Portable Apple Internal Quality Orchard Grading System Postprint

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Abstract

To meet the requirements for orchard-based detection and grading of apple internal quality, this study developed detection and grading modules to constitute a mobile apple internal quality orchard grading system. Based on this system, and using apple sugar content and moldy core disease as representative quality indicators, a spectral correction method based on Multiplicative Effect Elimination (MEE) was proposed to eliminate the influence of effective optical path length variations caused by differences in apple physical attributes on the spectra. Using this system to acquire diffuse transmittance spectral data of apples in the 600~900 nm range, and after preprocessing the apple spectra with Multiple Scattering Correction (MSC), Standard Normal Variate Transform (SNV), and MEE algorithms respectively, sugar content Partial Least Squares Regression (PLSR) prediction models and moldy core disease Partial Least Squares-Discriminant Analysis (PLS-DA) models were established. The results demonstrated that the MEE algorithm yielded better modeling results compared to MSC and SNV algorithms, with the sugar content prediction model achieving correlation coefficient of calibration set (Rc), Root Mean Square Error of Calibration (RMSEC), correlation coefficient of prediction set (Rp), and Root Mean Square Error of Prediction (RMSEP) of 0.959, 0.430%, 0.929, and 0.592%, respectively; the moldy core disease discrimination model achieved calibration set sensitivity, calibration set specificity, calibration set accuracy, prediction set sensitivity, prediction set specificity, and prediction set accuracy of 98.33%, 96.67%, 97.50%, 100.00%, 90.00%, and 95.00%, respectively. After importing the established optimal prediction model into the grading system for testing, the results indicated that the system achieved a grading accuracy of 90.00% with a grading speed of approximately 3 apples/s. The system offers advantages such as low cost, simple structure, and convenient mobility, and can satisfy the requirements for orchard-based detection and grading of apple internal quality.

Full Text

Preamble

Development of Mobile Orchard Local Grading System of Apple Internal Quality

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Abstract: To meet the demand for on-site detection and grading of apple internal quality at orchard origins, this study developed a detection module and a grading module to constitute a movable apple internal quality orchard origin grading system. Based on this system, with apple sugar content and moldy core as representative quality indicators, a spectral correction method based on Multiplicative Effect Elimination (MEE) was proposed to eliminate the influence of effective optical path length variations caused by differences in apple physical attributes. Using this system, diffuse transmittance spectral data of apples in the 600–900 nm range were acquired. After preprocessing the apple spectra with Multiple Scattering Correction (MSC), Standard Normal Variate Transform (SNV), and the proposed MEE algorithm, Partial Least Squares Regression (PLSR) prediction models for sugar content and Partial Least Squares-Discriminant Analysis (PLS-DA) models for moldy core were established, respectively. The results showed that the MEE algorithm achieved the best modeling performance. For the sugar content prediction model, the correlation coefficient of calibration set (Rc), root mean square error of calibration (RMSEC), correlation coefficient of prediction set (Rp), and root mean square error of prediction (RMSEP) were 0.959, 0.430%, 0.929, and 0.592%, respectively. For the moldy core discrimination model, the sensitivity, specificity, and accuracy of the calibration set were 98.33%, 96.67%, and 97.50%, respectively, while those of the prediction set were 100.00%, 90.00%, and 95.00%, respectively. When the optimal prediction models were imported into the grading system for validation tests, the results demonstrated a grading accuracy of 90.00% and a grading speed of approximately 3 fruits/s. The system offers advantages of low cost, simple structure, and convenient mobility, and can satisfy the requirements for on-site detection and grading of apple internal quality at orchard origins.

Keywords: apple; internal quality; visible/near-infrared spectroscopy; spectral correction; nondestructive detection; grading

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1 Introduction

China is a major apple producer and consumer, with both apple cultivation area and consumption volume ranking among the highest in the world [1]. As living standards improve, consumers increasingly focus on the internal quality of apples, among which sugar content is closely related to apple flavor and represents a primary internal quality attribute [2]. Apple moldy core is a major disease affecting apple edibility, and infected apples are generally unfit for consumption, necessitating removal of diseased fruits before marketing [3, 4]. Grading apple quality through sugar content and moldy core detection constitutes an effective approach for enhancing apple added value, safeguarding public health, meeting consumer demands, and improving market competitiveness [5].

