L = \max D[i]$$

4. Automatic Classification of Chestnuts Based On Decision Fusion

4.1. Principle of L-M nerual network

A number of classification methods have been developed to grade agricultural products (see, e.g., [1-2]). However, the precision is not very high, and it is very difficult to deal with all kinds of products using the same method. Consequently, combining many classification methods together and fusing the sub-results to obtain more accurate classification results would be reasonable [8]. This paper proposes an automatic classification method based on decision fusion. The decision fusion strategy in this study is implemented by the multiple-layer feed-forward network back propagation (BP) neural network to classify different types of chestnuts.

There are three layers in BP network: input layer(s), hidden layers(s), and output layer(s). Stimulation is applied to the inputs of the first layer, and signals propagate through the middle (hidden) layer(s) to the output layer. Each link between neurons has a unique weighting value. The BP learning process works in small iterative steps: the network produces some output based on the current state of its synaptic weights (initially, the output will be random). This output is compared to the known-good output, and a mean-squared error signal is calculated. The error value is then propagated backwards through the network, and small changes are made to the weights in each layer. The weight changes are calculated to reduce the error signal for the case in question [9]-[10]. The whole process is repeated for each of the example cases, then back to the first case again, and so on. The cycle is repeated until the overall error value drops below some pre-determined threshold.

However, the convergence rate of conventional BP neural network is very low [11]. So improved neural network based on L-M algorithm has been applied to classify the chestnuts in this paper. L-M algorithm leads to global convergence with faster convergent speed than BP algorithm.

In the BP algorithm, the performance index F(w) to be minimized is defined as the sum of squared errors between the target outputs and the network's simulated outputs, namely:

$$F(w) = e^T e$$

where $w = [w_1, w_2, ..., w_N]$ consists of all weights of the network and e is the error vector comprising the error for all the training examples [12]. When training with the L-M method, the increment of weights Δw can be obtained as follows:

$$\Delta w = \left(J^T J + \mu I\right)^{-1} \cdot J^T e$$

Where *J* is the Jacobian matrix, μ is the learning rate which is to be updated using the β depending on the outcome. In particular, μ is multiplied by decay rate β ($0 < \beta < 1$) whenever *F*(*w*) decreases, whereas μ is divided by β whenever *F*(*w*) increases in a new step.

The standard L-M training process can be illustrated in the following pseudo-codes,

- a) Initialize the weights and parameter μ ($\mu = 0.01$ is appropriate).
- b) Compute the sum of the squared errors over all inputs F(w).
- c) Solve (b) to obtain the increment of weights Δw .

d) Recomputed the sum of squared errors F(w) Using $w + \Delta w$ as the trial w, and judge *IF trial* F(w) < F(w) in step (b) THEN

$$w = w + \Delta w$$

$$\mu = \mu \cdot \beta \ (\beta = 0.1)$$

Go back to step (b)

ELSE

$$\mu = \beta/\mu$$

Go back to step (d)

END IF

4.2. Decision fusion based on L-M nerval network

In "GB/T 22346-2008", three grades of chestnuts is defined according to the qualities which include the area, the defect, etc. The 1st grade is the top level which stands for the good chestnuts [5]. And the 2nd grades is the middle level, the 3rd grades is the bottom level, in which the quality is poor than the other two.

We design an L-M neural network with 4 input layer nodes because there are 4 parameters which we have extracted in the section 3. And the network has 3 output layer nodes with the output (100), (010),

 $(0\ 0\ 1)$ which respectively stand for the grades 1st, 2nd, 3rd. The number of the hidden layer nodes can be calculated according to the formula:

$$n = \sqrt{n_i + n_0} + a$$

In which *n* is the number of the hidden layer nodes, while n_0 , n_i are respectively the number of the input and the output layer nodes. And the parameter *a* is a constant between 1 and 9. In this study, the number of the hidden layer is 8 according to experimental results of 50 chestnut samples. In order to ensure the convergence of the L-M algorithm, but also make the convergence rate as fast as possible, we give the value of parameter μ 0.01.

4.3. Classification results based on decision fusion

We choose 30 chestnuts to simulate the decision fusion strategy based on L-M neural network designed above. And the classification results are shown in table I.

Grades	Decision fusion	Manual
1	10	10
2	9	10
3	11	10

TABLE I. RESULTS OF DECISION FUSION AND MANUAL METHOD

The results show that the precision of classification with the decision fusion method can arrive 90%. Compared with the method of the manual, the productivity has raised greatly.

5. Conclusion

This study proposes an automatic classification method based on decision fusion to sort chestnuts. The simulation results of 30 chestnuts show that the decision fusion strategy using the L-M neural network can greatly improve the precision.

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