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Recognition of worm-eaten chestnuts based on machine vision

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ABSTRACT

The overall qualities of chestnuts are greatly affected by worm-eaten chestnuts, as they lead to a reduction of profits. Hence a fast, accurate and non-destructive method for sorting chestnuts is in great demand. In this study, the technology of machine vision was employed to grade chestnuts. A recognition method to identify worm-eaten chestnuts is presented based on the edge image of the wormhole. First, by applying a Sobel operator, binary images were gained through extracting the edges of the gray images, which were preprocessed with the denoising method of a Wiener filter. The binary image contained both the edge of the contour and the wormhole. The wormhole edges were obtained through separating the wormhole edge in light of the character that the gray degree of pixels in the neighborhood of the wormhole edge is lower than the threshold value set. Second, through morphological dilating and eroding, the denoised wormhole edge images were obtained. The connected component of the binary images of the wormhole edge were labeled, and the first three longest components were considered as feature values of the worm channel, which were then normalized. Third, the normalized data were input to a back-propagation (BP) neural network for training, where the hidden layer was 7. And only three steps were needed for iteration. When the model was utilized for prediction, the recognition rate was as high as 100%. The results showed that the proposed worm-eaten chestnut recognition method is accurate and fast, and it can provide a basis for on-line detection. Since the gray degree of the wormhole region is close to the normal region, this study used an enhanced boundary detection method to extract the edge of the worm channel solely, rather than the normally used region segmentation.

1. Introduction

The chestnut is one of China's important economic crops and fruit; it has rich nutrition value and high food and medicinal value. Chestnuts are popular among domestic and foreign consumers. As many worm-eaten chestnuts exist, which seriously affect the overall quality of chestnuts, the separation of chestnuts is an important process. Therefore, developing a fast and accurate non-destructive testing (NDT) method for sorting chestnuts will be significant for the chestnut industry.

Machine vision (MV), which uses machines instead of human eyes in carrying out measurement and judgment, is a new subject which is related to artificial intelligence, neurobiology, psychophysics, computer science, image processing, pattern recognition and other emerging interdisciplinary fields. With continuous development and improvement of computer technology, especially multimedia technology, digital image processing and analysis theory, machine vision is now widely used [1–5]. The research and application of machine vision in agriculture began in the late 1970s, mainly for non-destructive testing of the quality and classification of fruits and vegetables [6–9].

Li et al. studied a method for the detection of mouldy chestnuts based on near-infrared spectra [10–12]. Fang et al. [13] designed an MV-based real-time chestnut rating system. The system used the results of image processing and pattern

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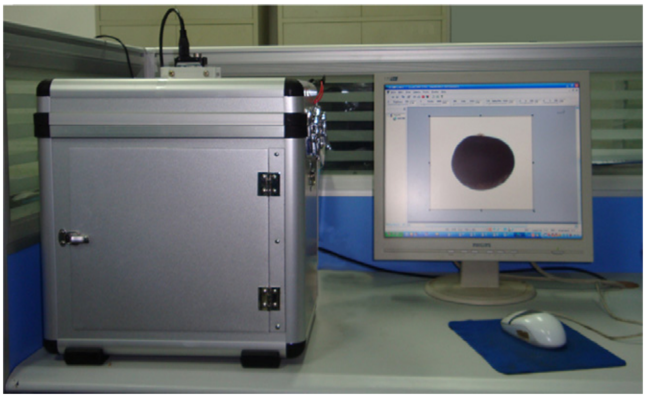


Fig. 1. Chestnut sorting testing platform based on machine vision.

Fig. 2. Typical samples of chestnut RGB images.

recognition to control the mechanical equipment system. Tests showed that the classification accuracy of the system was above 98%, but the speed of the image processing needed to be improved. Liu [14] developed an MV-based chestnut fine grading device, which controls the electromechanical integration equipment with the result of the recognition. Their experiments showed that the classification rate reached 40–50/min with an accuracy of 95.33%.

This paper presents a technique using machine vision to sort worm-eaten chestnuts. We first used digital image filtering techniques, then chose an enhanced border extraction technique according to the characteristics of chestnut image to extract the feature parameters, and finally constructed the identification model based on a neural network.

2. Materials and equipment

2.1. Chestnut sorting testing platform based on machine vision

The system in the experiment consists of an aluminum alloy box, light source, CCD image sensor, image grabbing card and PC. The CCD image sensors include an scA1390-17fc-type camera by German company, Basler and the M1214-MP lens. The image grabbing card's model is Meteor2-1394. The light source is a 32 W ring fluorescent lamp, which is placed on the internal top of the aluminum alloy box. The background of the box is white. Fig. 1 shows the chestnut sorting testing platform based on machine vision. When the system works, the AD converter converts the image signals acquired by the CCD image sensors to digital signals, which are sent to the PC by the image grabbing card for digital imaging processing.