Traditional physicochemical testing methods for apple internal quality suffer from drawbacks such as long detection times and destructive sampling [6]. Visible/near-infrared (VIS/NIR) spectroscopy detection technology offers advantages of accuracy, rapidity, and non-destructiveness, and has developed rapidly [7, 8]. Many researchers and enterprises have developed apple internal quality detection and grading devices based on this technology [9-11]. However, current detection and grading systems feature complex structures, large volumes, high costs, and poor mobility, making them generally suitable only for post-harvest pipeline production rather than real-time detection and grading in the complex orchard environment [12].

Orchard-origin detection and grading represents a crucial link in the entire apple industry chain [13]. On one hand, controlling apple quality at the source by eliminating moldy core apples can reduce cross-infection during storage and transportation, thereby minimizing economic losses [14]. On the other hand, automated and intelligent detection and grading at orchard origins can satisfy the grading needs of small-scale farmers, substantially reduce labor and transportation costs, shorten storage periods, and improve economic benefits. The complex and narrow operating environment at orchard production sites necessitates the development of a movable apple internal quality detection and grading system with simple structure, small size, lightweight design, and low cost, which holds significant importance for enhancing the mechanization and intelligence level of orchard production in China.

For apple internal quality detection and grading systems, developing effective and stable prediction models is essential. During online detection and grading, differences in apple physical attributes (size, shape, etc.) cause variations in the effective optical path length of light within the apples, resulting in varying degrees of "scaling" in the spectra of apples with identical chemical composition but different physical properties. This multiplicative scattering effect can mask spectral differences caused by variations in chemical composition, thereby reducing detection accuracy for apple internal quality [15-17]. Researchers have employed preprocessing algorithms such as Multiple Scattering Correction (MSC) and Standard Normal Variate Transform (SNV) to preprocess spectra, which can partially eliminate the influence of physical attribute differences on spectra [18]. Others have attempted to construct global models by mixing samples with different physical properties, though this approach requires large sample sizes [19]. Therefore, researching a spectral correction method suitable for apples to improve online detection accuracy holds significant importance and value.

In summary, to address the demand for apple quality detection and grading at orchard origins and reduce interference caused by irregular apple shapes, this study developed apple internal quality detection and grading modules to constitute a movable orchard-origin grading system. Regarding prediction model improvement, a Multiplicative Effect Elimination (MEE) based spectral correction method was proposed to eliminate the multiplicative scattering effect caused by differences in apple physical attributes, thereby enhancing detection accuracy for apple internal quality. By comparing prediction models for apple sugar content and moldy core established using different algorithms, the optimal prediction models were identified and imported into the system for grading experiments to validate the effectiveness of both the system and the correction method.

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2 System Structure and Composition

2.1 Overall System Architecture

The system employs a modular design, primarily consisting of an internal quality detection module, a grading module, and a control system. Featuring compact size and convenient mobility, the system meets on-site detection and grading requirements at orchard origins. The detection and grading modules are connected via a transition channel. The overall structural composition is illustrated in [Figure 1: see original paper].

The system technical parameters are listed in . The grading workflow proceeds as follows: after starting the equipment, apples are placed horizontally on the fruit holders with the stem-calyx axis aligned with the conveying direction. When an apple reaches the detection position, a photoelectric sensor in the detection module detects its presence and triggers the spectrometer to collect spectral information. The spectral data are input into the established prediction model to obtain detection results and determine the grade. The grade information is then transmitted to the memory of the grading module’ s microcontroller and stored. When the grading module’s photoelectric sensor detects the apple reaching the designated position, it sequentially reads the grade information from the microcontroller memory. A speed measurement photoelectric sensor obtains the conveyor belt velocity. Based on the acquired speed and the distance from the grading module’ s photoelectric sensor to the corresponding grade channel, the delay time for the grading action is calculated. After the corresponding delay, the apple moves from the photoelectric sensor position to the appropriate grade channel, the actuator executes the grading action, unloading apples of different grades into their respective channels, thus completing the grading process. The system workflow diagram is shown in [Figure 2: see original paper].

2.2 Internal Quality Detection Module Design

To achieve non-destructive online detection of apple sugar content and moldy core, an apple internal quality detection module was developed based on VIS/NIR spectroscopy technology. Since diffuse transmittance spectra can reflect the quality information of the entire apple and are beneficial for moldy core detection, the module adopts a diffuse transmittance approach for spectral acquisition. The main structure of the module includes a dark chamber, fruit holders, conveyor chain, and frame, as shown in [Figure 3: see original paper].

