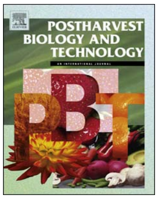
Postharvest Biology and Technology xxx (xxxx) xxx–xxx

Contents lists available at ScienceDirect

Postharvest Biology and Technology

journal homepage: www.elsevier.com/locate/postharvbio



Watermelon ripeness detection by wavelet multiresolution decomposition of acoustic impulse response signals

Xuan Chen[a], Peipei Yuan[b], Xiaoyan Deng[a,c,*]

[a] College of Science, Huazhong Agricultural University, Wuhan 430070, China
[b] College of Engineering, Huazhong Agricultural University, Wuhan 430070, China
[c] Institute of Statistical Science, Huazhong Agricultural University, Wuhan 430070, China

ARTICLE INFO

Keywords:
Watermelon
Ripeness
Acoustic signal
Detection
Multiresolution analysis
Hypothesis test

ABSTRACT

Ripeness is an important index for evaluating the quality of watermelons. This paper presents a simple, effective, and inexpensive approach to detecting watermelon ripeness based on wavelet multi-resolution decomposition (WMRD) and a statistical hypothesis test. The key idea in the proposed method is to model each WMRD coefficient as a random variable. For a specific coefficient, two samples are obtained by the multi-scale decomposition of watermelon acoustic signals, where one is for ripe watermelons and the other is for unripe ones. It is found that that many coefficients can be regarded as normal random variables, both for ripe and unripe watermelons. A discrimination index is proposed to estimate the separation degree of two samples, in order to determine the best WMRD coefficient. The probability density functions for ripe and unripe watermelons are obtained using the samples with the best coefficient. As a result, an inequality based on the hypothesis test at a 5% significant level is established for detecting watermelon ripeness. Using the proposed method, the training and test accuracies can reach 91.67% and 91.76%, respectively.

1. Introduction

Presently, the internal qualities of watermelons are mainly assessed by humans according to appearance, flavor, texture, sound, and so on. However, none of these factors constitutes reliable indicators, as such methods are prone to human error (Abbaszadeh et al., 2014). A number of approaches for nondestructive quality determination of watermelons have been proposed, such as acoustic and dynamic methods (Armstrong et al., 1997; Diezma-Iglesias et al., 2002; Jamal et al., 2005; Abbaszadeh et al., 2013, 2015a), electrical and magnetic methods (Kato, 1997; Nelson et al., 2007), X-ray methods (Tollner, 1993), and near infrared spectroscopy methods (Ito et al., 2002; Abebe, 2006; Flores et al., 2008; Tian et al., 2009; Jie et al., 2014). These approaches can successfully achieve their goals. However, it remains an open challenge to develop easily implementable, low cost, high accuracy methods of evaluating watermelon quality.

Among the methods mentioned above, acoustic detection technology has developed rapidly and become a primary method for the nondestructive quality assessment of watermelons, owing to its high speed, effectiveness, and low cost. Acoustic technologies are based on the hypothesis that good quality watermelons yield a different acoustic resonance to those of bad quality, and many interesting relationships between the acoustic features and internal qualities of watermelons have been reported by researchers. Ito and Sugiyama (2000) found that the transmission velocity of the impulse waveform becomes slower as a watermelon ripens. Hayashi and Sugiyama (2001) reported that the amplitude of the internal transform wave exhibits a correlation with the firmness of watermelons. Lee et al. (2005) employed multiple acoustic sensors to assess the internal qualities of watermelons, and established a prediction model using partial least squares regression. Jamal et al. (2005) studied the relationship between the resonant frequency and firmness of watermelons. Diezma-Iglesias et al. (2004) used the acoustic impulse response to detect internal defects in watermelons, and determined that a band amplitude parameter displayed the best ability to detect internal disorders. Abbaszadeh et al. (2013) developed multiple linear regression model between the data extracted from the vibration spectrum and internal watermelon quality. A comprehensive overview of nondestructive detection for internal qualities of watermelons has been provided by Sun et al. (2010). The majority of these investigations have involved ripeness detection.