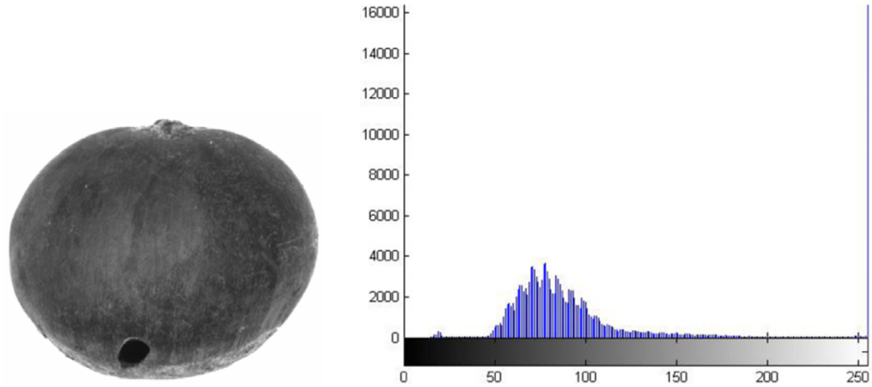
2.2. The establishment of a typical chestnut sample set and image sample set

The samples for the experiment were Luotian chestnuts; 60 worm-eaten chestnuts and 60 normal chestnuts were included. The samples were bagged after being wiped by a dry dish cloth, and were stored. The samples were labeled CH1–CH60 and YH1–YH60. CH1–CH30 and YH1–YH30 constitute the training sample set, while CH31–CH60 and YH31–YH60 constitute the testing sample set. 560×432 RGB images were taken from the samples. Fig. 2 shows the typical samples of chestnut RGB images.

3. Feature extraction

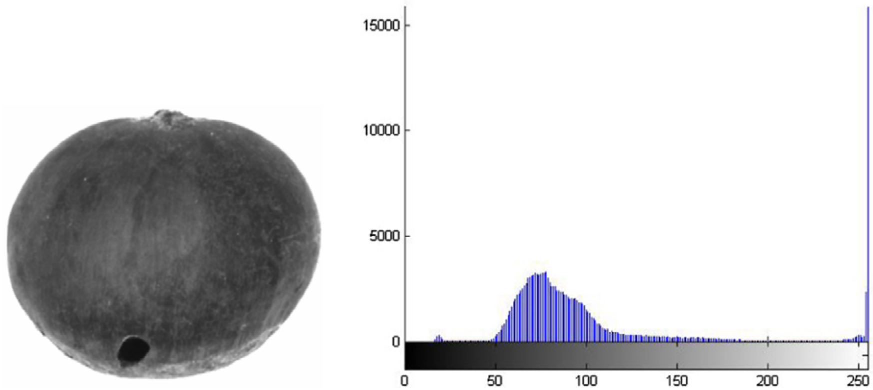
3.1. Digital image filtering

Since the chestnuts are of uniform color, to reduce computation, the RGB image was converted to a gray image, and the following conversion formula was used: $\text{Gray} = R \times 0.299 + G \times 0.587 + B \times 0.114$, where R, G and B indicate the corresponding color value of the red, green and blue components of the RGB image, respectively. Gray indicates the pixel gray value (range 0–255). The picture shows a chestnut image and its gray image, and the gray image typifies the characterization



(a) Gray image. (b) Gray-level histogram.

Fig. 3. The gray image and gray-level histogram of CH8.



(a) Gray image. (b) Gray-level histogram.

Fig. 4. The gray image and gray-level histogram of CH8 after processing by auto-adapted filtering.

of chestnut features (edges, texture and the characteristics of the wormhole, etc.). From its gray-level histogram, we found that the gray-level range of the wormhole region is from 0 to 50, while the background gray range is from 250 to 255. Fig. 3 illustrates the gray image and gray-level histogram of CH8.

As image acquisition will inevitably introduce noise, image preprocessing was done mainly for considering how to reduce the noise. The commonly used filtering methods for digital images are median filtering, mean filtering and auto-adapted filtering. Auto-adapted filtering can reduce the noise while preserving the image details better. After filtering, the histogram became more smooth, indicating that auto-adapted filtering can realize smoothing, and can better preserve the trough between the two peaks in the original histogram. Fig. 4 shows the gray image and gray-level histogram of CH8 after processing by auto-adapted filtering.