The dark chamber houses the spectral acquisition structure to avoid environmental light interference. The fruit holders transport apples and ensure stable positioning at the spectral acquisition location. The conveyor chain is driven by a motor, with fruit holders installed at intervals. The spectral acquisition system comprises four symmetrically arranged 50 W halogen lamps (Philips MR16), a halogen lamp power supply, a spectrometer (Ocean Optics USB2000+), and optical fibers, as shown in [Figure 4: see original paper]. The light source irradiates from above the apple, while spectral information is collected via optical fibers positioned below the fruit holders.

2.3 Grading Module Design

To implement grading functionality after quality detection, a quality grading module based on microcontroller and multi-sensor integration was designed. The module consists of grading channels, an inclined conveyor, grading gates, rotary solenoids, photoelectric sensors, and a control box, as shown in [Figure 5: see original paper].

The grading channels include three grades: premium, first-grade, and second-grade. Each channel has a width of 120 mm and is lined with anti-collision foam to ensure smooth apple passage while minimizing bruising damage. The lower end of each channel can be opened to connect to a conveyor or hopper. The inclined conveyor is driven by a motor, with the belt surface at a 35° angle to the horizontal, allowing apples to slide into the grading channels under gravity. The grading gates and rotary solenoids constitute the grading actuator, as shown in [Figure 6: see original paper]. When an apple reaches the designated grade position, the grading gate rotates 90° along the red arrow direction under the drive of the rotary solenoid to open, allowing the apple to fall into the grading channel before closing. The time from signal reception to complete gate opening is 0.01 s, which is maintained for 0.3 s to allow the apple to pass through, after which the gate closes within 0.01 s, with the entire grading action taking 0.32 s. Photoelectric sensor 1 in [Figure 5: see original paper] detects apple position information; photoelectric sensor 2 measures the speed of the inclined conveyor; the control box houses the microcontroller, power supply, and rotary solenoid driver board.

2.4 Control System Design

The upper computer software of the system was developed based on MFC Windows, with the interface shown in [Figure 7: see original paper]. The lower computer program was developed using Arduino IDE. The hardware includes a microcontroller (Arduino UNO), photoelectric sensors, and grading actuators. The control system enables functions such as starting/closing serial ports, turning equipment on/off, setting integration time, acquiring references, detecting position signals, controlling spectrometer acquisition, processing spectral data using built-in models, displaying quality and grade information, transmitting grade information to the grading module microcontroller, and controlling grading actions.

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3 Materials and Methods

3.1 Experimental Materials

To construct prediction models for apple sugar content and moldy core, Qixia Fuji apples produced in Qixia City, Shandong Province were used as research samples. A total of 300 apples without mechanical damage or external defects were selected, including 100 for establishing and validating the sugar content model and 40 for validating the grading system. After purchase, the apples were transported to the laboratory and stored at 4 °C. Before spectral acquisition, the apples were placed at room temperature (20 °C) for 24 h to minimize temperature effects on spectral acquisition. Moldy core conditions were simulated by injecting mold into the apples. The mold source was derived from rotten apple flesh, which was homogenized, mixed with distilled water at a 1:1 ratio, centrifuged at 2500 r/min for 10 min, after which 1 ml of the supernatant was extracted using a syringe and injected into the apple core through the calyx [20]. After mold injection, the apples were cultured at room temperature (20 °C) for 3 days before spectral information acquisition. Prior to modeling, samples were divided into calibration and prediction sets using random grouping at a 3:1 ratio for both sugar content and moldy core prediction models.

3.2 Spectral Acquisition

Before spectral acquisition, the light source was preheated for 30 min to stabilize the system. The integration time was set to 30 ms, and the conveyor was started. Apples were placed horizontally on the fruit holders with the stem-calyx axis aligned with the conveying direction. When an apple reached the spectral acquisition position, its spectral information was automatically collected. To eliminate spectral noise effects, the 600–900 nm spectral range was selected for analysis. After acquisition, MATLAB (R2016a, The MathWorks, Natick, MA, USA) was used for data analysis.

3.3 Determination of Apple Sugar Content Standard Values and Moldy Core Identification

Sugar content determination followed the agricultural industry standard NY/T 2637-2014, using a refractometer (PAL-1, ATAGO Co. Ltd., Tokyo, Japan) combined with a destructive method. After spectral acquisition, the entire apple was juiced using a handheld juicer, the juice was placed in a beaker and stirred evenly, and the sugar content was measured by dropping the juice onto the refractometer using a rubber-tipped dropper. Each sample was measured three times and averaged to obtain the sugar content value. Apples were cut vertically along the stem-calyx axis to observe internal moldy core conditions and determine whether moldy core was present.