Recently, some new techniques have been introduced to evaluate watermelon ripeness, such as the finite element model (Abbaszadeh et al., 2014), the support vector machine method (Wei Zeng et al., 2014), and the K-nearest neighbor method (Abbaszadeh et al., 2015b).

---

[*] Corresponding author at: College of Science, Huazhong Agricultural University, Wuhan 430070, China.
E-mail address: dxygh@mail.hzau.edu.cn (X. Deng).

http://dx.doi.org/10.1016/j.postharvbio.2017.08.018
Received 16 November 2016; Received in revised form 18 August 2017; Accepted 23 August 2017
0925-5214/ © 2017 Elsevier B.V. All rights reserved.

Please cite this article as: Chen, X., Postharvest Biology and Technology (2017), http://dx.doi.org/10.1016/j.postharvbio.2017.08.018

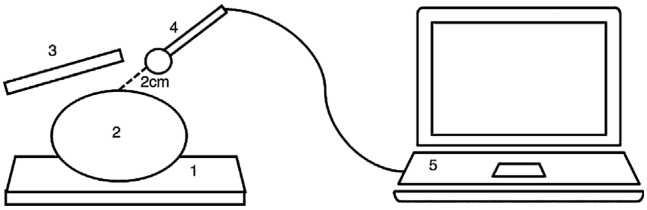


Fig. 1. Schematic diagram of experimental system: (1) supporting platform; (2) watermelon; (3) wooden stick; (4) microphone; and (5) notebook computer.

These new ideas provide powerful approaches to evaluating the internal structure of watermelons. The present paper focuses on the acoustic detection of watermelon ripeness. It is found that watermelon ripeness can be effectively detected in terms of an inequality obtained by combining the methods of wavelet multiresolution decomposition (Daubechies, 1992) and a statistical hypothesis test.

2. Materials and methods

2.1. Experimental system

A system based on acoustic impulses was developed for detecting watermelon ripeness. The experimental equipment consisted of product support, a light exciting stick, a microphone, a notebook computer(with a built-in 16-bit data acquisition card), and Matlab software to acquire and analyze the results. A schematic diagram of this system is presented in Fig. 1.

A rectangular wooden board of size 60 × 80 cm (2.5 cm thick) is used to support the watermelons. The exciting stick consists of a round wood stick with a diameter of 15 mm and length of 160 mm. The force of an excitation is controlled manually, and the impact point is at the equator of the watermelon surface. A microphone (BCM705, Beijing, China) with a frequency response of 20 Hz–20 kHz is placed 2 cm away from the impact point (see Fig. 1). The acoustic impulse emitted from the watermelon surface is picked up and converted into an electrical voltage signal by the microphone, and an acquisition program based on the Matlab function *analoginput()* is used to extract signals.

2.2. Watermelon samples

The samples used in this study are from Jingxin No.4 watermelons planted in a local farm (Wuhan, Hubei province, China). The Jingxin No.4 is an early maturing variety, with an entire growing period of around 90 days and a fruit development period of around 28 days. The fruit shape index is 1.1, the average weight of a ripe fruit is around 7 kg, and the central sugar content is around 11.4%.

The period of fruit development is closely related to environmental conditions, such as temperature, illumination, and moisture, and there are also individual differences in maturity levels under the same environmental conditions. As a pre-sampling analysis, 24 watermelons were selected for destructive detection. The watermelons were cut at the equator, and the sugar content at the central point of the watermelon was determined using a saccharometer (Model LB32T, Guangzhou, China). The results are presented in Table 1.

In this work, watermelons taken from the 22nd day after fruit setting were used as unripe watermelon samples, and ripe watermelon samples were taken on the 28th day after fruit setting. For the ripe watermelon samples, the destructive detection was implemented after measuring the acoustic response, and some unripe watermelons were removed from the ripe watermelon samples using color-viewing, sugar-detection, and fruit-tasting. Typical cross sections and corresponding sugar contents of the watermelon samples are shown in Fig. 2.