3.2. Image segmentation

There are two main defect detection methods based on machine vision. One is segmentation based on the gray value, and the other is segmentation based on boundary detection.

3.2.1. Segmentation based on gray value

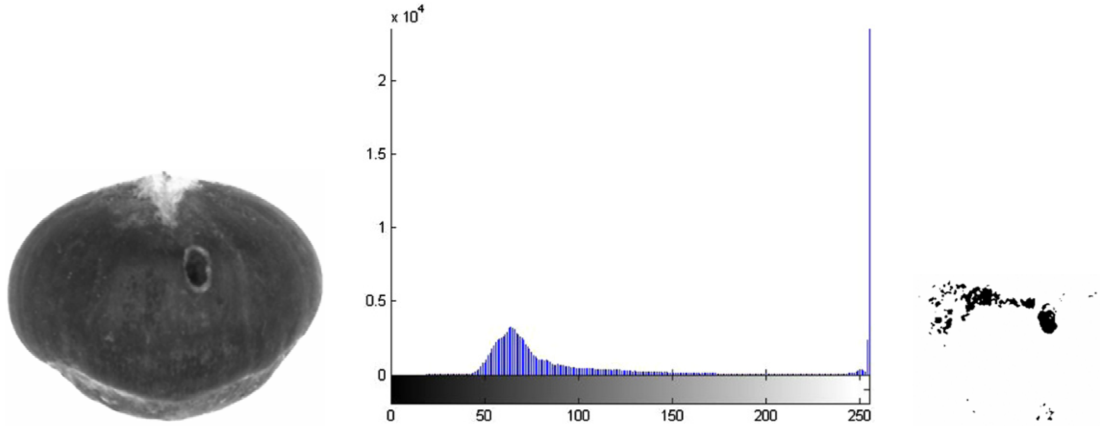
The basic thought is to divide the pixels with gray-level value higher than a particular threshold into one region, and those lower into another region. The threshold-based segmentation of gray value is called the gray-level threshold method. Fig. 5 shows the wormhole area of sample CH8; the gray threshold is 50.

But a chestnut has the following characteristics, which make the segmentation results of the method not significant.

First, the uneven surface makes the gray values in the recesses of the chestnut lower. Second, the location of the wormhole is not fixed: the area and the gray value of the wormhole are different, and there is no definite rule. Fig. 6 shows the histogram of CH55 after auto-adapted filtering, in which there is only one peak. The figure also shows the segmentation rustle of CH55 when the gray threshold was set to 50. This shows that the method is not effective.

(a) Filtered image. (b) Image after segmentation.

Fig. 5. The filtered image and segmentation based on a gray value of 50.



(a) Filtered image. (b) Histogram. (c) The image after segmentation.

Fig. 6. CH55 images and histogram.

Table 1
The areas of the connected regions.

Connected region	1	2	3	4	5	6	7	8	9
Area	6	2	14	116	3	4	4	11	2

These features led to easily mistaken division of the wormhole area and recess area into the same region by using the gray-level threshold method. So the method is not suitable for the test for feature extraction.

3.2.2. Edge-based segmentation method for feature

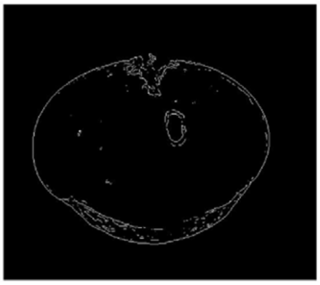
The common feature of a wormhole for all chestnuts is that the edge of the wormhole is obvious. Based on the character, we proposed an enhanced edge detection method to complete the feature extraction of the chestnut wormhole. The algorithm, which selectively retains the boundary points based on a Sobel operator is the following.

(1) A Sobel operator was employed to obtain the boundary image; the pixel value of the border points was 1, and pixel value of the background was 0.
(2) After observation of a large number of sample images, we found that the gray value of a wormhole is less than 70. After finding the gray value of an individual boundary point in the corresponding gray image, we compared it with 70: if it is larger than 70, this point will be considered as a background point, and simultaneously its pixel value is set as 0; otherwise, it is considered as a boundary point, and the pixel value is not changed.
(3) After expansion, thinning, removing isolated and bright points, acquisition of the wormhole edge image is completed.

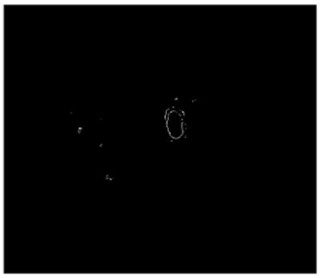
Fig. 7 show the images processed by the edge-based segmentation method.