3.4 Spectral Correction Method

For complex heterogeneous mixtures such as apples containing J chemical components, differences in sample physical attributes cause variations in the effective optical path length of light within the sample. Therefore, the spectrum of sample i can be represented using a multiplicative effect model, as shown in formula (1) [21]:

$$X_i = p_i \sum_{j=1}^{J} c_{i,j} s_j \tag{1}$$

where X_i represents the raw spectrum of the i-th sample, $i = 1, 2, \dots, I$; s_j denotes the spectrum of the j-th chemical component in the mixture; $c_{i,j}$ represents the concentration of the j-th chemical component in the i-th mixture; parameter p_i is the multiplication coefficient, indicating the multiplicative effect on the spectrum of the i-th mixture sample caused by effective optical path length variations due to changes in sample physical properties; and I is the number of samples.

According to formula (1), eliminating the multiplication coefficient in the spectrum can reduce the influence of multiplicative scattering effects. Assuming that the multiplication coefficient in each sample spectrum is closely related to the spectral data at a certain wavelength point, the Multiplicative Effect Elimination (MEE) algorithm corrects the spectrum as shown in formula (2):

$$X_{\mathrm{cor},i} = \frac{X_i}{x_\gamma} \tag{2}$$

where $X_{\mathrm{cor},i}$ is the corrected spectrum of sample i, and x_γ is the spectral data at wavelength point γ that is closely related to the multiplication coefficient. When correcting a batch of sample spectra, x_γ represents the spectral data at the same wavelength point across all samples.

Due to multiplicative effects, raw spectra of a batch of samples exhibit large fluctuations. After eliminating the multiplicative effect caused by physical attribute differences, spectral fluctuations decrease and correlation with chemical composition content further improves, facilitating the construction of more robust prediction models. To identify the optimal x_γ, the concept of least squares loss function was employed to define a loss function. After spectral correction, the loss value e is calculated; when e is minimized, it indicates minimal fluctuation in the corrected spectra, and the corresponding wavelength point is the optimal x_γ. The loss functions are defined in formulas (3) and (4):

$$e_i = \sum_{n=1}^{N} (x_{c,i,n} - \bar{x}_{c,n})^2 \tag{3}$$

$$e = \sum_{i=1}^{I} e_i \tag{4}$$

where N is the number of wavelength points; e_i is the loss value for sample i; e is the overall loss value for all corrected sample spectra; $x_{c,i,n}$ is the spectral data at the n-th wavelength point of sample i after correction; and $\bar{x}_{c,n}$ is the average spectral data at the n-th wavelength point of all corrected samples.

In summary, the spectral correction process involves: first, acquiring raw sample spectra; then sequentially using different wavelength points as x_γ in formula (2) to calculate corrected spectra and computing e using formulas (3) and (4); finally, selecting the optimal x_γ based on the principle of minimizing e to complete spectral correction.

3.5 Data Preprocessing

Common data preprocessing methods such as MSC and SNV can also correct spectral scattering effects caused by physical attribute differences [22]. Therefore, this study employed MSC, SNV, and the proposed MEE algorithm to preprocess raw spectra for establishing apple sugar content and moldy core prediction models, with the optimal preprocessing algorithm selected based on modeling performance.

3.6 Modeling and Evaluation Methods

This study used Partial Least Squares Regression (PLSR) to establish apple sugar content prediction models. As a multivariate regression analysis method, PLSR can reduce dimensionality of spectral data, perform comprehensive screening, and analyze correlations between two variable sets, offering high modeling stability [23]. The number of latent variables (LVs) for the PLSR model was selected based on Monte Carlo cross-validation results. Model performance was evaluated using the correlation coefficient of calibration set (R_c), correlation coefficient of prediction set (R_p), root mean square error of calibration (RMSEC), and root mean square error of prediction (RMSEP). Generally, models with higher correlation coefficients (R) and lower root mean square errors (RMSE) exhibit better performance.

Partial Least Squares Discriminant Analysis (PLS-DA) was employed for apple moldy core discrimination. Since PLS-DA is based on a linear regression model, a threshold must be set for classification [24]. In this experiment, healthy apples were assigned a category variable of 1, moldy core apples were assigned 0, and the threshold was set to 0.42. Predicted values below the threshold were classified as moldy core, while values above were classified as healthy. LVs were selected based on the minimum root mean square error of cross-validation (RMSECV) principle from Monte Carlo cross-validation. With moldy core as positive and healthy as negative, sensitivity, specificity, and accuracy were calculated to evaluate modeling performance.

