Chestnuts quality online detection technology based on acoustics

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Abstract: In order to overcome the influence of various uncertain factors on the quality of chestnuts in the process of manual detection, an online detection method based on acoustics was proposed. In this paper, a multilevel inspection platform for chestnut surface defects based on acoustics is constructed to realize real-time acquisition and measurement of chestnut surface defects. Through acoustic detection, the sound collected from the feature area is converted into a time-frequency map, and image processing was performed using matlab software. At the same time, in the return air detection, the chestnuts with wormholes will produce a return air, which was used as the secondary detection of the chestnuts. This study provides a useful reference for chestnuts quality testing and improves the objectivity and accuracy of chestnuts quality testing.

1. Introduction

Chestnut is a famous dried fruit traditionally planted in China. The total annual output is 469,800 tons, accounting for 60% of the world's total output [1]. However, because the chestnuts are prone to pests during the growth process and its water content is not resistant to preservation, which cause the overall quality is reduced and the competitiveness is insufficient, and seriously affects the overall price and sales volume of the chestnuts. Fig.1 shows the picture of chestnuts with worm holes.

Fig.1. The picture of chestnuts with worm holes

In the early stage, chestnuts were mainly tested manually, and the test results lacked objectivity and accuracy, and cost a lot of manpower and material resources [2]. With the introduction of fruit grading technology, some chestnuts were mechanically graded, but they were not promoted because of the fast grading speed and easy damage to the appearance. Compared with the above methods, machine vision...
detection technology [3] has attracted wide attention of scholars due to its high efficiency, accuracy, non-contact and other characteristics.

In this paper, a new type of acoustic detection mechanism was adopted, which used high-speed airflow generated by a gas needle with a diameter of 1mm under a pneumatic machine with a pressure of 0.8Mpa to blow out the suspected chestnut wormhole area. The acoustic characteristics of the frequency mutation were used to realize the recognition of the worm holes chestnuts. Return air detection further determines the position of the worm holes to achieve secondary screening of the defective chestnuts.

2. Selection of chestnuts experimental material

In this experiment, the chestnuts from Qianxi, Hebei Province were selected. 100 chestnuts were selected from the total samples as experimental samples, 70 of which were defective chestnuts with different positions, sizes and quantities of worm holes, and 30 normal chestnuts. The experimental sample of chestnuts in this paper were shown in Fig.2.

![Fig.2. Experimental chestnuts samples](image)

3. Sound signal analysis and feature extraction of chestnuts with worm holes

3.1. Processing of sound signals

In the experiment, 10~20 seconds of sound signals were collected for each chestnuts, and 2D and 3D time-frequency charts were obtained through matlab playback. Fig.3(a) shows the time-frequency diagram of normal chestnuts, while Fig.3(b), (c) and (d) show the time-frequency diagram of defective chestnuts.

![Fig.3. (a) The time-frequency diagram of normal chestnuts; (b), (c) and (d) The time-frequency diagram of defective chestnuts.](image)

It can be seen from the above figure that there is a significant difference between the time-frequency diagram of normal chestnuts and that of chestnuts with worm holes. Therefore, it can be concluded that it is feasible to collect sound signals by blowing chestnuts surface with air needle and judge the quality of chestnuts by the difference of sound signals.
3.2. Time domain feature extraction

In the time domain feature, since the energy of the speech signal changes with time, and the short-term average energy and the short-term average amplitude can clearly distinguish the normal chestnuts and the chestnuts with worm holes, it is necessary to analyze them.

3.2.1. Short-term average energy

The short-term average energy is one of the important time-domain characteristic parameters of the sound wave, which can well detect the energy of each frame after the waveform function is framed. The energy corresponding to the chestnuts with worm holes is much different than that of the normal chestnuts. Therefore, for this difference, the short-term average energy of the chestnuts sound signal is first analyzed.

The short-term average energy \[ E_n \] of a frame signal of the speech signal \( \{x(n)\} \) is:

\[
E_n = \sum_{m=n-(N-1)}^{n} x(m)w(n-m)\]

(1)

Among them, \( w(n) \)- window function, \( N \)- window length.

Order:

\[
h(n) = w^2(n)
\]

(2)

Then there is:

\[
E_n = \sum_{m=-\infty}^{+\infty} x^2(m)h(n-m) = x^2(n)*h(n)
\]

(3)

In the experiment, 40 chestnuts samples were randomly selected from 100 chestnuts samples from Qianxi (30 normal chestnuts samples and 70 wormholes chestnuts samples) for short-term average energy data processing. And Fig.4 is a short-term average energy scatter plot of normal chestnuts and chestnuts with worm holes.