3.2.3. Feature parameter extraction

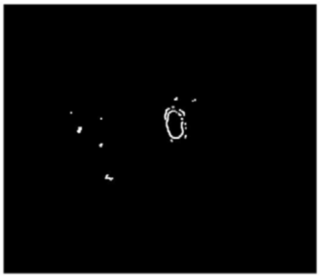
The wormhole border images were labeled in units of eight connected components, and there are a number of connected regions. Table 1 show the area of the connected regions in Fig. 7(e). By sequencing the area of connected regions of each image



(a) Edge image obtained by the Sobel operator.



(b) Image after process (2).

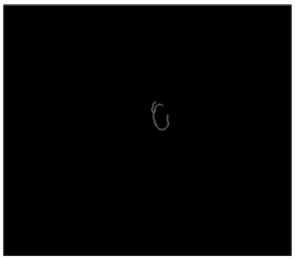


(c) Image after expansion.

(d) Image after thinning.

(e) Image after removing the isolated and bright points.

Fig. 7. Images processed by the edge-based segmentation method.



(a) The largest connected region.

(b) The second largest connected region.

(c) The third largest connected region.

(d) The synthesized image.

Fig. 8. The three largest connected regions and their synthesized image.

from large to small, the first three make up a one-dimensional vector: { 116, 14, 11}; the images are the three connected regions, and the synthesized image is obtained from the three connected regions by an add operation. The wormhole boundary image acquired by the enhanced boundary extraction algorithm showed that the total area of the boundary is 162. After feature extraction, the total area of the three connected regions is 141, which makes up 87.04% of the total boundary area (162). This indicated that the feature extraction method can extract the wormhole boundary information, including most of the wormhole boundary information, and, moreover, restrain the noise information and compress the data. Fig. 8 show the three largest connected regions and their synthesized image.

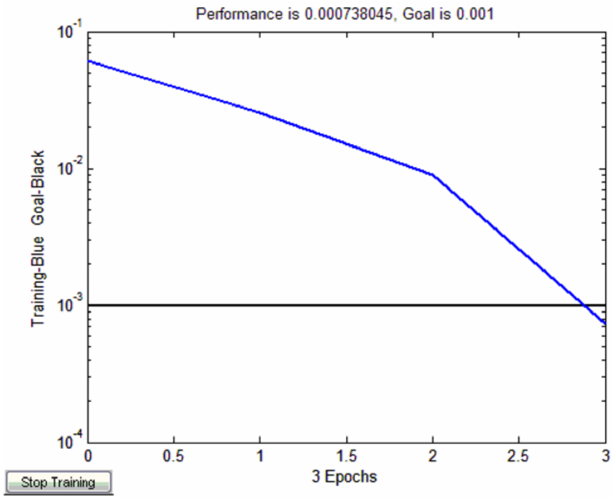


Fig. 9. The training result of the BP neural network identification model.

4. Establishment of the BP neural network identification model

The BP (back-propagation) neural network, that is, a learning algorithm based on back propagation of the error, consist of two processes: the forward propagation of the information and the back propagation of the error. As a classifier for pattern recognition and clustering technology, the BP neural network has such a strong capacity for learning, fault tolerance and information processing that it is widely applied in many fields.

The *S*-tangent transfer function, 'tansig', was used for the hidden layer neuron, with the *S*-logarithm transfer function, 'logsig', used for the output layer. Besides, the training function of the network is 'trainlm'. The input layer is the one-dimensional vector from the wormhole feature extraction. The output layer is a unit, in which 0 means normal chestnut (no wormhole) and 1 means worm-eaten chestnut. The expected error is 0.001.

BP neural network identification models were established. The best training result was obtained after only the iterations, when the number of hidden layer was 7, shown in Fig. 9. It converged so rapidly that only three iterations were needed. Then the feature vectors of the prediction set were imported into the BP neural network model for simulation, and the results showed that the recognition rates for the normal chestnuts and the worm-eaten chestnuts were both 100%. This desirable simulation result is due to the enhanced edge detection algorithm, which separated the wormhole boundary.

5. Conclusion

(1) Since the gray value of a wormhole is close to that of other areas of a chestnut, this study does not choose the commonly used region segmentation method, but an enhanced edge detection algorithm to separate the wormhole boundary for the sorting of agricultural products, which provides a new method for detection.
(2) The feature extraction method of the images used in this study can extract the wormhole boundary information, including most of the wormhole boundary information, and, simultaneously, restrain the noise information and compress the data.
(3) The BP neural network identification model converges after only three iterations, and the recognition rates of normal chestnuts and worm-eaten chestnuts are both 100%.

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