After internal quality detection, apples must be graded according to their quality and unloaded into corresponding grade channels. Based on national standard GB/T 10651-2008, agricultural industry standard NY/T 2316-2013, and Beijing local standard DB11/T 599-2016, combined with the sugar content and moldy core conditions of this apple variety, apples were divided into three grades ().

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4 Results and Analysis

4.1 Apple Spectral Analysis

Using the spectral acquisition method described in Section 3.2, dynamic raw spectra of apples were collected, with results shown in [Figure 8: see original paper]. The spectral curves exhibit similar trends and peak/valley positions, with major peaks primarily related to O-H and C-H bond stretching vibrations, which are associated with apple sugar content and other internal components [25]. The peak near 650 nm is related to apple peel pigment content, the peak near 700 nm is mainly associated with the first overtone stretching vibrations of C-H and O-H bonds, and the peak near 800 nm is primarily related to the second overtone absorption of C-H bonds [26, 27]. The average spectra of healthy and moldy core apples are shown in [Figure 9: see original paper].

As shown in [Figure 9: see original paper], within the 600-900 nm spectral range, the overall trends of healthy and moldy core apple spectra are similar, with consistent peak and valley positions, but significant differences in overall spectral intensity. The spectral intensity difference is greatest near 720 nm and smallest near 900 nm. In the 600-760 nm visible range, spectral intensity differences are significantly more pronounced than in the 760-900 nm near-infrared range, with healthy apples exhibiting higher overall spectral intensity than moldy core apples. This is because moldy core apples rot from the core outward, with diseased areas appearing blackened and exhibiting stronger light absorption, resulting in lower transmitted spectral intensity compared to healthy apples [28]. Visual analysis indicates that discernible intensity differences exist between healthy and moldy core apple spectra, providing a foundation for moldy core identification through spectral information.

4.2 Sample Standard Value Statistics

Using the apple sugar content detection method described in Section 3.3, sugar content data for 100 apples were measured (). The calibration set contained 75 apples with sugar content ranging from 8.00% to 14.30%, mean value of 10.98%, and standard deviation of 1.58%. The prediction set contained 25 apples with sugar content ranging from 8.40% to 14.00%, mean value of 11.50%, and standard deviation of 1.45%. The sugar content distributions of the calibration and prediction sets were similar, with the calibration set covering the sugar range of the prediction set and both sets exhibiting broad coverage, indicating reasonable sample division conducive to building robust prediction models. presents the statistical results of apple moldy core samples.

4.3 Comparative Analysis of Apple Sugar Content Modeling Results

To eliminate irrelevant information and noise from raw spectra and improve model prediction performance, different preprocessing algorithms including SNV, MSC, and MEE were used to establish apple sugar content PLSR prediction models. presents the PLSR modeling results for apple sugar content using different preprocessing algorithms.

The raw spectra modeling performance was relatively poor, likely due to influences from stray light, noise, baseline drift, and physical attribute differences, resulting in reduced model prediction performance. After preprocessing raw spectra using SNV, MSC, and the proposed MEE algorithm, sugar content modeling performance improved, indicating that all three algorithms could improve spectral quality to some extent and enhance apple sugar content prediction model performance. The MEE algorithm achieved the best preprocessing results, with R_c, RMSEC, R_p, and RMSEP of 0.959, 0.430%, 0.929, and 0.592%, respectively. This demonstrates that the MEE algorithm' s spectral correction effect is superior to MSC and SNV algorithms.

The MSC algorithm assumes an approximate linear relationship between sample spectra and a set of average spectra, performing univariate linear regression between each sample spectrum and the average spectrum to derive multiplicative and additive coefficients, then subtracting the additive coefficient and dividing by the multiplicative coefficient to achieve spectral correction [29]. The SNV algorithm preprocesses individual spectra by subtracting the sample' s mean spectrum and dividing by the sample spectrum' s standard deviation [30]. Both algorithms share certain similarities in eliminating multiplicative and additive coefficients for spectral correction.

The proposed MEE algorithm achieves spectral correction by eliminating only the multiplicative coefficient and yields better modeling results than MSC and

SNV. This suggests that eliminating the multiplicative coefficient is more suitable for apple spectral correction, and that the multiplicative scattering effect caused by physical attribute differences has the greatest impact on apple spectra. The scatter plot of apple sugar content prediction results using the MEE-PLSR model is shown in [Figure 10: see original paper], where the x-axis represents actual sugar content values and the y-axis represents predicted values. The data points for both calibration and prediction sets cluster near the fitted line with relatively uniform distribution, indicating good prediction capability of the model for apple sugar content.