Table 1
Central sugar contents of pre-sampling watermelons, mean and SD denote the mean and standard deviation, respectively.

Fruit period (day)	Contents (%)						Mean	SD
19	6.5	6.9	7.2	7.8	7.9	8.0	7.38	0.56
22	7.8	8.6	8.9	9.1	9.5	9.9	8.97	0.67
25	9.4	9.8	10.0	10.3	10.8	11.2	10.25	0.61
28	10.5	10.8	11.4	11.5	11.8	12.1	11.35	0.55

2.3. Training and testing sample sets

100 watermelons were pre-labeled on the day of fruit setting, and acoustic signals were extracted at two different time points, the 22nd and 28th days. During the entire process of the experiment, there were six broken watermelons and four watermelons were removed from ripe samples on the 28th day by destructive detection. A total of 90 watermelon samples were actually used, and 180 signals were obtained. The signals from the 22nd day after fruit setting were labeled as unripe samples, and those from the 28th day were labeled as ripe. These signals, obtained by the field experiments, were employed as the training sample set.

Another 85 unlabeled watermelons were randomly collected and processed in a laboratory. The acoustic signals were first extracted by performing one excitement per watermelon, and 85 signals were obtained. Then, cutting a watermelon to check its ripeness, it was found that 45 signals came from ripe watermelons, and 40 signals from unripe ones. These signals were employed as the testing sample set.

Note that the acoustic signals of watermelons were detected using a sampling frequency of 27 kHz, with 4096 points per signal. All signals were treated as non-dimensional. Let $x = \{x_1, x_2, \ldots, x_n\}$ be the signal, and $\|\cdot\|$ the 2-norm. Then, the non-dimensional transform used in this study is defined as follows:

$$x \to 100 \times \frac{x}{\|x\|}. \tag{1}$$

Typical watermelon acoustic signals and their Fourier transforms are illustrated in Fig. 3.

2.4. Wavelet multiresolution decomposition

In this section, we provide a short synopsis of wavelet multiresolution decomposition (WMRD) that is relevant to our objective. A complete exposition of WMRD theory and its applications is provided by Daubechies (1992). A wavelet multiresolution decomposition of $L^2(R)$ is a sequence of closed subspaces $V_{j-1} \subset V_j$, $j \in Z$, where each subspace V_j is an approximation space of $L^2(R)$ on the scale j. Let W_j be the orthogonal complement of V_{i-1} in V_j. Then, $V_j = V_{j-1} \oplus W_j$. Repeating this process leads to the decomposition

$$V_J = V_0 \oplus W_1 \oplus \cdots \oplus W_J, \tag{2}$$

where $j = 1, \ldots, J$ is the scaling parameter in a J-level decomposition. There are two basic wavelet functions, which are called the father wavelet $\phi(t)$ and mother wavelet $\psi(t)$, and the dilation and translation functions $\phi_{jk}(t)$ and $\psi_{jk}(t)$, $k \in Z$ form orthogonal bases of V_j and W_j, respectively. Here, $\phi_{jk}(t)$ and $\psi_{jk}(t)$, $k \in Z$, are defined as follows:

$$\phi_{\mathrm{jk}}(t) = 2^{\frac{j}{2}}\phi(2^j t - k), \tag{3}$$

and

$$\psi_{\mathrm{jk}}(t) = 2^{\frac{j}{2}}\psi(2^j t - k), \tag{4}$$

where k is the translation parameter. Corresponding to Eq. (2), the wavelet multi-resolution decomposition of a signal $f(t)$ in space V_J is given by

$$f(t) = \sum_k d_{0,k}\phi_{0k}(t) + \sum_k d_{1,k}\psi_{\mathrm{jk}}(t) + \cdots + \sum_k d_{J,k}\psi_{\mathrm{Jk}}(t), \tag{5}$$

Download English Version:

https://daneshyari.com/en/article/8881944

Download Persian Version:

https://daneshyari.com/article/8881944

Daneshyari.com