![Short-term average energy](image)

As can be seen from the scatter diagram, among the 40 randomly selected samples, the short-term average energy in time domain of chestnuts with worm holes signal is much higher than that of normal chestnuts sound signal.

3.2.2. Short-term mean amplitude

Short-term average amplitude \[ M_n \] is defined as:

\[
M_n = \sum_{m=-\infty}^{+\infty} |x(m)|w(n-m) = \sum_{m=n-(N-1)}^{n}|x(n)|w(n-m)
\]

(4)

Among them, \( M_n \)- the short time mean amplitude of frame n, \( N \)- window length, \( w(n-m) \)- linear filtering of signals, \( x(n) \)- time domain signal of frame n. Fig.5 shows the short-term average amplitude values of normal chestnuts and chestnuts with worm holes.
It can be concluded from the experiment that the time-domain related parameters of the sound signal extracted by the high-pressure air-flowing chestnut surface are stable relative to the experimental results, and can be used as the identification detection of the chestnuts with worm holes defects.

4. Return air detection

4.1 Return air concept

When the high-speed airflow is concentratedly blown onto the chestnut surface through the gas needle, for normal chestnuts, the airflow is either blocked by the chestnut surface or spreads in the forward direction. For the wormholes chestnut, due to the presence of the wormholes, part of the airflow that is blown out will return along the original path to form a so-called return airflow, referred to herein as return air.

4.2 Experimental data

40 chestnuts as samples for the measurement of return air speed. Blowing was performed at a constant pressure of 0.8 Mpa. Fig.6 shows return air speed detection.

As can be seen from the scatter diagram, the return air speed of the chestnuts is mostly above 4m/s, and only a few values are below 4m/s. The reasons are as follows: (1) Normal chestnut with low return air speed. (2) Too many worm holes on the surface of chestnuts, forming ventilation effect, which has a certain impact on the experimental results. (3) With the continuous output of the air pressure machine, the pressure value may not always be stable at the constant value of 0.8 Mpa. To sum up, the air return detection device for chestnuts with worm holes can be used as an auxiliary detection method for the detection of chestnuts wormhole, and it is difficult to make it become an independent detection unit.

5. Identification and classification based on BP neural network

5.1 BP neural network construction

(1) Based on two sets of chestnut samples with two characteristics of extracted sound signals, a
Three-layer BP neural network with a single hidden layer was constructed.

(2) The number of input/output node: because with the neural network classification is chestnut surface for normal or wormholes, therefore the result of the requirements for normal for "1", wormholes for the "0", and input the information of the two parameters in time domain features, frequency-domain characteristics take two parameters, so choose the number of neurons for four.

(3) Selection of transfer function: the speed of the integrated operation and the optimized structure of the neural network, and the trainlm function is selected as the training function of the neural network.

5.2 BP neural network training and recognition classification

Neural network classification is performed on short-term average energy samples and short-term average amplitude samples. According to multiple experimental data, when the number of hidden layers is 8, the number of iterations is 1000, and the display frequency is displayed once per step. The training result, the minimum mean square error is 0.001. In order to increase the learning rate, the coefficient momentum factor \( c = 0.9 \) in front of the momentum, using the additional momentum method, will stop the training when the variance result in the neural network operation is less than the set result. The data fit is predicted as shown in Fig.7, and the test samples were classified with the trained chestnut samples. When the discriminant is normal chestnut, the output is "1". When discriminating for the worm eye chestnut, the output is "0". The output results are as follows: Fig.8 shows the comparison of accuracy of test results.

![Fig.7. Degree of data fitting](image1)

![Fig.8. The comparison of accuracy of test results](image2)

From the data on the figure, it can be concluded that the acoustic detection of chestnut can reach up to 99% under the classification of neural network, so the research on the mutation signal in the surface sound of chestnut has basically reached the expectation.

6. Conclusions

Through experiments, it can be concluded that:

(1) Acoustic and air return detection based on machine vision is feasible.

(2) Through acoustic characteristics detection of chestnut quality defects, acoustic characteristics detection can be nondestructive, fast and low-cost.

(3) Air return test can only be used as an auxiliary testing device, not an independent testing unit.

7. Acknowledgements

This research is supported by the Science and Technology innovation foundation for postgraduate of Zhengzhou university of light industry(2018032)

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