4.4 Comparative Analysis of Moldy Core Modeling Results

To improve apple moldy core prediction performance, different preprocessing algorithms including MEE were used to establish apple moldy core PLS-DA discrimination models. presents the PLS-DA modeling results for apple moldy core using different preprocessing algorithms.

Raw spectra modeling performance was relatively poor, with a prediction set discrimination accuracy of 87.50% and 5 misclassified apples. SNV preprocessing yielded similar results to raw spectra, also with 87.50% accuracy and 5 misclassifications. MSC preprocessing improved performance compared to raw spectra, achieving 90.00% accuracy with 4 misclassifications. The MEE algorithm achieved the best preprocessing results, with a prediction set discrimination accuracy of 95.00% and only 2 misclassified apples. Misclassifications may arise because diffuse transmittance spectral acquisition causes spectral variations due to apple physical attribute differences such as size, affecting moldy core discrimination model accuracy [31]. Compared with raw spectra and SNV, both MSC and MEE algorithms can partially eliminate the influence of physical attribute differences on spectra and improve modeling performance, with MEE demonstrating superior performance to MSC. The MEE algorithm not only improves apple sugar content model prediction performance but also enhances moldy core prediction performance, indicating that preprocessing algorithms can eliminate spectral differences caused by physical attribute differences to improve moldy core discrimination model accuracy, and that eliminating multiplicative scattering effects caused by physical attribute differences can enhance overall apple internal quality prediction model accuracy.

The prediction set scatter plot of the apple moldy core MEE-PLS-DA model is shown in [Figure 11: see original paper], where the red horizontal line represents the classification threshold of 0.42. All 20 moldy core apples had predicted values below 0.42 and were correctly classified, while 2 of the 20 healthy apples had predicted values below 0.42 and were misclassified. Of the 40 total apples, 2 were misclassified, yielding an overall discrimination accuracy of 95%.

4.5 System Grading Performance Validation

To validate the system' s grading performance, the established sugar content MEE-PLSR and moldy core MEE-PLS-DA models were imported into the system. Forty apples were selected for grading validation tests, including 5 cultured moldy core apples. After system grading, manual methods were used to measure apple sugar content and moldy core conditions, and apples were graded according to the established grading standards to obtain true grade information. The grading results are presented in .

The results show that premium-grade apples were relatively few in number with 100% grading accuracy; first-grade apples were more numerous with 90.63% accuracy; second-grade apples had one misclassification with 80.00% accuracy. The overall system grading accuracy was 90.00% with a grading speed of approximately 3 fruits/s. The test results demonstrate that the system achieves high grading accuracy and relatively fast grading speed, meeting the requirements for apple internal quality detection and grading.

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5 Conclusion

To satisfy the demand for on-site detection and grading of apple internal quality at orchard origins, this study developed apple internal quality detection and grading modules to constitute a movable orchard-origin grading system. The system acquires apple diffuse transmittance spectral information and implements apple sugar content and moldy core detection based on built-in prediction models, performing grading according to the established grading standards.

When using this system for apple internal quality detection and grading, multiplicative scattering effects caused by apple physical attribute differences affect detection accuracy. This study proposed a spectral correction method based on multiplicative effect elimination. To validate the method' s effectiveness, apple spectral information was collected using this system, and MSC, SNV, and MEE algorithms were applied for spectral processing to establish PLSR models for sugar content and PLS-DA models for moldy core. The results demonstrated that the MEE algorithm achieved the best modeling performance, with sugar content R_c, RMSEC, R_p, and RMSEP of 0.959, 0.430%, 0.929, and 0.592%, respectively; moldy core sensitivity, specificity, and accuracy of 98.33%, 96.67%, and 97.50% for the calibration set, and 100.00%, 90.00%, and 95.00% for the prediction set, respectively. When the optimal prediction models were imported into the system for grading tests, the results showed a grading accuracy of 90.00% and a grading speed of approximately 3 fruits/s.

In summary, the proposed spectral correction method is more suitable for apple transmittance spectral correction. The movable apple internal quality orchard-origin grading system, combined with the proposed spectral correction method, can accurately detect apple sugar content and moldy core and grade apples accordingly. The system features compact size, low cost, and convenient mobility, meeting the requirements for on-site detection and grading in complex orchard environments.

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Note: Figure translations are in progress. See original paper for figures.